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Evidence of Herding Behaviour in Stock Markets

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by

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Acknowledgement

At this point, I have reached the final step of my thesis, which means that my PhD journey is coming to an end. The Chasing dreams at University of Hull in the autumn of 2017 and finished before the Christmas of 2021. The sense of entering University in 2017 seems like yesterday. In the past years I have longed for, rejoiced, and struggled. I have mixed feelings, but I am most grateful for people who have given me help and warmth throughout the PhD journey.

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It has been such a long journey, and after enduring great hardship, I have finally presented this doctoral thesis here. The idea is not noble, but despite the

vicissitudes of advancing age, I still remain a young man with passion. Hopefully, there are still opportunities to establish a new understanding of this world so that all my efforts have not been in vain. Last but not least, it would be a big achievement if I can make contributions to the better life of others.

Abstract

This thesis investigates herding behaviour among major world stock markets from 2002 to 2018. It also studies the herding behaviour at sector level from 2001 to 2020. In the first chapter, we introduce the background and motivation for this study. In the second chapter, we review herding behaviour and relevant prior research. In chapters 3, we use the standard CCK method on a recent data sample to detect herding behaviour in a comprehensive study of the world's major stock markets that have previously been investigated for herding. This allows comparison with previous results in the literature. We have captured clear evidence of anti-herding behaviour in most of the world's major stock markets, and the presence of herding behaviour in emerging markets during larger price movements in the market. Then in chapter 4, we explain and evaluate the theoretical and empirical difference between using the log and simple return calculation methods in tests for herding. Most of the theoretical work on herding would tend to indicate that one would expect to observe herding in the financial markets. In practice, most empirical studies to date have not found this to be the case. This could be due to problems with the procedures used to test for herding. In chapter 5, theoretically and empirically, we discuss the major drawbacks of the CAPM based CCK method which is the method most commonly used to find herding in the literature. We show that the test is highly biased against finding herding. The bias arises because the test assumes that, in the absence of herding, stock prices follow the CAPM but does not account for the implications of the CAPM not being a perfect asset pricing model. We provide alternative and tractable ways to overcome the disadvantages of the CCK method. Also, we show these methods theoretically may give very different conclusions to the CCK method. In chapter 6, we then apply the new testing methods we have developed to the comprehensive world data we have previously investigated for herding using the CCK method in chapter 3. The empirical results give quite strong evidence of herding which is

in contrast to our results in chapter 3 and most of the prior literature. In chapter 7, we investigate herding at the industry sector level for the major European economies of Britain, France and Germany. This allows us to detect whether certain sectors are particularly likely to herd. We can also detect how different sectors react over different time periods which is clearly a question of interest given the experience in the financial crisis and later in the COVID pandemic. We again use the CCK method and the new methods we have developed. We capture clear evidence of herding behaviour in different time periods, we have observed significant herding behaviour in most sectors among the different markets. We can observe there is more herding behaviour in different sectors than in the entire market. We also find there is more herding behaviour when the market is in turmoil or has larger movements which is consistent with prior literature. Then we compare the strength of herding behaviour between the Financial Sector and the Banking Sector. These sectors are of particular interest because of their interconnected nature and the fact they have been implicated in system risk particularly in the case of banks. There are, however, some important differences between the two sectors involving their business models, the extent and nature of regulation and perhaps the extent to which they are monitored by sophisticated investors. The results show that the Financial Sector has more herding behaviour than the Banking Sector under most market conditions. In chapter 9, we Investigate the impact of herding on market volatility. Drawing on previous research in the area we use GARCH models linked with measures of herding. Past work in this area directly uses dispersion as a measure of herding and we initially duplicate these studies. However, dispersion is unlikely to be a good herding measure as it is probably itself driven by volatility, regardless of whether herding is present. Hence, we adopt a new approach by measuring herding using the residual values from a model estimating the amount of dispersion expected if no herding is present which is a more valid approach. We find that using CSAD results as the proxy of herding,

market volatility has a positive relationship with herding behaviour in the market while using residual values as the measure of herding, we have mixed results for the contemporaneous link between herding and volatility which is consistent with prior research. We do, however, find that market volatility is positively influenced by our lagged measure of herding. The final chapter presents the conclusions of our research.

Keywords: Herding; CCK test; CSAD; CAPM; Stock Markets

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1.0 Introduction

The concept of herding is the idea that investors suppress their own beliefs and instead are guided by the collective behaviour of other market participants. Herding behaviour in financial markets occurs when the information environment is uncertain, and the behaviour of investors is influenced by other investors. This causes the imitation of others' decisions, or over-reliance on the overwhelming notion in the market, regardless of the investor’s private information. Because herding behaviour involves multiple investors, it may have a significant impact on market stability and efficiency and is closely related to financial crises (Chose et al, 1999; Kaminsky et al, 1999). Therefore, herd behaviour has attracted widespread attention from academics and government regulators. In an early empirical study, Christie and Huang (1995) examine the investment herding behaviour in the US stock market and put forward the cross-sectional standard deviation (CSSD) method to measure herding behaviour among investors under different market conditions. Chang et al. (2000) improved the model developed by Christie and Huang (1995), they extended the model by applying a non-linear regression specification to estimate the cross-sectional absolute deviation (CSAD) (for convenience we refer to this as the CCK test), and this has become one of the most popular methods to detect herding behaviour in recent empirical research.

Chang, et al., (2000) did not find any clear evidence of herding behaviour in developed markets such as US and Hong Kong market, but just captured herding behaviour in emerging markets like South Korea and Taiwan. In the European markets, Economou, Kostakis and Philippas (2011) found partial evidence of herding behaviour in the Portuguese market, but they do not capture the existence of herding behaviour in the Spanish market. Galariotis, Krokida and Spyrou (2016) also find no evidence of herding behaviour in the primary G5 markets, including France, Germany Japan, UK, and the US, some evidence of herding was only found in the German market. Guney, Kallinterakis and

Komba (2017) only find limited evidence of herding behaviour in an Africa frontier market. Lee (2017), using the Fama-French three-factor model instead of the CAPM model, found little evidence of herding behaviour during rising market conditions in the US stock market. Some research has found the existence of herding behaviour in selected markets during extreme market conditions or when the market has been suffering turmoil. Bekiros et al., (2017) indicates that in the US market, herding is more likely to appear during periods of market turmoil period such as during the financial crisis. Clements, Hurn and Shi (2017) find that herding in the US market was influenced by the global financial crisis as well as the Eurozone crisis. BenMabrouk and Litimi (2018) also find herding behaviour in the US oil market during extreme market conditions. In the European markets, Mobarek, Mollah and Keasey (2014) shows that the herding behaviour is mainly evident in the Eurozone crisis. In summary, we see that many of the prior research studies do not find any clear evidence to show the existence of herding behaviour in the selected market, or just find partial evidence in certain circumstances. Some papers have captured evidence of herding behaviour under extreme market conditions such as when the market was influenced by the financial crisis.

Below we describe the investigations undertaken in this thesis. In chapter 3, we use the standard CCK method developed by (Chang et al, 2000), and use the log returns calculation method to estimate herding behaviour in major world stock markets including Denmark, Finland, the US, Germany, France, Greece, Italy, Norway, Portugal, Spain, Sweden, Hong Kong as well as the UK market. The main findings supports most of the prior research that there is limited evidence of herding in major markets, herding tends to be present in emerging markets, and we are more likely to capture evidence of herding behaviour under market conditions with larger price movements. In chapter 4, we explain and evaluate the theoretical and empirical difference between using the log and simple return calculation methods in tests for herding. Most of the previous literature on herding used the log return calculation method in their analysis. Much of this literature found that herding was strongest in times of market turbulence which is when variance will be highest which is also when the difference between log and simple returns will be greatest. The mean value of the securities return calculated by using log return is smaller than using the simple return by an amount depending on the variance of the returns, but the variance is hardly influenced by the two different return calculation methods. This indicates that there is not a one-to-one relationship between the two methods and the difference will be greatest when the variance of the returns is greatest. Thus, it is logical to compare herding results based on both log return and simple return calculation methods to see the extent to which they are driven by the calculation method. Thus, in chapter 4, we use the same CCK model and simple return calculation method to investigate herding behaviour in our data sample around the world and compare the results to those reported in chapter 3. The empirical results of logarithms and simple calculations are relatively similar, but not identical. We can see that for nearly all of the formulae some of the tests for anti-herding or herding change significance when simple returns are used instead of log returns. Thus these findings can have both economic and statistical significance in some circumstances.

In chapter 5, we discuss the major drawbacks of the CAPM based CCK method which is the method most commonly used to find herding in the literature. We challenge the standard approaches to testing for herding by introducing some new ways to investigate herding in different international markets. The results indicate that there is more herding behaviour in the markets than has generally been found in the previous literature. The test for herding using the traditional standard CCK method is testing whether a graph related to the method is a line that curves upwards, shown as:

Figure 1.1: Fitted line for CCK regression results:

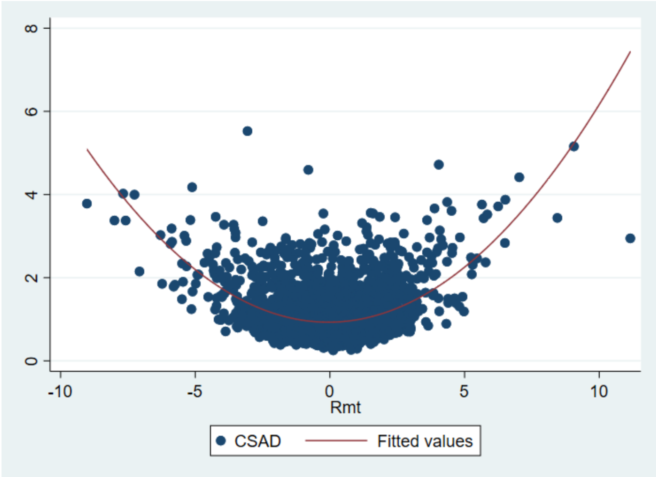


Figure 1.1

Horizontal axes are the equally weighted average market return.
Vertical axes are the cross-sectional absolute deviation (CSAD).

However, no matter whether the market has herding or not, it curves anyway. The reason that CSAD regression line is curved even when there is no herding is because of the error term in the Capital Asset Pricing Model (CAPM). Thus, the standard CCK test is highly biased against finding herding. The bias arises because the CCK test assumes that, in the absence of herding, stock prices follow the CAPM but does not account for the implications of the CAPM not being a perfect asset pricing model. The CAPM model describes the relationship between systematic risk and expected return for assets, particularly stocks, and has been in use for many years by investors as a universal tool to analyse risks associated with an investment in the stock market. When the single security return follows the CAPM model in the CCK method and the average market return tends to zero, the influence of the error term in CAPM causes the CSAD result to be higher than anticipated, and this will lead the final result regarding herding to the wrong conclusion. Based on this traditional method, most of the previous literature analysing international stock markets have not rejected the null hypothesis of no herding. Given the evident problems of the normal approach to testing for herding, we suggest several very simple but robust alternative approaches to test for herding that avoid the bias in the normal method. Our proposed approaches are as simple to apply as the CCK test and so can be easily taken up by researchers which is important given the extensive use of the CCK test. The first way is to estimate the herding behaviour in the market by fitting the standard CCK regression model without a constant value, which can provide more accurate results and without the influence of the error term in the CAPM model. Also, our calculations show that there is strong evidence of herding behaviour in the international market by using the symmetry approach test method (SCSAD), which can reduce the influence of the error term in the CAPM. The third way is to detect herding under market conditions where there are larger movements in the market. We select data to estimate herding when the market return is larger than a specified value and also when we look at the largest market returns as a proportion of all the returns. In chapter 6 and 6* (in the appendix), we fit our three alternative approaches to estimate the existence of herding behaviour in the major world stock markets. We show that the new tests give radically different results to the CCK test finding herding in many of the world's major financial markets even though the CCK test rejects herding. Also, in these two chapters, the empirical results support our discussion in chapter 4, which shows different results based on log and simple return calculation methods. In chapter 7, we fit the CCK model and our new tests to estimate herding behaviour by using new data sample which is narrowed down to sector level among the markets of Germany, UK and France. The major finding shows that there are different levels of herding in different sectors, especially during periods of market turmoil. Also, the entire market has less herding behaviour than herding in different sectors. In chapter 8, We also compare the strength of herding between the Financial sector and the banking industry. These sectors are of particular interest because they are interconnected and they are associated with systemic risk, especially in banking. However, there are some important differences between the two sectors regarding their business models, the scope and nature of regulation, and the degree to which they may be monitored by sophisticated investors. We observe more herding behaviour in the whole Financial sector than in the banking industry. In chapter 9, we investigate the impact of herding on market volatility. We have adopted a new method of measuring herding effect using residual values of a model that estimates the amount of dispersion expected in the absence of herding effect, which is a more efficient method. Based on previous research in this particular field, we use a GARCH model associated with herding measures. Past work in this area has directly used dispersion as a measure of herding, and we initially replicated these studies. However, dispersion is unlikely to be a good herding measure, as it may itself be driven by volatility, with or without herding. Using residual values from our first solution developed in Chapter 5, which are a more valid measure of herding, only a few sectors in the market show that herding contemporaneously contributes to market volatility. However, using lagged the lagged residual values, we have captured clear evidence that herding contributes to market volatility among different sectors in different markets.

The structure of this thesis is as follows: chapter 2 is a review of the relevant literature, most of which used the traditional CCK method based on the log return calculation method; chapter 3 presents the widely used CCK method to investigate the herding behaviour in the international stock market based on the Log return calculation method; chapter 4 reports the herding estimation results under the CCK method based on simple return calculation method; chapter 5 reviews the drawbacks of the standard CCK method and introduces some alternative ways to detect herding which can avoid the disadvantages of the CCK method. Also, we use a simulated market to compare the results under different approaches. In chapter 6 and 6*, we use these new methods to detect herding across the major world stock markets based on the log return calculation method, and also estimate herding behaviour based on the simple return calculation method. After this, in chapter 7, we use the CCK method and the methods we have developed to investigate herding behaviour narrowed down to sector level in the markets of the UK, Germany and France. This allows us to detect whether certain sectors are particularly likely to herd. We can also detect how different sectors react over different time periods which is clearly a question of interest given the experience in the financial crisis and later in the COVID pandemic. In chapter 8, we compare the strength of herding in the banking industry and the Financial sector which excludes the banking industry. In chapter 9, we investigate the impact of herding behaviour on market volatility. Finally, chapter 10 presents our conclusions.

2.0 Literature Review

2.1 Introduction

This literature review is structured to support the various objectives and research questions of the thesis. The review provides an outline of each area of study, showing why it is justifiable to essentially combine them to determine the most appropriate way to explain herding behaviour. Initially, in Section 2.2, we look at the relevant underlying financial theories of neoclassical finance and behavioural finance which give the setting for the herding literature. In Section 2.3, we then look at the theory specifically relating to herding and anti-herding. In Section 2.4, we discuss we discuss the links between herding and the nature of investors. In Section 2.5, we examine previous empirical work on measuring herding. Section 2.6 presents our conclusions.

2.2 Underlying Relevant Financial Theories

2.2.1 Neoclassical Finance

Neoclassical finance, which is the mainstream of modern academic finance, is a theoretical system developed on the basis that investors are rational utility maximisers. In this approach modern portfolio theory and the market efficient hypothesis are key to understanding how investors determine different types of securities prices under the optimal portfolio decision and capital market equilibrium. Modern portfolio theory (MPT) was first introduced by Harry Markowitz in 1952. The theory shows the relationship between the expected return and standard deviation of a stock or a portfolio and relates to stocks or mutual funds. An efficient portfolio could contain any type of financial asset such as stocks or bonds and can provide maximum expected return or have the lowest risk for a given expected return. The Efficient Market Hypothesis (EMH) indicates that the price of security or the market value reflects all the available information in the market. Also, the current price of the bond or stock is trading at today's fair value. Since stocks are considered to be at their fair value, proponents argue that active traders or portfolio managers cannot receive higher expected returns through the market over time without taking extra risk. Therefore, they believe investors should just own the "entire market" rather attempting to "outperform the market". Behavioural finance has begun to emerge as an alternative to the theories of neoclassical finance as discussed in the section below.

2.2.2 Behavioural Finance

The combination of finance and other social sciences to produce behavioural finance has given us a better understanding of financial markets. Compared to standard finance, behavioural finance is a young research field. It uses behavioural portfolio theory instead of the mean-variance portfolio model, and substitutes behaviour asset pricing models for the CAPM and some other models which only use risk to determine the expected returns (Ricciardi and Simon, 2000). Behavioural finance is under construction as a solid structure of finance. It incorporates parts of standard finance, replaces others, and includes bridges between theory, evidence, and practice. As a multidisciplinary research area, it combines psychology and finance to investigate the issues which could have influence on the decision-making process. Also, behaviour finance explains the irrational nature of individuals, groups and organizations (Fabozzi, Gupta, & Markowitz, 2002). This approach provides ideas to look at the reasons that people make different choices about money and at the same time to determine whether those choices might be irrational and illogical. Also, it describes the decision process for different people when they are making investment decisions under different market situations, and consider the possible issues that investor might be faced with, such as why they consume more money from the dividend dollar, why they are more willing to invest in companies focused on social responsibilities, or to invest in hedge funds (Fabozzi, 2008).

The study of stock markets can also be improved by behavioural finance, as it helps people to have a better understanding of how cognitive or reasoning inaccurately have an influence on investors' decision making and stock prices. From a broader perspective of social sciences, including psychology and sociology, behavioural finance is now one of the most important research programs. It's findings forms a sharp contradiction with many of those based on efficient market theories. In efficient market theory, speculative asset prices, such as stock prices, always contain the best information about basic values, and prices change only because of new information. Consider the stability of dividends and stock prices. Managers use dividends to provide more stable business expenditures. Under this kind of situation, it can be expected that stock prices will change faster than dividends. A seminal paper by Shiller (1981) shows that stock prices have greater volatility than the efficient market hypothesis can explain. Further, Marsh and Merton (1986) argue that a more stable and smooth dividend payment increase, could make the stock price become more unstable, and within finite samples, the stock price is shown more volatile than the present values. They tend to confirm the overall assumption that stock prices have greater volatility than the efficient market hypothesis can explain. For efficient market theory, the anomaly represented by the concept of excessive volatility seems to be more troublesome than other financial anomalies. The evidence of excessive volatility seems to imply that there is no fundamental reason for price changes, and the reason for the changes is "sunspots" or "animal spirits" or simply public psychology (Shiller, 2003). With relation to the study of Tuyon & Ahmad (2016), the impact of behavioural factors on UK stock market prices can be seen as an influence on investors who make financial investment decisions after seeing the trend of the latest falls in the currency. In general, there may be a direct connection between the stock market and behavioural finance, in that, the market could be influenced by psychology. As Meir Statman so succinctly puts it, "Standard finance people are modelled as “rational,” whereas behavioural finance people are modelled as “normal”.” Traditional or standard finance assumes that at a given level of risk, rational investors will always try to maximise their expected return of their investment by fully evaluating all of the available information related to the market. From a traditional financial perspective, the behaviour and results of normal people may seem unreasonable or unsatisfactory. Due to the obvious difference between the observed decision and the theoretically optimal decision, the global investment community has begun to realize that it cannot completely rely on scientific, mathematical or economic models to explain individual investor and market behaviour. Hargrove & Haslem (1977) indicates that the investors tend to have a better balance between risk and return if they behave rationally regarding investment. In behavioural finance, some of the hypotheses are not consistent with rational mathematical analysis but are supported by empirical studies (Fabozzi, 2008). Behavioural finance aims to have a better understanding how people make decisions as individuals as well as collectively. By understanding the behaviour of investors and markets, it may be possible to modify or adapt investor behaviour to improve economic outcomes. Under various different situations, this may require identifying the behaviour and then modifying the behaviour in order to make it closer to the assumptions under traditional financial models. In other cases, it may be necessary to adapt to the identified behaviour and make decisions that adjust to the behaviour. The integration of behavioural finance and traditional finance may produce excellent economic results; the final financial decision may produce economic results that are closer to the optimal results of traditional finance, and at the same time make it easier for investors to practice. One particular instance of behaviour finance is introduced by Hong et al. (2005), with a simple model to evaluate stocks in which investors verbally spread information about stocks. This can explain a series of situations such as momentum trading as well as bubbles in assets. Daniel, Hirshleifer and Subrahmanyam (1998) indicate that investors are divided into two types: those who have information sources (informed investors) and those without. Informed investors can be further divided into two categories: those with overconfidence and those with self-attribution biases. Overconfidence leads to negative long-lag autocorrelations, excessive volatility and predictability of returns based on public events when management behaviour is associated with stock mispricing. Self-attribution leads to earning drift in the short term. However, there is a negative correlation between future returns and the stock market and accounting performance in the past, which may increase the positive short lag autocorrelation, thus insufficient response to public information. Hong and Stein (1999) divided investors into news watchers and momentum traders. The former base trades on information about future values and do not rely on past price changes. The latter relies on past price changes. The model used unifies herding and anti-herding effects into a gradual spread of basic value information and does not include other emotional stimuli for investors or the need for liquidity trading. The model shows that the bounded rationality of the news watchers causes prices to underreact to private information in the short run. This makes the momentum traders attempt to take advantage of this through a set of strategies which make the market overreact.

2.3 Herding

Kallinterakis & Ferreira (2007) indicate that since behavioural finance was introduced during the 1980s, a great deal of attention has been paid in the financial and academic research domains to herding behaviour. According to the observations made by Kallinterakis & Ferreira (2007), in the financial market, herding behaviour suggests that the investors in the market follow other market participants' behaviour. Under extreme market conditions or when the market has great fluctuations, this kind of behaviour tends to be strong, as the market fluctuations and information flow during this period could block the reliability and accuracy of investment forecasts (Mobarek, Mollah and Keasey, 2014). Kallinterakis & Ferreira (2007) mentioned that peoples' investment behaviour could be influenced by the market-trend. If they have been making investment decisions based on the historical price, this could cause the development of a market-trend, and when the investors herd on this behaviour, it would enlarge the trend. When the market participants make investment decisions trends could have an influence on the psychological state of mind of the investors. The research results of Kallinterakis & Ferreira (2007) clearly show that investors' herding behaviour could have a primary influence on any nation's stock market. When the stock price increases in investors' domestic market, they would buy the stocks and conversely sell stocks when the market is down. Thus, when these investors try to follow others investment behaviour, the financial markets could be affected by them. In addition, the investors could have more willingness to ignore their own information and seek consensus in the market, rather than to collect reliable and accurate information during periods of market fluctuation and instability. Under situations of market fluctuation and instability, with investors' herding behaviour, the market price for the underlying assets could be led in the wrong direction, compared to the underlying asset value. In these types of circumstances, herding behaviour in the financial market could increase the formation of bubbles (Gleason, Mathur, and Peterson 2004).

After reviewing theories and evidence relating to herd behaviour. Hirshleifer and Teoh (2003) indicate that herding involves a "similarity in behaviour". Hence people observe the investment decisions or portfolio selection of other people, no matter whether they are profitable or not, and then mimic their behaviour to make their own investment decisions. It is not always possible to decipher the causes of imitation, as it can be ascribed to a variety of motivations both psychological as well as rational. In financial markets, there are several potential reasons for rational herding behaviour the most important of these are compensation structures, concern for reputation and imperfect information.

2.3.1 Types of herding

The basic form of the efficient market hypothesis (EMH) assumes that the market is perfect, there are no transaction costs, all information is available and is costless, and that market participants are rational. This hypothesis could eliminate the notion that the herding behaviour could cause irrational market conditions, as the large majority of market participants are rational and well informed, the commodities in the market are homogeneous and any transactions are free of charge, the securities are priced at fair value and the price will reflect information related to the relevant securities fully and quickly. Based on the EMH theory, security prices move randomly and cannot be predicted by analysing the past performance of the security (Devenow and Welch, 1996). However, some situations in financial markets are difficult to explain using the EMH, such as the fact that market movements in general and those caused by IPOs or mergers and acquisitions tend to have greater fluctuations than one would expect based on fundamental analysis. In addition, many influential market participants continuously emphasize that their decisions are highly influenced by other market participants. This means that these types of investors' decisions are not based on private information indicating that independent decision-making across all market participants is fiction. Devenow and Welch (1996) also indicates that the investment decisions made by some investors have higher influence on the market, they also emphasized that their investment decisions were also affected by other market participants. In order to explain this type of market situation, some recent papers such as Bikhchandani and Sharma (2000) provides an overview of the recent theoretical and empirical research and identify three types of rational herding which are compensation-based herding, reputation-based herding and information-based herding. Devenow and Welch (1996) divided herding into rational herding and irrational herding. Information-based herding is more likely to tend to be rational herding as rational market participants with similar investment preferences have similar responses to information about the characteristics and fundamentals of companies. When investors have similar responses to the new information, herding will push the price to the value of the asset and the price trend is unlikely to reverse (Lin, Tsai and Lung, 2013). In contrast, when investors have insufficient information and unclear risk preferences, they may not be clear what they will be facing in the market. This will make it easier for them to ignore their previous beliefs and blindly follow the behaviour of other investors and irrational herding behaviour will occur (Lin, Tsai and Lung, 2013). Welch (1996) also indicates that investors who support the existence of irrational herding behaviour could believe that market participants blindly follow others' decisions and give up rational analysis.

2.3.2 Rational Herding

(1) Compensational

Compensation-based herding is based on professional considerations. Investment professionals working in financial institutions such as fund managers or financial analysts, are subject to periodic evaluation (Scharfstein and Stein, 1990) which is normally of a relative nature. If an investment manager’s compensation depends on how their performance compares with other similar professionals, then this could distort the agent's incentives. Under such situations, those managers with lower abilities or lower performance compared to other investment professionals, will have a significant incentive to copy the actions of peers who have better performance, if this will help them appear as “better” professionals. On the other hand, “good” investment professionals may also choose to follow the investment decisions of the majority of their peers, even if these are sub-optimal if the risk from a potential failure is perceived as higher than the benefits accruing from a potential success by “going-it-alone”. Doing this may lead to herding behaviour and may also produce an inefficient portfolio.

(2) Reputational

Considering reputation is relevant as well, as it may encourage investment professionals to herd. Under this type of situation, people make their investment decisions based on the consideration not only of expected risk and return but also their future reputation. For a particular manager who has uncertainty about their own ability and skills, reputation or career concerns will arise. Normally, if an investment manager of a financial institution such as a hedge fund, is not sure about whether they have the ability to choose the right portfolio or pick the right stocks, the best approach is to mimic other managers' investment decisions, which could reduce the uncertainty regarding the ability of the manager to manage the portfolio. This behaviour could benefit the manager. If other investment professionals are in a similar situation, then herding occurs. A professional who enjoys a strong reputation in his capacity also has an incentive to imitate others in order to preserve his reputation (Graham, 1999), if the damage to his reputation by a potential failure outweighs the expected benefits from potential success. Assuming that the well-reputed professionals are also the more able ones, this may help explain the herding tendencies denoted previously with regards to “good” investment professionals. Ill-reputed professionals, however, may also resort to herding as a means of free-riding on the reputation of better-reputed colleagues (Truman, 1994). As a consequence, decisions made based on reputation are more likely to be sub-optimal, as they have given more consideration to personal reputation rather than investment quality. However, it can only explain the herding behaviour for employees of financial institutions like fund managers, it cannot explain the herding behaviour of private investors, as this group of investors do not need to consider reputation when they make decisions.

(3) Imperfect information

If investors find it could benefit them to mimic the investment decisions of others or use information accruing from such an imitation, then they could find it rational to follow others. Under this kind of situation, investors may have no private information, or they believe others may better informed, receive better quality information and could have better ability to analysis the information. This would lead the investors to suppress their own information, and this is bound to have an adverse impact on the public information pool by slowing/temporarily blocking the aggregation of information in it, thus fomenting the rise of informational cascades (Banerjee, 1992; Bikhchandani et al, 1992). This is known as information-based herding, Park and Sabourian (2009) analyse and confirm the presence and extent of rational informational herding in a financial market test. Compared with the market under normal trading conditions, although there could be some similar trading behaviour caused by irrational decisions, when the existence of herding behaviour increases in the market, it is most likely that herding is led by those people who have the theoretical potential to herd. As mentioned above, herding behaviour will make these investors suppress their own beliefs so that they can follow other market participants' investment actions. As a result, with the existence of herding behaviour in the financial market, the underlying assets will tend to be not priced appropriately, because the investors' decisions are not made based on all the available information included in the market, which makes their actions tend to be irrational. Therefore, it is of paramount importance to detect herding behaviour in the financial markets, since if herding behaviour exists, which would lead to an inefficient market. Under this situation, the financial models based on rational economic behaviour or the efficient market hypothesis such as asset pricing models cannot apply properly (Vidal-Tomás, Ibáñez and Farinós, 2019). Zhou and Lai (2009) confirm the existence of informational cascades which shows the significantly important role of outstanding market leaders in "noise" trades by informed investors. They also found that during periods of economic downturns, herding behaviour is often more common in the market, and investors are more inclined to herd when selling rather than buying stocks. Herding is the tendency of a group of market participants to trade in the same direction during a period of time, feedback trading is a response to the return of risky assets, while information cascading is the sequential reaction of agents to agents under the leadership of other investors who are completely independent of private information. These phenomena could provide an explanation of some financial phenomena such as excess returns in the market.

2.3.3 Irrational Herding

This refers to psychology-driven factors or conformity which can be seen as irrational behaviour. That is to say, the condition whereby following what other people do makes people feel more confident compared with making investment decisions by themselves. As the communication between each other tends to be more accurate and efficient, this could lead to a tendency towards conformity (Daniel, Hirshleifer and Teoh, 2001), and is well related to the normal interactions between people.

Lin, Tsai and Lung (2013) suggest that rational herding is more likely among institutional investors who have sufficient information and irrational herding will tend to be led by individual investors, as they are more likely to be influenced by investor psychology and to be less informed. When investors exist in the market who are less informed, and evaluate their investment risk insufficiently, they may give up their own beliefs and mimic other market participants' investments decisions blindly. This could increase the presence of the irrational herding behaviour. The existence of irrational herding behaviour could lead to market inefficiency, the price of securities could be moved in the wrong direction and assets mispriced. DeLong et al. (1990) suggest that the investors' irrational behaviour could be mainly influenced by trading noise in the financial market, which is caused by asymmetric information. The truth is that herding behaviour among individual investors often involves limited information and the friction that accompanies investor trading (Lin, Tsai and Lung, 2013). Stoll (2000) also indicates that trading noise would lead to trading friction affecting investors' trading. With an increase of the level of information asymmetry, the friction will increase and cause more irrational trading behaviour. Zhou and Lai (2009) confirm the existence of informational cascades, they show the significantly important role of outstanding market leaders in "noise" trades by informed investors. They also found that during periods of economic downturns, herding behaviour is often more common in the market, and investors are more inclined to herd when selling rather than buying stocks.

2.3.4 Anti-Herding

As discussed above, herding describes the situation where market participants mimic and follow the investment decisions of other people without using their own private information. In a sense anti-herding is the opposite phenomena. Anti-herding occurs when a group of investors makes investment decisions using their private information, but another group of investors choose to contradict the first group, even if their information proves conclusively to them that the first group was right (Effinger and Polborn, 2001). Herding behaviour can be considered to be an overreaction to the information contained in the whole security market, while anti-herding behaviour is an underreaction in which the value of this information is underestimated. When market herding occurs, investors ignore their information and make investment decisions which follow the market leaders, and this could place the market in a state of 'excitement' and possibly overreaction. However, investors exhibiting anti-herding behaviour lack response to any type of information related to the market, and an inability to make corresponding investment decisions which could make the market fluctuations much smaller than it under the situation where herding exists. Compared to herding behaviour, anti-herding behaviour shows more tendency for prices to be dispersed. Investors have fewer reflections on any news relating to the market, resulting in irregular investment decisions, or possibly no decision being made by investors based on this news. Even if the investor believes that the information or advice is correct, they may still go against it. Barberis, Shleifer and Vishny (1997) believe that investors pay too much attention to recent changes in stock market data, which leads to neglecting the characteristics of the overall data, resulting in selective bias, which makes stock prices unable to respond to changes in related good or bad information promptly, and leading to deviations from market efficiency.

Levy (2004) notes how anti-herding is a behaviour associated with a unique informative equilibrium, even if the decision-maker cares only for reputation and has no outcome concerns, such as they are unduly resistant to public information, such as prior or other advice in order to ensure their independence and objectivity as well as the accuracy of their own information. Under this kind of situation, when investors make decisions, once the motivation of the decision is related to concern for reputation, the decision-maker will tend to anti-herding. Moreover, some decision makers act unilaterally rather than consulting a consultant, even though their information is free, since the information may not be provided truthfully. Even if consultants and advisers only care about results, they will prefer their own opinions and suggestions because they expect decision-makers to adopt inefficient anti-herd behaviour.

As Zwiebei (1995) indicates, in many cases, the reputation gained from performing well seems likely to be more important than the reputation gained from equal success with peers. Therefore, investors will make decisions which tend to anti-herd and reject advice. By analysing nine metal prices with over 20,000 forecasts at four different forecast horizons, Pierdzioch, Rülke and Stadtmann (2013) did not find any herding behaviour The forecasters tend to adopt anti-herding behaviour, and the level of this anti-herding behaviour differs over time. Their findings also suggest that the forecaster's anti-herding is the origin of the empirically observed cross-sectional heterogeneity of forecasts. In the commodities market, Babalos, Stavroyiannis and Gupta (2015) did not find evidence which shows the existence of herding behaviour. However, they detected significant evidence of anti-herding behaviour in the market by using rolling window analysis and robust time-varying stochastic volatility models before the global financial crisis.

In the US mutual fund market, Jiang and Verardo (2018) analysed the relationship between herding behaviour and the fund managers' skills. Herding behaviour in the market heavily influenced and has a negative correlation with the predicted mutual fund cross-section returns. They found returns were significantly different between the fund managers that managed herding and anti-herding funds and indicated that anti-herding funds made consistently better investment decisions. When fund managers have more experience and trading skills, and mutual fund managers have better opportunities to invest, the performance gap between the funds with herding and anti-herding behaviour will become larger, and this gap will hold for a long period. Also, with inexperienced managers, the gap will increase, suggesting that the choice of herding or anti-herding could be more important for those managers with stronger career concerns. By applying Monte Carlo simulations, Stavroyiannis, et al., (2019) found spurious anti-herding behaviour might emerge even if the series is random and uncorrelated providing the residuals of the model fail to conform to some of the assumptions of standard linear regression. In this study simulations from a t-student distribution are examined as a function of the degrees of freedom, the length of the simulations and the number of series.

2.4 Herding and the Nature of Investors

Empirical research and the literature on behaviour finance has already provided a number of theoretical models as well as empirical results about herding behaviour based on different types of investors in different market situations in financial markets. Examples include institutional or individual investors and explanations of their herding co-movement based on different theoretical backgrounds. To analyse herding behaviour among institutional investors, we need a data sample detailing each transaction made by this group of investors. Therefore, these analyses generally have the disadvantage of the difficulty of collecting the related dataset and identifying the concerned traders (Kremer and Nautz, 2013). Also, for the analysis among the individual investors, a similar type of data is needed, which consists of transaction details or full investment portfolio data. Because of the various empirical designs among studies, there is no universal model to detect the existence of herding behaviour among individual investors (Yao et al., 2014; Litimi et al., 2016). For institutional managers with reputational risk, private information may be ignored with these managers preferring to trade with the crowd (Sharfstein & Stein, 2000) to ensure more consistent results. Also, basing trades on the same factors could influence the price determined by institutional managers, as they may receive similar private information (Hirshleifer et al., 1994). Institutional managers have been suggested to infer private information from trades of other managers and this could produce informational cascades (Bihkchandani et al., 1992). Finally, stocks with lower liquidity or higher risk, may cause similar aversion amongst institutional managers (Falkenstein, 1996).

2.4.1 Herding among analysts

A number of authors have considered the effects of herding behaviour among analysts. Graham (1999) apply a model to check whether the investment recommendations given by a market leading analyst with a high reputation could be the newest opinion considered by the market followers. According to their empirical results, analysts are more likely to herd when they have a higher reputation but have less analytic ability. Also, under situations such as when the public information available in the market is not consistent with their own information, it could increase the probability of their herding. Similarly, regarding which analyst recommendations could have influence causing herding behaviour in the financial market, Welch (2000) provides evidence that, among securities analysts, a buy or sell trading recommendation revision given by an analyst will have a positive influence on the next two analysts' revisions. The effect tends to be stronger when the recommendation revision provides an accurate prediction of the short-run ex-post stock returns, and the revision has occurred very recently. At the same time, the prevailing consensus also has a positive influence on the analyst recommendation revision. When market conditions show good expectations for stock prices, this will weaken the impact of consensus. Therefore, the effect of consensus may not have much to do with analysts' prediction attempts, and it will only help them improve and revise their suggestions. It supports the theories that rational behaviour and aggregation of efficient information are not the reasons causing herding behaviour among analysts. In contrast, the prevailing consensus could have a stronger influence when market conditions have been bullish. Their finding indicates that during rising market conditions, the ability to aggregate information is poor, this could lead the market to be more fragile. As a result, the chance of a crash in rising market conditions would be higher than in falling market conditions. Industrial and geographical diversification may cause herding behaviour amongst analysts. Research carried out by Kim and Pantzalis (2003) shows evidence to support the notion that with an increase in the industrial and geographical diversification level, the probability of herding will increase. The results also indicate that the existence of herding behaviour among the analysts of a company would have a negative effect on the value of the company, this can be seen as the penalty from the market to the securities analysts who have exhibited herding behaviour. As the diversification of companies by industry and geography increase, this penalty will become much stronger. Diversification can exacerbate herding tendencies because it increases the complexity and difficulty of an analyst's task. Diversified companies tend to be larger, more complex, and less transparent in their operations. In addition, they are more likely to show agency conflict and information asymmetry problems. An association between the return of a security and the analyst recommendation revision, shows that investors pick up useful information related to the upcoming potential gain from the revision of analyst forecasts. Herding among analysts could reduce the efficiency of information incorporation as the analysts do not have enough confidence to revise their forecast revision by fully using their private information, or they just simply revise their forecasts close to the average level and ignore their new private information (Clement and Tse 2005). By accessing the reasons for herding by analysts and its consequences, Clement and Tse (2005) try to find out whether the characteristics of an analyst have any relationship with their prediction boldness. They also compare the accuracy of bold forecasts and forecasts based on herding. According to the research with a sample of 57,596 analyst–firm-year observations, they found an association between several characteristics of analysts and bold forecasts. Analysts are more likely to issue a bold forecast in several situations such as when they have a good accuracy of historical forecasts, they are employed by a big company, they need to make forecasts with high frequency or they are experienced. As mentioned above, Pantzalis (2003) indicates that a well-diversified industry could be associated with increased herding, or if the analysts need to issue revisions for number of industries, it is less likely for them to issue bold forecast revisions. Regarding the accuracy of the forecast revisions, Clement and Tse (2005) also find evidence to support that bold forecasts are more accurate than herding forecasts on average. Also, bold forecasts rely more on the analysts' private information. After comparing the accuracy of original and revised forecasts, a large improvement of accuracy appears in bold forecasts compared to herding forecasts. Which shows bold forecasts incorporate a better and more complete reflection of relevant private information from the analysts than herding forecasts, which could just be the result of following the average forecast of other analysts. Among the analysts and institutional investors, herding behaviour tends to be reduced with an increase in experience. It is likely that an experienced manager would have a better understanding of the true volatility of asset prices and would also have better awareness and ability to use their public and private information to make investment decisions (Menkhoff, Schmidt and Brozynski, 2006). Using a multi-national data set, Kerl and Pauls (2014) examine herding behaviour among financial analysts. According to their analysis across different countries, analysts have consistently deviated from their true forecasts, issuing earnings forecasts with an anti-herding streak, due to the different levels of investor protection. The deviation could differ between countries. They believe that this difference may be due to differences in investor protection and corporate governance levels. As when the overall information environment is more transparent and the quality of company disclosures is higher, analysts are less out of line with true forecasts. Naujoks et al. (2009) found less deviation among German analysts in larger companies, as the company size can be seen as synonymous with investor protection. Also, earning forecasts issued were biased by anti-herding. Anti-herding represents a situation in which analysts overemphasize their own private information, so anti-herding is far from the consensus of precedent analysts. The level of this kind of bias differs between countries, compared to the US and Japan, the European countries tend to have more bias. They suggest that this bias could be affected by the multiple levels of investor protection and corporate governance as analysts deviate less from true forecasts when the overall information environment is more transparent and company disclosures are of higher quality. With high levels of company-level investor protection and corporate governance, the bias caused by the anti-herding behaviour will be significantly reduced. When countries have a higher level of investor protection and the companies in such countries and held by an increasing number of institutional investors, analysts are less likely to issue biased forecasts. Frontier markets are a type of market where institutional investors' behaviour has been little researched. Economou, Gavriilidis, Kallinterakis and Yordanov (2015) use data from markets in Bulgaria and Montenegro regarding funds' quarterly portfolio holdings to examine whether there is herding behaviour among the fund managers and whether their herding behaviour is intentional or not. Their results show that both markets have clear evidence of herding behaviour among the fund managers especially when the market has a positive market return with high trading volume. The Montenegro market also has herding behaviour during lower volatility periods. In terms of anticipation of informational or professional payoffs, fund managers deliberately follow the herd. To determine the effect of analyst herding, Xu et al. (2017) examine the relationship between herding behaviour and price crash risk. According to their research, herding and crash risk have a positive relationship so that analyst herding could have an undesirable result for firms and lead to firm stock price crash risk. When firms have high information asymmetry, this positive correlation will be more pronounced. In contrast, firms with strong and weak corporate governance do not exhibit a significantly different relationship between herding among analysts and crash risk. Consequently, the main reason for the positive correlation between the analyst herding and firm crash risk is information production. Blasco, Corredor and Ferrer, (2018) investigate the investor sentiment effect, which can be seen as the market participants' attitude towards a specified financial market, which may influence analysts' herding behaviour. They indicate that sentiment clearly affects herding among analysts. Depending on the different types of information received whether optimistic or pessimistic, this effect would be asymmetric. Optimistic information could reduce herding behaviour and pessimistic information increase herding behaviour. Also, easily valued stocks, especially in the presence of pessimistic information, could have reduced herding behaviour, while hard-to-value stocks do not have significantly increased herding behaviour and do not have much interaction with market sentiment.

2.4.2 Herding between institution and individuals

There are two different types of investors in financial markets, individuals and institutions. To date, several studies have investigated and compared herding and feedback trading between individual and institutional investors. Compared with individual investors, institutional investors are well informed and less influenced by market sentiment or unexpected situations such as periods of turmoil in the stock market (Kaniel et al., 2008).

Nofsinger and Sias (1999) used data from 1977 to 1996 on the annual market capitalisation and the annual fractions of shares, which were held by institutional investors for the New York Stock Exchange (NYSE) firms, to investigate the cross-sectional relationship between changes in institutional ownership and stock returns. They used this information to assess the comparative importance of herding trading by institutional and individual investors. They found that there was a strong positive relationship between annual changes in institutional ownership and returns over the same time period. According to their results, either institutional investors use positive feedback trading more than individual investors or institutional herding has more influence on price than herding by individual investors. Institutional herding was positively correlated with lagged returns and appeared to have a relationship with stock return momentum.

Banks are some of the most important financial institutions and may herd with each other. This could result in information passing between them, like contagion, by sharing information, which would help to maximise their profits. Also, as they are sharing the same information, this could lead them to herd together. (Acharya and Yorulmazer, 2008). When adverse news or information relating to other banks appears in the market, it would have a negative influence on the banks, causing the cost of borrowing to increase. Under these conditions, banks will try to herd and engage in co-ordinated investments to minimise the influence of the adverse information spreading and affecting the cost of borrowing. This type of herding behaviour is led by reputational considerations. Also, when several banks chose to invest in the same industry together, there would be a strong correlation between the performance of the banks and the returns of the industry. It will become difficult to reveal additional information about a particular bank by looking at another bank's results at that time. Countering this herding will reduce the profit margins on loans invested in similar industries. For related industries, if there is a high concentration of banks' lending to them, this will increase the incentive for banks to herd through this industry. Therefore, this type of herding behaviour may cause production inefficiency and waste resources, because banks could fail to invest in a profitable project in other industries (Acharaya and Yorulmazer, 2008).

Taking into consideration institutional investors, Choi and Sias (2009) examined whether they have herding behaviour causing them to mimic each other when making or cancelling investments in the same industries. They revealed significant evidence that proved the existence of herding between institutional investors in industries, and that industry herding occurred on both the buy-side and sell-side. The study also finds some other factors which could influence industry herding. Consistent with reputational herding, most different types of investors such as banks and insurance companies have herding behaviour whereby they follow institutions with similar classifications. There is, however, little evidence to show that mutual funds and independent advisers exhibit as much herding behaviour as other institutional investors which may have more consideration about their own reputation factors. Other institutional investors were more likely to follow institutions that had the same classification. In addition, the research found that when some institutions' lag trades were easily viewed by other institutions, this slightly increased institutional herding behaviour. Over the herding period, the demand for the industry by institutional investors had a strong positive correlation with the returns from the industry.

For institutions in the Australian market, Douglas Foster, Gallagher, and Looi (2011) analysed the relationship between institutional trading and share returns using the equity fund managers' daily trading data. They found that institutional investor trades had statistically and economically significant predictive power to forecast future stock returns for 10 days. In addition, they found an important factor that could help to provide a better explanation of the link between institutional trading and stock returns, which was the management style of the institution manager. Managers with a neutral style and growth-oriented management style tended to be momentum traders, whereas the value managers appeared to buy on weakness and sell on strength.

Bonfim and Kim (2012) looked for herding behaviour in both European and North America commercial banks and banks holding companies during the global financial crisis period, and their results confirmed the analysis carried out by Jain and Gupta (1987), who analysed the herding behaviour between commercial banks in the US and found little evidence of herding behaviour. Bonfim and Kim's (2012) found that herding was only significant between the largest banks, after adequately controlling for relevant endogeneity problems associated with the estimation of peer effects.

For the Taiwan stock market, Hsieh (2013) used the Lakonishok, Shleifer and Vishny (LSV) herding measure method which uses portfolio data as the indicator to examine herding behaviour between institutional and individual investors. They focus on both types of investors to investigate the cause and influence of herding on stock prices when the market was under high pressure.

Herding could be intensified under extreme market conditions if the herding was derived from behavioural factors. Compared with individual investors, institutional investors show higher levels of herding. They found that both individual and institutional investors were more likely to herd on small capitalised firms. When the market was fluctuating a lot and appeared uncertain, the institutional investors tended to exhibit herding behaviour on buying behaviour, in contrast, individual investors appeared more active exhibiting both buying and selling herding behaviour. In addition, the institutional investors made increased profits through their buying behaviour during periods of market turmoil compared with the whole period from 2002 to 2003, whereas the individuals suffered increased losses, although they were more active under conditions of greater market volatility.

Therefore, for the Taiwan stock market, the herding behaviour in the financial market depended on the information collected for the institutional investors. But, for individual investors, personal emotions, such as overconfidence, would be a better explanation. In addition, Lin and Lin (2014) used daily trading data from stocks listed on the Taiwan Stock Exchange to investigate the herding behaviour of foreign and domestic institutional investors and margin traders using the CSSD and CCK methods. According to their research, the CSSD results showed that herding behaviour existed in foreign and domestic institutional investors when the market was uncertain and experienced large movements, especially during rising periods. Investors and margin buyers tended to buy during rising market conditions and sell during a falling market. Their trading style in herding was closely aligned to firm characteristics, trading stocks with high volatility. The CSAD results showed that strong evidence of herding behaviour existed between the different types of traders analysed, and the results were similar across different sizes, market volatility, and turnover based stocks.

Choi and Skiba (2015) examined institutional herding behaviour in the international market on a large scale. By using actual holding data, they captured significant evidence that herding behaviour existed in 41 target countries and that the herding was being driven by fundamental information and appeared to be price stabilising rather than related to irrational behaviour. In markets where information was transparent, the presence of herding behaviour could increase the speed of price adjustments to the fundamental value. In addition, they indicated that information asymmetry based on the characteristics of the country could explain the difference in herding tendency across target countries because the level of information asymmetry was negatively related to herding tendency.

Zheng, Li, and Zhu (2015) analysed the influence of institutional herding on future excess stock returns in the Chinese stock market. Using stock trading information, they found that future excess stock returns and herding had a positive relationship in both the short and long-term. If herding behaviour appeared on the buy-side, the excess stock returns in the future would be higher, and if the herding behaviour was present on the sell-side, then the future excess stock returns were more negative. The results demonstrated that the price effect was influenced by the different types of stocks involved in herding behaviour because institutional investors herded on stocks with higher value and higher liquidity. This effect was strong but tended to be short-lived, in contrast, if the stock was stagnant and its value was small, there was an effect that lasted much longer. The results indicated that herding behaviour and excess stock return had a positive relationship in the short and long-term time range.

Li, Rhee, and Wang (2017) used data from the Chinese stock market and trading data from institutions in China to examine the differences in herding behaviour between individuals and institutional investors under different market conditions. This study differs from previous studies carried out by Christie and Huang (1995) and Tan et al. (2008) which only focused on the herding behaviour that existed in the stock market as a whole rather than between different types of investors. Li, Rhee, and Wang (2017) found that the trading style of well-informed institutional investors tended to be more selective, while the less informed individual investors preferred to allocate their investment equally across all of the selected stocks. Because of the influence of market conditions and the possibility of unexpected situations in the market, individual investors tended to rely on publicly available information to make their trading decisions. The reaction was asymmetrical for institutional investors when facing rising and falling market fluctuations, while individual investors did not react in this way. Compared with institutions, herding behaviour among the individuals, buying is more sensitive to the upward and downward movement of the market, while the individual selling is only more sensitive to the downward movement of the market. Also, they found that the measurement of herding behaviour for both individuals and institutions had a negative relationship with the absolute market return and had a positive relationship with the average trading volume. Lantushenko and Nelling (2016) examined the herding behaviour that existed in institutional investors in the Real Estate Investment Trusts (REIT), and they captured important evidence of herding behaviour. Most of the investors in REIT were positive feedback traders, but momentum trading was not the primary source of property type herding. They found no evidence of return reversals by examining returns around changes in demand this would indicate that signals are more likely to drive herding in REITs.

Huang, Wu, and Lin (2016) analysed the relationship between institutional herding and risk-return on Taiwan stock market. The empirical results showed that the contemporaneous returns presented a positive correlation with the change in risk when institutional herding occurred to purchase stocks. They also analysed institutional herding by magnitude using quintile ranking. The evidence revealed that higher quintiles, which implied stronger herding, better explained the risk-return relationship, and provided evidence that the institutional herding could be linked to the risk-return relationship.

Gemayel and Preda (2017) investigated whether individual investors were influenced by the scopic regime defined as an intuitive system constituting a permanent state of mutual observation and scrutiny among the participants. By trading in a transparent trading environment which could lead to a higher level of herding behaviour in the market compared with the market under normal environmental conditions their results indicated that the scope regime increased the presence of herding in the market when the available information was scarce. Between individual investors, the herding existed at a higher level for larger trades, investors make similar trading decisions to avoid large, underperforming positions associated with disappointment and the risk of loss. Also herding is at a lower level for risk-seeking investors which can be seen as a sign of overconfidence among these market participants. Compared with the market under traditional trading conditions, the scopic environment, where trading takes place in a transparent trading environment with more information exposure to the market, increased the limitations and personal biases of individual traders and caused herding behaviour in the market.

Gavriilidis, Kallinterakis, and Ozturkkal (2017) examined the relationship between mood and institutional herding using data from Turkish mutual funds. The results indicated that fund managers in the institutions displayed significant evidence of herding behaviour, because of the increase of active funds holding each stock and it appeared that there was more herding on the buy-side compared to the sell-side. They also found that the institutional herding was not significantly influenced by mood. As a result, the trading behaviour between the fund managers did not necessarily render them mood-prone in their trading conduct.

Brodocianu and Stoica (2017) investigated the herding behaviour between the institutional investors in the Romanian stock markets. The results revealed significant evidence of herding between the institutional investors in this country and a high level of herding behaviour was present in open-end funds.

Ganesh, Gopal, & Thiyagarajan, (2018) analysed institutional investors herding in Indian industries to find whether their herding behaviour was intentional or unintentional. The findings showed that in most industries in India, they uncovered evidence of herding behaviour. However, the herding in industries overall was not significant during the whole period from 2005 to 2015. In addition, they suggested that the herding behaviour found in some industries was unintentional because it was related to economic performance during that period. The herding observed in well-performing industries has proven to be unintentional and therefore seen as rational herding.

In the US corporate bond market, Cai et al. (2019) examined the herding behaviour of institutional investors and the influence of their herding behaviour. Their empirical results indicated that the institutional herding in the corporate bond market was much higher than in the equity market, especially for lower-rated bonds, and there was more herding behaviour in speculative-grade bonds than in investment-grade bonds. In addition, the herding on the sell-side tended to be much stronger than on the buy-side. The sell-side herding tended to be more persistent, which was probably driven by mimicking behaviour. For sell-side herding, they documented a price destabilising effect, which could cause risks to financial stability. This points to the financial vulnerabilities associated with institutional herding in the corporate bond markets.

In a recent study, Buchner, Mohamed, and Schwienbacher (2020) examined the herding behaviour between international buyout funds and analysed the impact of herding behaviour on risk and return in the buyout industry. In these institutions, private equity (PE) was more liable to have industry herding when the market was falling or facing uncertainty. With an increase in the capital inflow to PE, herding tended to occur more frequently. Therefore, these types of herding could generate more profit at a lower risk for the PE fund that was leading the herding behaviour in the market.

Hudson, Yan and Zhang (2020) examine herding behaviour among the institutional investors when they are making investment decisions. By using the bivariate GARCH model, they found significant evidence of herding behaviour among investors when their investment decisions are related to factors such as the size and value of the market portfolio. Also, investors sentiment could be one of the factors to affect fund managers herding behaviour. Due to the difference in fund structure, sentiment factors have a different effect on the level of herding for open-end and closed-end fund managers.

2.5 Previous empirical work on measuring herding

2.5.1 Measurement of herding behaviour

Herding measurement is vital in financial markets since it sheds light on the behaviour of market players, shows how investors behave when making investment decisions, reveals the risks within the market, and helps to prevent market risks (Ah Mand, 2021). This section outlines and discusses how the concept of herding can be quantified and the models used to measure herding in empirical work. Initially, it discusses the most commonly used the cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) model. It then goes on to cover and critically analyse other models including the Lakonishok, Shleifer and Vishny (LSV), portfolio-change measure (PCM), and the Hwang and Salmon (HS) herding measurement methods.

The CSSD and CSAD Methods

Once investors give up their private information and mimic the behaviour of others because they believe that those people were better informed or have better ability to analysis the available information, herding behaviour exists in the financial market. The basic idea of herding measurement based on regression analysis is to detect and capture the degree of returns dispersion across assets at a specific time period. If we consider the return dispersion-based models, the cross sectional standard deviation (CSSD) was introduced by Christie and Huang (1995) and Chang et al. (2000) extend the previous work to create the cross-sectional absolute deviation (CSAD) model. The CSSD model is an econometric method to test the herding behaviour by utilizing the cross-sectional standard deviation of returns (CSSD) as a measure of the average proximity of individual asset returns to the realized market average, which is calculated as:

$$CSSD = \sqrt{\frac{\sum_{i=1}^{N}(R_{it} - R_{mt})^2}{N-1}}$$

R_{it} *stands for the return for security i at time t*

R_{mt}*is the average market return at time t*

The basic idea of CSSD approach is to analysis the relationship between the deviations between the individual securities return and the market return. It assumes that there should be a linear relationship between the single security return dispersion and the average market return. However, once the market participants try to mimic each other and the investment action follows the main trend of the market, then the deviation from the market return of the single security would be less significant. As a consequence, we should find the dispersion level has a decreasing trend during the periods of high fluctuation (Litimi, BenSaïda and Bouraoui, 2016). It is also suggested that during large market movements, the return of individual assets will not have substantial divergence as the investors in the market will suppress their predictions about the asset price, as well as making their investment decisions only based on the whole market conditions. Due to the different sensitivity of the individual assets, these divergences should be related to certain underlying asset pricing models such as the Capital asset pricing model (CAPM), which describes the relationship between systematic risk and expected return for assets, particularly stocks. Lee (2017) indicates that the capital asset pricing model (CAPM) anticipate that the CSSD results will increase along with the absolute value of the market return, as the stock beta times the market return is the predicted individual security return, assuming that the risk-free rate is zero or small. On the other hand, with the existence of herding, where market participants have the willingness to inhibit their own beliefs in favour of the market consensus, single security returns should move along with the market movement, so the CSSD is predicted to be significantly lower than the CAPM predicts it should be. When we apply the CSSD to determine the herding behaviour in the market, the herding behaviour can only be detected in extreme market movement conditions by the CSSD method, because when very serious herding behaviour exists in the market, most of the investors' investments are concentrated in a single asset or contracts, under this situation, such herding behaviour can be verified by the CSSD model. So, the CSSD model underestimates the herding effect in the market. As mentioned by Economou et al. (2011), the CSSD approach has a greater ability to detect the influence of the outliers. When Christie and Huang (1995) applies the CSSD approach to detect the herding behaviour in their data sample from Jul/1962 to Dec/1988, they find that, within the US market, both the daily stock returns and monthly stock returns are inconsistent with the existence of herding behaviour in the market, including periods of large positive and large negative movements.

Chang et al. (2000) extend the model introduced by Christie and Huang (1995), they use a non-linear regression specification to detect herding behaviour in the market, and it is measured by cross-sectional absolute deviation of returns (CSAD). Compared with the CSSD approach, the new CCK method is more powerful in detecting herding behaviour, and it is less sensitive to outliers than the CSSD method. Also, the CSSD was a linear model, but herding behaviour tend to entail nonlinearities (Lux, 1995). Thus Christie and Huang (1995) effectively only test for herding behaviour during extreme market movement conditions. Also, Christie and Huang (1995) argued that when the CAPM is the rational asset pricing model assumed, and if there is no herding behaviour in the financial market, the CSAD and the absolute value of the market return should have a linear relationship. On the other hand, they indicate that there should be a negative and nonlinear relationship between the market return and CSAD results once herding occurs in the market. If there is herding behaviour, the investors will tend to make trading decisions and actions in the same direction, which would make stock prices cluster around the main market consensus. As a result, the positive linear relationship between the single security return and the market return will no longer hold as the absolute value of the market return increases, the CSAD result should decrease (Chang et al, 2000). In order to confirm the herding behaviour in the market, we need to find a negative and nonlinear relationship between the single security return and the CSAD result.

the CCK method formula is:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \qquad \text{(Equation 2.1)}$$

R_{it} stands for the return for security i at time t

$R_{mt}$is the average market return at time t

In this method, the regression formula contains constant, absolute market return and squared market return:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \qquad \text{(Equation 2.2)}$$

In the capital asset pricing model (CAPM), when the market price has a large volatility, it will increase the difference between the return on the investors' portfolio and the expected rate of return on the market, the influence will be shown as the value of cross-sectional absolute deviation (CSAD) and the expected rate of return has a linear relationship and the value of CSAD increases with the expected return of the market. In order to detect herding behaviour in the market, we need to find a significantly negative coefficient of the squared market return γ_2, which indicates declining return dispersions in periods of market stress, that investor tend to engage into the herding behaviour to follow the market consensus. Chang et al. (2000) did not find any evidence to show the existence of herding behaviour among the U.S. and Hong Kong market participants, and only find some partial evidence to show the presence of herding in Japan. However, within the two emerging markets in their sample, South Korea and Taiwan, they recorded important evidence of herding.
In the prior literature, a large number of researchers have applied the CSSD and CCK method, they investigate different markets in different time periods. Relevant studies include Chang, Cheng and Khorana (1999), Chiang and Zheng (2010), Mobarek, Mollah and Keasey (2014), Vidal-Tomás, Ibáñez and Farinós (2019), Ju (2019) and so on. For the rational asset pricing model to analysis the returns, most of them applied the the log return calculation method. A securities' log return is calculated as:

$$R_{it} = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad \text{(Equation 2.3)}$$

R_{it} stands for the return for security i at time t

P_t stands for the stock price for the security I at time t

The basic idea of CSSD is to analyse the deviation between the return of individual stocks and the market return when the price in the market fluctuates greatly, and this method can only be used when the herding behaviour is very obvious. When the herding behaviour is weak, it is difficult to detect by this method. As the CCK method measures the degree of deviation of a single financial asset's rate of return from the market's overall rate of return. It has better accuracy and sensitivity than the previous CSSD method. The CCK method has been widely used in the empirical research to detect herding behaviour in the relevant market. Most of the empirical research has relied on the CCK method and has reached similar conclusions such as that herding behaviour is more likely to be detected in the emerging markets than in developed markets, and compared with the institutions, individual investors are more likely to have herding behaviour while they make investment decisions. Most importantly, it seems that the traditional CCK method is the most popular way to detect herding behaviour. At the same time, the result also could be influenced by the different security return calculation methods. When they detect and analyse herding behaviour in different stock markets, no matter whether they use daily returns for single companies or the market index, many current studies apply the logarithmic return in the calculation method.

The Lakonishok, Shleifer and Vishny (LSV) Herding Measurement Method

The LSV herding measurement method was developed by Josef Lakonishok, Andrei Shleifer, and Robert Vishny in 1992 to measure herding in institutional trading and its impact on stock prices. LSV (1992) proposed the following equation for measuring herding in stock markets:

$$H = \left|\frac{B}{B+S} * p\right| * AF$$

- Where B is the number of money managers increasing their quarterly holdings in the stock (net buyers),

- S is the number of money managers decreasing their quarterly holdings (net sellers),
- p is the expected proportion of money managers buying within the quarter relative to the number active,
- AF is the adjustment factor

The LSV (1992) herding measurement method is one of the oldest in the securities market. The LSV model is best designed to measure herding in institutional trading and its impact on stock prices (Lakshman, 2015; LSV, 1992). If used appropriately, the LSV approach can yield the best results since it relies heavily on actual portfolio data. Studies have demonstrated the accuracy of the model in predicting/studying herding in major markets like the UK and the US (Wylie, 2005). Bellando (2010, p. 1) concluded that the LSV model is “accurate only under very strong assumptions.” The LSV model of measuring herding has since become standard for fund managers.

Unfortunately, the LSV model poses numerous biases in its measurement of herding in the securities market. For instance, several studies have found significant biases in the LSV (1992) model, particularly those arising from e short-selling constraint and invariance assumption (Vieiraa & Pereira, 2015; Wylie, 2005). The bias that this approach causes can be worsened by the absence of detailed trading activities data. As such, this model should be used with caution since the biases can cause inaccurate results. Bellando (2010) further cites the inability to provide relevant measure of institutional herding, the inability to distinguish between intentional herding and spurious herding, the failure to take into account the trading intensity, and the failure to identify inter-temporal trading patterns at a fund level as some of the key drawbacks of the LSV method. Another study also found significant bias in the LSV model and, although the bias was positively linked with the level of herding (Bellando, 2010). In other words, the LSV herding measurement method uses only the number of market buyers and sellers regardless of the volume of assets they buy or sell. Additionally, the method does not detect herding persistence for a particular fund.

The Portfolio-Change Measure (PCM) Herding Measurement Method

The PCM herding measurement method is an approach proposed by Wermer in 1995. The method is designed to capture investors' direction and intensity of trading. The method measures herding using the formula below:

$$HM_{i,t} = \left|p_{i,t} - E\left[p_{i,t}\right]\right| - E\left|p_{i,t} - E\left[p_{i,t}\right]\right|$$

- Where $HM_{i,t}$ is the measure of herding by funds into/out of stock i
- t is the stock-quarter
- $p_{i,t}$ is the proportion of all mutual funds trading stock-quarter
- E|pi,t – [Epi,t]| is a term that allows random split

The PCM herding measurement method is relatively newer than the Lakonishok, Shleifer and Vishny (LSV) but older than the HS model since it was proposed in 1995. Wemers (1998) argues that the PCM method was designed to capture both the direction and intensity of trading by investors. Although older methods like the LSV captured the intensity of trading, their formulas did not accurately capture the direction of trading (Bellando, 2010). The PCM model has been widely compared with the HS model since both use the risk-return (beta) as a key factor in their calculation of herding in the securities markets. The approach has been praised for its measurement of herding in absolute terms (Choi & Yoon, 2020). This method is also applicable even when multiple funds are available in the market. Notably, Bikhchandani and Sharma (2001) demonstrated that the PCM method can be used to measure herding in markets that have 5-25 active funds within their stock. This makes the method one of the most useful in institutional herding and in diverse portfolios.

Unfortunately, this approach has been criticised for its need for vast datasets. Like the LSV model, the PCM model of herding measurement requires detailed trading activities and information concerning the relevant portfolios, which may not be readily available in the market. For these reasons, it may be impractical and difficult to use the model in many cases. In fact, Hwang and Salmon (2001) argue that this limitation means that the PCM model can only be used to measure market-wide herding rather than herding by a small group of investors. However, this limitation can be overcome by calculating the market portfolio from equally weighted stock returns available at a given time. Although the resultant market portfolio returns calculated through the PCM model are not exactly the same as equally weighted market index returns, experts note that the results are sufficiently close to the real index return. As such, they can still be reliable if the available data is utilised appropriately (Hwang & Salmon, 2001). As such, the PCM model is one of the most reliable herding calculation methods in economics and finance.

The Hwang and Salmon (HS) Method

Hwang and Salmon proposed the HS herding measurement method in 2004 to explain market stress and herding. Unlike other existing herding measurement methods, the HS method was designed to enable stakeholders to "detect herding which is based on the cross-sectional dispersion of the factor sensitivity of assets within a given market" (Hwang & Salmon, 2004, p. 2). In other words, the method enables stakeholders to evaluate the presence of herding towards particular sectors or market styles and critically separate the herding from common asset returns movements that may be induced by movements in fundamentals. Hwang and Salmon (2003) believed that their approach would overcome limitations reported in older herding measurement methods by detecting herding biases in the risk-return relationship on the Capital Asset

Pricing Model (CAPM). In this case, the approach revealed investors' herd behaviour toward the performance of market portfolio that could lead to betas that are biased away from their equilibrium values. The equation for the HS (2004) herding measurement method extends from the CAPM equilibrium below:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt})$$

- Where r_{it} and r_{mt} are the excess returns on asset (*i*) and the market at the time (t),
- β_{imt} is the systematic risk measure,
- E_t is the conditional expectation at time t

In case there was some herding in the market, the equilibrium would shift accordingly and will follow the following equation:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1)$$

- Where $E_t^b(r_{it})$ and β_{imt}^b are the biased short-run conditional expectation in the market on the excess asset returns and the beta (risk) at time t,
- h_{mt} (Which is always less than 1) is a latent herding parameter whose value fluctuates over time

The effectiveness and practicality of the HS (2004) model have been widely studied in the literature. The model is considered practical and rational by economists since it considers how investors' behavioural biases distort the risk-return and the role of fundamental factors at the market and firm-level on herding and stock returns (Hachicha, 2010). Additionally, Júnior et al. (2020) argued that the HS (2004) model presents a more accurate method of measuring herding due to its use of a standardised beta adaptation model. The HS herding measurement method is also one of the few methods that present an accurate impact of information symmetry on stock price by studying the cross-sectional dispersion of trading volume (Hachicha, 2010). Other studies have also demonstrated that the HS model is more effective in measuring herding intensity and its relationship with investor sentiment (Vieiraa & Pereira, 2015). As such, it was deemed the best in studying how prevailing attitude of the investors based on anticipated price developments affect the market.

However, the HS (2004) model has some limitations. Hachicha (2010) writes that the model is unreliable for the commodities context, which could significantly affect the accuracy of its results and the decisions that investors take. Instead, Júnior et al. (2020) proposed a more recent herding measurement method by Hwang et al. (2018) that corrects the heteroscedastic distribution of errors in beta estimation. Equally, Hachica (2010) criticised the HS (2004) herding measurement method, an inefficient CAPM principle and its failure to accurately measure the systematic risk of the market. The author argues that these assumptions are far from reality and instead propose a dynamic volatility approach to systematic market risk estimation.

Some other alternative test of herding provided by Gurdgiev and Loughlin (2020), who use sentiment analysis to model the effects of public sentiment toward investment markets in general, and cryptocurrencies in particular on crypto assets' valuations to determine the herding behaviour in cryptocurrency markets, shows that investor sentiment can predict the price direction of cryptocurrencies, indicating the direct impact of herding and anchoring biases. Rahayu, Rohman and Harto (2021) investigate herding by using a method which is a randomized experiment. According to Fafchamps and Mo (2018), a randomized experiment is done by choosing participants randomly from a population. The intention of this experiment is to find out the causal relationship between social influence and information about Book Value Per Share on herding behaviour in the investment decision. They also suggest that investors know their psychological factors, thereby increasing self-control and investment analysis skills. Bhaduri and Mahapatra (2013) present an alternative approach to test herding behaviour in the Indian equity market using symmetric properties of the cross-sectional return distribution. Using the proposed approach, the paper finds evidence of herding in the Indian equity market during the sample period. Blasco and Ferreruela (2008) use a new approach that permits the detection of even moderate herding over the whole range of market returns. This approach compares the cross-sectional deviation of returns of each of the selected markets with the cross-sectional deviation of returns of an "artificially created" market free of herding effects. They suggest that intentional herding is likely to be better revealed when we analyse familiar stocks. Also, their empirical results show that only the Spanish market exhibits a significant herding effect.

2.5.2 Herding in Financial Market Prices (Empirical evidence from different markets)

Herding-related research among global financial markets has attracted the interest of many researchers. Early studies to detect herding behaviour mainly focused on the US market, before subsequent researchers increased the coverage to include the European and Asian markets. Some research papers combine most markets and discuss the existence of herding in the global financial markets. In this section, this thesis will firstly look at prior research focused on the US financial market, followed by the research on the European markets and the Asian and global markets. This geographically based structure is logical to capture any common geographical features of herding and also to keep the analysis of the large number of papers in the literature tractable. We have also considered research on herding in emerging markets, such as the P2P, fund and the cryptocurrency markets but this is less directly relevant to the thesis and so has been put in an Appendix.

2.5.3 Herding in the US Market

Earlier studies used cross-sectional standard deviations, introduced by Christie and Huang (1995), to detect herding in financial markets. They focused on the US market between 1962 and 1988 and did not capture significant evidence of herding during either rising and falling market conditions. Moreover, in heavily falling markets, the daily and monthly returns on stock prices are inconsistent with the expected movements consistent with herd behaviour. Philippas, Economou, Babalos and Kostakis (2013) has provided comprehensive evidence to show the existence of herding behaviour in the US equity REIT market. They also found that deterioration of investor sentiment and adverse macro shocks affecting real estate investment trust fund conditions are significantly related to the emergence of herding behaviour and an asymmetric herd effect was recorded during the period of negative market returns. Litimi, BenSaïda and

Bouraoui (2016) tested herding behaviour in the US stock market to see whether it is a leading factor of excessive market volatility and whether it could increase bubbles in the market. Evidence of herding behaviour in the US market was captured by their research. The existence of herding behaviour was found in eight out of twelve sectors, most of which were basic industries, such as energy, technology and transportation. The factors which could influence investors to present herding behaviour differs between different industries, and herding depends on whether the market is having large fluctuations. Also, in the US market, with different sizes and different levels of market concentration, a relatively small number of specific stocks' volatilities were influenced by the presence of herding behaviour in the market. With the decrease in the volatility level of the remaining stocks, which are not affected by herding behaviour, the overall volatility of the whole market decreases. Therefore, herding has an inhibiting effect on average return fluctuations across all industries.

In the US stock market at the industry level, BenSaïda (2017) examined the effect on the idiosyncratic volatility of the market, which was affected by herding behaviour. For some industries, the stock volatility for the market was inhibited by the trading volume, as well-informed investors might trade more than those less informed. They prove that only a small number of stocks' volatility was affected by herding behaviour in the market. The remaining large number of stocks which were not affected by herding behaviour in the market could have a lower level of changes in volatility. Therefore, among all industries, herding has a restraining effect on the volatilities of the average stock return.

Bekiros, et al., (2017) analysed the influence of herding behaviour in the US under the condition of market uncertainty during the global financial crisis. The results indicate that market participants in different US markets trade in different ways, and herding behaviour is more likely to appear during extreme market conditions, especially during periods of financial crisis, with the level of herding tends to be high at the beginning of the crisis before decreasing to insignificant levels towards the end. They also found that among the US markets, due to the influence of different markets' idiosyncratic factors related to market sentiments there is more evidence of herding behaviour in the Dow Jones Industrial Average (DJIA) indices compared to the S&P100 market. According to their analysis, there is also a significant correlation between herding behaviour and market volatility and market sentiments like investors' fear could also enhance herding behaviour.

Lee (2017) introduces a new method using the Fama-French (FF) three-factor model, instead of the CAPM, as a rational asset pricing model to detect herding behaviour using weekly data from the New York Stock Exchange (NYSE). During the time period from Jul-1963 to Dec-2014, they found significant evidence of herding behaviour when the market has moderate or large negative movements, and little herding behaviour during positive movement market conditions. During the global financial crisis, no significant evidence of herding was found. They note that the herding behaviour present in the market is likely influenced by contemporaneous market-wide information.

Clements, Hurn and Shi (2017) examine herding behaviour using data from the Dow Jones Industrial Average. They detect herding by using a model based on the time-varying Granger causality test to estimate herding towards a market consensus, and found significant evidence of herding behaviour during each period when the market has turbulence. The turbulent periods examined include the global financial crisis, the Eurozone Crisis, the US debt-ceiling crisis and the Chinese stock market crash.

BenMabrouk and Litimi (2018) analysed the existence of herding behaviour in the US oil market during extreme market movement periods. The results indicate that sector herding is more pronounced during extreme oil market movements although industries other than the energy sector do not have significant evidence of herding behaviour. The oil market's volatility and sentiment reduce industry herding, and herding is highly related to the available information in the market. As fear increases, investors make decisions according to their private information, which reduces herding behaviour.

In summary, the evidence of herding in the US market is quite mixed. There is little evidence of consistent herding in the whole market over extended periods of time. There is evidence of herding in different market sectors at particular times and dependent on certain market conditions such as periods of turbulence. There is also evidence of positive connections between herding and volatility and that positive findings of herding may depend on the empirical test used.

2.5.4 Herding in European Markets

Lobao and Serra (2003) have found significant evidence of herding behaviour in Portuguese mutual funds, and the herding behaviour is much stronger than was found for institutional investors in mature markets. They found it is more likely that herding was present in medium-cap funds. Also, herding tends to decrease when there is more volatility in the stock market, and under good market condition.

For cross-country market analysis in Europe, Economou, Kostakis and Philippas (2011) provide comprehensive evidence about the presence of herding behaviour in the Portuguese, Italian, Spanish and Greek markets by using daily stock market returns between 1998 and 2008. For these four countries, the global financial crisis did not cause an increase in herding behaviour. The results also indicate that significant herding behaviour exists in the Greek and Italian markets, there is partial evidence of herding in the Portuguese market and no evidence of herding in the Spanish market.

Using comprehensive transaction data from institutions trading on the Germany stock market (DAX30), Kremer and Nautz (2013) have found that herding behaviour is exhibited among institutions in DAX30 on a daily basis. Due to the different characteristics of stocks such as price, expected return and volatility, the intensity of herding also differs. In the short term, return reversals also indicate that herding in the stock market has affected the stability of the market. The research also suggests that the existence of herding is mainly influenced by those institutions using similar financial risk models, and most of the herding tends to be unintentional.

For cross-country analysis, Mobarek, Mollah and Keasey (2014) investigate herding behaviour in the European market (Germany, France, Portugal, Italy, Ireland, Greece, Spain, Sweden, Norway, Denmark and Finland), which includes continental, Nordic and the PIIGS (Portugal, Italy, Ireland, Greece and Spain) markets. The results show that herding behaviour exists in the financial markets of countries in the European continent which were affected by the global financial crisis, while the Nordic markets were mainly influenced by the Eurozone crisis. However, the PIIGS have herding behaviour during both crisis periods. During the global financial crisis, herding was present in most continental countries and in northern Europe during the eurozone crisis. The findings support the view that herding behaviour may still be present in developed financial markets. Kostakis and Philippas (2011) also found herding behaviour in the PIIGS during the global financial crisis.

Klein (2013) examined time-variations in herding behaviour in the US and European stock markets. The evidence shows that when the stock market was in turmoil, the large fluctuations could amplify herding behaviour. This finding applies to the conditional herding based on the market volatility, as well as unconditional herding. In particular, during the periods when the market is suffering turmoil, the market tends to have stronger herding behaviour present and the stock prices appears persistent and deviate from rational stock pricing. Also, Markets appear in sync with each other and there is an intensification of adverse herding behaviour.

Economou, Gavriilidis, Goyal and Kallinterakis (2015) examine herding behaviour among Euronext stocks to see if herding in a stock market is influenced by it joining an exchange group. Euronext is one of the first exchange groups to be established and comprises four European stock markets (Belgium, France, the Netherlands and Portugal). The authors found significant evidence of herding in the constituent equity markets of Euronext in their data sample. The eurozone sovereign debt crisis caused significant herding in Belgium, the Netherlands and Portugal had a huge herd effect, which was driven by the influence of the group's two largest markets (France and the Netherlands).

Galariotis, Krokida and Spyrou (2016) applied the cross-sectional absolute deviation (CSAD) approach, introduced by Chang, et al. (2000), to capture evidence of herding behaviour in European government bond prices. Based on the result using daily trading data, they found no significant evidence of herding behaviour among investors before and after the Eurozone crisis. Some evidence, however, shows that macroeconomic information released during the Eurozone crisis could have significant influence on market participants' investment behaviour and promoted herding behaviour in the market.

Using the CCK model, Galariotis, Krokida and Spyrou (2016) examined the European and North American markets and provided new evidence to show the relationship between the liquidity of equity markets and herding behaviour. Using analysis of the full data sample, they did not find any proof that herding behaviour exists in the market. However, they found herding behaviour for more liquid stocks, especially for high liquidity stocks, across all their selected countries, except Germany. They indicated that herding has a significant influence on the average equity market liquidity, especially during the crisis period as well as the post-crisis period.

In the emerging market of Turkey, Akinsomi, Coskun and Gupta (2018) use daily closing prices to examine herding behaviour in REITs. The empirical results have found herding behaviour and the presence of directional asymmetry in REITs. They also suggest that there is a presence of directional asymmetry and a linear relation between volatility and herding in the models both with and without an asymmetry term in the sub-periods. Transitivity was found in both the fluctuation periods with and without asymmetric term models. A period of low volatility is followed by a period of high volatility and the high volatility is followed by a period of low volatility again. Turkish REITs consistently exhibited herding behaviour through different cycles of volatility, but the degree of herding increased during periods of market stress. Finally, the herding effect in high volatility periods is relatively shorter than that in low volatility period.

In Russia, Indārs, Savin and Lublóy (2019) have captured the herding behaviour of investors in the Moscow Exchange, they found that investors herd without any reference to fundamentals during an unexpected financial crisis accompanied by a falling market and higher risk and uncertainty. During periods of high liquidity, herding behaviour is driven only by fundamentals. These results show that the motivation of investors' herding behaviour differs according to market conditions, such as different market trends, changes in liquidity as well as market uncertainty.

Overall, across the European financial markets, prior research has found clear evidence of herding behaviour in several European countries. Herding often depends on the particular market conditions and tends to be present in the market when the market suffers turmoil such as during the Eurozone crisis which made the market have larger price movements. Also, smaller and emerging markets, such as the Nordic countries and Turkey, are more likely to show herding behaviour under unstable market conditions.

2.5.5 Herding in Asian Stock Markets

Jeon and Moffett (2010) investigate whether the Korean market is affected by stock herding behaviour among foreign investors, and they have captured clear evidence of such herding behaviour. They found that in addition to the positive feedback transactions of foreign investors during the year, the conformity of foreign investors has a significant impact on stock returns. However, changes in the ownership of domestic institutions have no significant impact on stock returns. In addition to the positive feedback trading of foreign investors within the year, the herding effect of foreign investors has a significant impact on stock returns.

Lao and Singh (2011) examined herding behaviour in both the Chinese and Indian stock markets and found the existence of herding behaviour in both markets. The level of herding behaviour in these two countries is shown in different patterns, which depends on market conditions. In both stock markets, herding behaviour is more likely to occur when the stock market has large fluctuations. The difference is that in the Chinese market, during falling market conditions, herding behaviour is greater with the increase of trading volume whereas in the Indian market, herding occurs during rising market conditions. It seems that the Chinese market has a quick reaction to negative effects with investors trying to avoid potential losses, and in the Indian market, people tend to focus on the potential gains when the market has an upswing. Also, herding behaviour in the Chinese market is related to the trading volume, but in the Indian market, the trading volume is irrelevant. In the Chinese stock market, there is significant herding behaviour among different sized groups of shares, but it is only present in mid-size shares in the Indian market. During the financial crisis, due to the negative impact on the market, the Chinese stock market showed greater herding behaviour than the Indian market, which indicates that the Chinese market may need better governance and stricter regulations. In the Indian stock market, due to benefits from the effects of financial institutions, rational analysis was brought to the market and reduced speculative investment activity levels.

Chiang, Tan, Li and Nelling (2013) investigate herding behaviour among market participants in the equity markets of the Pacific-Basin. The results show that herding behaviour exists in selected markets under both rising and falling market conditions, and the level of herding changes over time. It is positively correlated with stock market performance but negatively correlated with market volatility. They also indicate that herding detection should consider its dynamic behaviour by applying the cross-sectional return distribution’s symmetric properties to detect herding.

Bhaduri and Mahapatra (2013) use daily stock price data for companies listed on the BSE-500 over the period from beginning of January 2003 to the end of March 2008, they captured clear evidence of herding behaviour in the Indian stock market over the sample period, especially during the 2007 crash time period. They also find that the growth rate of the dispersion of returns of securities is lower when the market is going up than when the market is going down.

Qiao, Chiang and Tan (2014) provided an analysis which included nine major Asian markets including Japan, South Korea, and Thailand. They captured evidence which shows herding behaviour exists in all nine markets, and the levels differ over time. They also confirm that there is a high degree of co-movement among the different markets and found that a strong two-way causality exists in pairwise variables among herding, stock returns and illiquidity. The results also indicate consistent bi-directional relationships between herding behaviour and returns for all nine Asian markets.

Arjoon, Bhatnagar and Ramlakhan (2020) investigate herding behaviour in the Singapore Stock Exchange(SGX), By assessing herding behaviour across the SGX as a whole and five size - based quintile portfolios. they capture strong evidence of herding at the overall market level and for all quintiles. In the smaller one-fifth quintile group, herding may be attributed to investors' low trading skills and high sensitivity to noisy information related to the market. However, herding in the larger quintile groups may be due to the presence of some less sophisticated retail investors and large institutional investors motivated by feedback and reputational concerns. They also capture some evidence to prove the existence of cross-group herding activity. The results also show that herding is more common during periods of rising market conditions. The lagging microstructure elements (liquidity and volatility) also appears to exacerbate the herding effect at the overall level and for different portfolio sizes. As market events, microstructures and investor sentiment change, the herding in the market develops over time. The herding behaviour over time in most size-based portfolios is usually consistent with the overall market.

The above literature has investigated and captured evidence of herding in most major Asian markets. According to the various results, there are different levels of herding mainly present in the markets during market turmoil periods such as rapidly rising and falling market conditions around the global financial crisis period. Jeon and Moffett (2010) captured evidence of herding in Korean market, Lao and Singh (2011) found herding behaviour in both the Chinese and Indian markets, especially during the market turmoil period. Chiang, Tan, Li and Nelling (2013) found herding behaviour exists in both rising and falling market conditions in the Pacific-Basin markets. Bhaduri and Mahapatra (2013) also find evidence of herding during the financial crisis period. Qiao, Chiang and Tan (2014) provide analyse to show that herding behaviour exists in major Asia markets, and Arjoon, Bhatnagar and Ramlakhan (2020) confirms that herding behaviour is present in the stock market of Singapore.

In the Chinese market, Demirer and Kutan (2006) investigate the presence of herding behaviour using data at both the individual firm and sector level. They found that equity dispersions become higher when the market index has large movements. However, they suggest that the investors in the Chinese market tend to make their investment decisions rationally as they did not find clear evidence to show that herding behaviour exists in the Chinese market in their data sample.

Tan, et al., (2008) investigated both Chinese A-share and B-share markets and found significant evidence of herding behaviour in both the Shanghai and

Shenzhen A-share markets, where herding was mainly caused by domestic investors. In the Shanghai A-share market, under rising market conditions, there tends to be more herding behaviour with higher trading volume, as well as higher volatility. In both of the B-share markets, in which the market participants are mainly foreign investors, herding behaviour's presence was found in both rising and falling market conditions.

In the Taiwan equity market, Chang (2010) investigated herding behaviour among the qualified foreign institutional investors (QFIIs). They found evidence of herding surrounding the institutional investors, with QFIIs increasing (decreasing) their weights in a specific industry, despite controls for return and momentum of trading, the positions/weights of traders, margin traders and mutual funds also increase (decrease) in the same week and subsequent weeks, this research also provides evidence that QFII trading is being tracked and mimicked by other market participants and the market as a whole. And this kind of herding behaviour could potentially destabilize the market causing prices to overshoot.

Yao, Ma and He (2014) investigates whether investors in Chinese A and B stock markets present herding behaviour. According to their research, investors show different levels of herding behaviour, especially in the B-share market. In the entire market, herding behaviour is more common at the industry level. Compared with value stocks, the largest and smallest stocks and growth stocks have stronger herding. Herding behaviour is also more obvious in the case of a decline in the market. During the sample period they investigated, the herding behaviour gradually decreases over time.

Xie, Xu and Zhang (2015) created a new method, the Weighted Cross-Sectional Variance (WCSV), and applied it to the Chinese A-share market. When compared to the previous approach, this method has a better discriminating power, as it can detect strong herding and filter out weaker behaviour.

According to the research, based on the data between 2006 and 2013, herding behaviour was detected in the market during the global financial crisis.

Gong and Dai (2017) investigated the presence of herding behaviour in the Chinese stock market and detected intentional herding. Their empirical results show that an increase in interest rates, and a depreciation of the exchange rate, will lead the occurrence of herding behaviour, especially during falling market conditions. This indicates that most investors tend to have more reaction to bad news than good. They also captured evidence which indicates that retail investors prefer and overweight lottery-type stocks, as high idiosyncratic volatility is one of the more important characteristics of these types of stocks.

By using daily industries' index prices and foreign institutional holding data from the Taiwan Economic Journal (TEJ), Tung and Yen (2018) examine herding behaviour's spill over effects from institutional investors in thirteen industries: Semiconductor; Finance; Other Electronic; Computer & Per.; Elec. Parts; Plastics; Optoelectronic; Comm. Internet; Others; Trading & Cons.; Foods; Elec. Machinery and Automobile. Their empirical results indicate that herding behaviour among these industries has a greater influence on the semi-conductor manufactory, and institutional investors are industry momentum traders. In addition, for zero-cost industry momentum strategies, profitability depends on the level of industry herding.

Ju (2019) analysed herding behaviour and its relative effect among the Chinese A and B-share markets. According to the empirical results, herding behaviour exists in both A and B-share markets. Investors in the A-share market prefer to invest in smaller businesses and growth stocks in all market conditions, and during the falling market conditions, they are more likely to herd on larger value stocks. In the B-share market, herding behaviour is stronger in any type of market condition with different investment styles. There is no spill-over effect related to herding in either market.

Most of the literature on the Chinese market related to the herding effect has captured clear evidence of herding behaviour in Chinese A and B share markets. Herding behaviour is present in both markets during the global financial period around the year 2008. In the A share market, the herding behaviour is mainly caused by domestic investors and there is clear evidence that herding exists in this market in rising market conditions with larger trading volume and volatility. In the B share market where the investors are mainly foreign investors, herding behaviour is common at the industry level, Overall, we have mixed results in the Asian market. Many markets have shown some evidence of herding. There is herding behaviour under both rising and falling market conditions. The level of herding behaviour in the market is changing over time in the Asian market. It is also influenced by the rising and falling market conditions, especially during periods of market turmoil.

2.5.6 Herding in Global Financial Markets

In global financial markets, Chang, et al., (2000) detected herding behaviour by using the CCK method, they did not find any evidence of herding behaviour in the US and Hong Kong markets, and only partial evidence of herding was captured in the Japanese market. However, they captured evidence of herding behaviour in emerging markets, including South Korea and Taiwan. In periods of extreme price fluctuations, the distribution of stock returns in the United States, Hong Kong and Japan increased. They assume that stock returns follow the CAPM model, and the distribution of returns increased more than expected. This offers strong evidence against herding in these developed markets, as was found by Christie and Huang (1995). In contrast, South Korea and Taiwan provided evidence for the existence of herding behaviour, recording relatively small dispersion of stocks returns during extreme periods of price rises and falls. The reason for the difference in market findings between emerging and developed markets could be that the disclosure of information in emerging markets is partial and incomplete.

Hwang and Salmon (2004) modified the traditional cross-sectional standard deviation method in an analysis of the US, UK, and South Korean stock markets. The method used is cross-sectional dispersion based on asset factor sensitivity in a given market. This enabled them to assess whether there is herding behaviour in the market for a particular industry and also to distinguish this herding from the common changes in asset returns caused by changes in fundamentals. They found that when market suffered great turmoil, such as during the Asian and Russian financial crisis period in 1997 and 1998, herding had a great influence on the selected market in the data sample. Contrary to popular belief that herding is more likely to appear under market pressure, they found that herding is more pronounced before crises occurs when the market is relatively quiet. Herding behaviour in advanced markets such as the United States and the United Kingdom is not as great as in emerging markets such as South Korea. This can be explained by the greater information asymmetry among emerging market investors. The size effect in the Korean market has greater explanatory power than in the U.S. and U.K. markets.

Chiang and Zheng (2010) apply 18 countries' daily trading data to examine herding behaviour in stock markets around the world. They divide these countries into different groups as being advanced stock markets (Australia, France, Germany, Hong Kong, Japan, the United Kingdom, and the United States); Latin American markets (Argentina, Brazil, Chile, and Mexico) and Asian markets (China, South Korea, Taiwan, Indonesia, Malaysia, Singapore, and Thailand). They found significant evidence which shows herding behaviour among some developed stock markets, as well as the Asian market. They find no evidence of herding in the US and Latin American markets. They show herding occurs during both rising and falling market conditions although herding in Asian markets appears more during rising market conditions. They also found evidence which shows most investors herd with the US market, as well as their domestic markets. Evidence suggests that stock return dispersions in the US market play a significant role in explaining the non-US market's herding activity. The financial crisis caused herding behaviour in the original country, before leading to a contagion effect, which has a negative influence on the neighbouring countries. As a consequence, they captured evidence of herding behaviour spreading from the US to the Latin American markets during the crisis.

Messis and Zapranis (2014) investigated the existence of herding behaviour among five major countries: US, UK, Germany, France and China. They examined the effect of herding on the skewness and kurtosis in the market. Their results indicates that the herding effect exists not only for market indices but also for skewness and kurtosis factors. When the market starts to rise, some herding declines, indicating that stocks with a higher-than-average sensitivity fall further, indicating that investors may have bought stocks with a low skewness or kurtosis. Also, herding was caused by the macroeconomic variables, particularly when the economy was suffering an unexpected shock. The infectious nature of herding during the crisis were confirmed by their findings, and this could lead to doubts about the benefits of international portfolio diversification. In the global financial markets, the potential benefits of international portfolio diversification tend to be smaller, even related to the Chinese market, as the unique characteristics of the financial markets still cannot prevent the existence of herding behaviour.

Galariotis, Rong and Spyrou (2015) investigate herding behaviour towards the market consensus for leading US and UK stocks. Their results show that during days when important macro data was released, American investors tended to herd. Also, during the global financial crisis period, the United States had a spillover effect on the United Kingdom. In the United States, they found that during different crises, investors present herding behaviour because of both fundamental and non-fundamental factors. In the UK, they herded only because of fundamentals and only when the Dotcom bubble burst. These results indicate that the driving factors of herding behaviour are specific to particular periods and countries.

Chang and Lin (2015) investigated how the herding behaviour of investors is affected by the national culture in the international stock and equity markets. When compared with the evidence of herding behaviour found by Chiang and Zheng (2010), they found a lower percentage of herding behaviour present in the stock market, and that it appears greater in less mature or emerging stock markets. Their findings, based on cross country culture comparison, suggest that national culture, which could include power distance, individualism and masculinity, could influence investors' herding behaviour. During the processes of investors making investment decisions, behavioural biases, such as, excessive optimism, overconfidence, and the disposition effect, could have some influence on investors' herding behaviour and could be key factors which lead to irrational behaviour.

Galariotis, Krokida and Spyrou (2016) found no general evidence of herding behaviour in major markets around the world, including the CAC40, the DAX, the NIKKEI 225, the FTSE 100 and the S&P 500. However, they found that stocks with high liquidity show significant evidence of herding behaviour.

Focusing on the African stock markets, which include BRVM, Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania and Zambia, Guney, Kallinterakis and Komba (2017) found some evidence of herding behaviour in these frontier markets. There was significant herding behaviour across all markets between 2002 and 2015, with the study finding that smaller stocks have increased herding. However, they captured clear evidence to show that herding appears asymmetric conditional on market volatility and is more likely to be present during low volatility trading days. While the "domestic" driven herding was significant in all eight markets, the return-induced herding from the US and

South Africa markets was not, and was only demonstrated in a few cases, it shows that non-domestic factors have only a limited effect on investors' behaviour in markets with less integration into the international financial system. Zheng, Li and Chiang (2017) investigated the existence of herding behaviour in the markets across the world at the industry level and explain different types of herding in different industries. Their research found that within Asian markets such as China, Japan, South Korea, Hong Kong and Malaysia, the participants are more likely to herd in industries rather than in domestic markets and international markets. In addition, investors in Japan and South Korea only show partial evidence of herding behaviour in the stock market, as they follow the US stock market more closely than other major markets in Asia. Under different market conditions, especially during falling markets, more evidence of herding was captured in most of the Asian markets, including Japan and Taiwan, which is consistent with the previous finding that investors tend to have more reaction to news which has a negative influence on the market. Also, there is more herding behaviour when the market has lower trading volume. Regarding herding across different industries, they indicate that herding is more likely to occur in industries such as Telecom and Financial industries, with less herding in industries such as Industrial and Consumer Services.

By using data from the S&P 500 and the Euro Stoxx 50, Bohl, Branger and Trede (2017) challenged the standard method for determining the existence of herding. The standard method regresses CSAD on the absolute and squared average market return and looks to find a significantly negative coefficient of squared market return, to confirm evidence of herding behaviour in the selected market. However, Bohl, Branger and Trede (2017) proved that the standard test was biased in detecting herding behaviour, and the results were misleading. They show that under the default null hypothesis, there is no herding in the market, and the true coefficient of the squared market return is positive. They examined the S&P 500 and the EuroStoxx 50 with daily return data from 2008 to 2013. The empirical results shows that the misleading implications of the CCK model were confirmed, and their modified experiment captured clear evidence of herding behaviour in the market.

In an analysis of a frontier market, Arjoon and Bhatnagar (2017) investigate herding behaviour in the Trinidad and Tobago Stock Exchange (TTSE). They captured evidence of herding behaviour across the market, especially among smaller stocks, and it occurs in both rising and falling market conditions, albeit it is more likely during rising conditions, as the market's participants may be affected by greater optimism. The stronger herding behaviour for smaller stocks suggests that there is more asymmetry in the information associated with smaller stocks and during the times of risk and uncertainty investors may be more inclined to give up their private information and skills and follow the market consensus. Also, an increase of liquidity could lead to herding in the market, which means that information dissemination may not be influenced by the market's liquidity.

Economou, Hassapis and Philippas (2018) use daily return data to investigate the herding behaviour of three developed stock markets: the USA, UK and Germany. They examined herd activities during the global financial crisis (2007-2009) and the period from January 2004 to November 20, 2007. The results indicate cross-market herd activity affecting the US, UK and German markets. The results also show that investor sentiment in other markets suggests that the relationship between the two European markets is more pronounced, presumably due to a herding effect.

Youssef and Mokni (2018) analysed herding behaviour in the markets of the Gulf Cooperation Council (GCC). Their empirical results indicate that, except for the Bahraini and Kuwaiti markets, herding behaviour exists in all GCC markets, which consist of Saudi Arabia, Qatar, Oman, Bahrain, Kuwait, and United Arab Emirates. The results differ according to market conditions. They indicate that herding behaviour exists in the Saudi Arabian market under normal market conditions where market volatility is relatively low. In the Qatari market, investors tend to present herding behaviour in periods of larger market stress. For the Omani market, herding is present under both conditions. But in Abu Dhabi, Bahraini and Kuwaiti markets, no evidence of herding was captured under any market conditions. The results also suggest that herding behaviours have a positive effect on dynamic conditional correlations for most of the GCC markets, which means that the integration level of GCC stock markets is related to herding behaviour. With more herding appearing in the markets, this phenomenon implies more dependency between the GCC markets, which could have implications for how market participants diversify their portfolios.

Stavroyiannis and Babalos (2017) investigated the presence of herding behaviour among markets with the background of Shariah-based ethical investments. By using a rolling window and time-varying parameter regression model analysis of the market's microstructure, the results reveal that during periods with larger movement in the market, the levels of anti-herding are increased. Their results imply significant implications for managers of Islamic funds, investment bankers and market authorities, which could mean financial market authorities need to revise their regulation and legislation to provide banks and markets with the opportunity to contain products with similar characteristics.

Based on the various results, there are different levels of herding in the global financial markets. In developed markets. partial evidence of herding in the Japanese market was captured by Chang, et al., (2000), they also capture clear evidence of herding in several emerging markets such as South Korea and Taiwan. Hwang and Salmon (2004) find that when markets are suffering great turmoil, such as in the global financial crisis, there is herding behaviour present in the developed UK and US markets as well as the emerging South Korean market. Chiang and Zheng (2010) investigate herding behaviour in 18 countries and find herding in most markets except the US and Latin American markets.

Messis and Zapranis (2014) found herding behaviour exists in G5 markets, which mainly caused by unexpected shocks. Galariotis, Rong and Spyrou (2015) find out that both US and UK investors have herding behaviour in their market. Chang and Lin (2015) suggest that the herding behaviour is more likely to exist in emerging markets, and that decision making may be affected by excessive optimism and overconfidence factors. Galariotis, Krokida and Spyrou (2016) have also found evidence of herding behaviour in the major world markets. Guney, Kallinterakis and Komba (2017) indicate that herding behaviour exists in African frontier stock markets. Zheng, Li and Chiang (2017) have investigated the herding behaviour at the sector level and find evidence of herding behaviour on an industry level. Bohl, Branger and Trede (2017) challenge the standard CCK method and find strong evidence of herding behaviour in the S&P 500 and the the Euro Stoxx 50. Arjoon and Bhatnagar (2017) captured evidence of herding behaviour across the Trinidad and Tobago Stock Exchange (TTSE) market, especially in small capital stocks. Economou, Hassapis and Philippas (2018) find out there have cross-market herding exists in three major markets of the US, UK and Germany. Youssef and Mokni (2018) analysed herding behaviour in the Gulf Cooperation Council (GCC) markets, they have found herding behaviour exists in all GCC markets except for the Bahraini and Kuwaiti. Stavroyiannis and Babalos (2017) suggest that the levels of anti-herding are increased during periods with larger market movements among markets with the background of Shariah-based ethical investments. In summary, around the global financial markets, prior studies have detected mixed evidence that herding behaviour exists. Herding tends to have more chance of being present in emerging markets around the world, and for developed markets, there is evidence that herding behaviour tends to exist when the market is suffering great turmoilDifferent empirical tests can produce various different results. Factors such as the macroeconomic environment and differences in national culture could have some impact on herding behaviour in the international financial markets. The presence of herding behaviour is also influenced by the size of the companies and market conditions, such as there is more likelihood of herding behaviour with smaller stocks during market turmoil periods.

2.6 Overall Summary of the Literature on Herding

Much of the empirical work in the prior literature has found herding behaviour in different financial markets such as stock markets and fund markets around the world. Evidence of herding is, however, by no means universal. For example, many studies of the key US market have not found evidence of herding. A variety of different factors have been found to influence herding behaviour in the financial markets. From the results, we can see that the level of herding behaviour tends to change over time. It also seems that the results may depend on the different methods applied to detect herding behaviour. Based on these results, the evidence of herding existing in the market is substantially dependent on different market conditions, such as when the market is suffering turmoil which causes larger price movements, there is more likelihood of herding behaviour in the market, especially when prices have extreme decreases. This means that the market participants may have more response to the bad news related to the market and tend to act to avoid potential losses in their investment. Also, some other factors could have an impact on herding behaviour such as the size of the companies. According to the results, smaller companies tend to present more herding behaviour in the market especially during periods of market turmoil. The microenvironment and different national cultures could also influence herding behaviour. For example, the emerging markets are more likely to present herding behaviour. Also, different types of market participants such as institution investors, foreigner and domestic investors with different investment preference could have an impact on level of herding behaviour as well. In conclusion, there is substantial evidence for herding, but it is influenced by many factors including the size and development of the market, the methods used to test for herding and the particular market conditions in a given time period.

3.0 Empirical Study 1 – Worldwide Herding Results (Log Returns)

In the view of the Capital asset pricing model (CAPM), the cross-sectional dispersion measurement would increase linearly with market returns. However, Christie and Huang (1995) show that, under extreme market conditions, investors tend to ignore the information they know as well as their beliefs and follow the primary market movements. Therefore, this kind of investment decision will lead to a decrease in cross-sectional dispersion during extreme market periods compared to what might otherwise be expected. Chang et al. (2000) argue that given rational asset pricing, as represented by the CAPM, the linear and increasing relationship between individual assets and market returns does not hold when there are large average price changes. The CSAD dispersion measure should increase linearly in line with the market return if there is no herding or anti-herding (stocks being less likely to move together as market returns increase). Therefore, the herding behaviour around the market consensus during price fluctuations is sufficient to transform the linear relationship into a nonlinear relationship.

In this exercise, we are using the daily stock price for each company in the European stock markets, Hong Kong and the UK as well as the US stock markets to calculate the return and use the standard CCK method to detect herding. This method was introduced by Chang et al. (2000). The formula is as follows:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \qquad \text{(Equation 3.1)}$$

R_{it} *stands for the return for security i at time t*

R_{mt}*is the average market return at time t (equally weighted)*

Chang et al. (2000) introduces a non-linear model, also known as the CCK model, which shows the relationship between the CSAD and the stock return, the initial formula uses the $R_{m,t}$ as an independent variable with coefficient γ_1, however, they later use the absolute value of the average market return $R_{m,t}$, as an independent variable and the formula is shown as:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \qquad \text{(Equation 3.2)}$$

$R_{m,t}$ is the cross-sectional average market return at time t, all the shares are equally weighted, and the $R_{m,t}^2$ is used to capture the non-linear relationship. The test for herding behaviour is that the coefficient γ_2 is negatively significant.

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \qquad \text{(Equation 3.3)}$$

Similar to the equation 3.1, $R_{m,t}$ is the equally weighted value of return for all securities in the index, and $|R_{m,t}|$ is the absolute value of them, we will capture the herding behaviour if the coefficient of the squared market return is statistically significantly negative. The equation 3.3 has extended the independent variable $R_{m,t}$ for the first coefficient γ_1, which can let us keep an eye on the asymmetric investor behaviour under different market conditions.

Also, the relationship between the market return and the CSAD could be asymmetric, and we investigate the influence of the market return movement in this scenario as well.

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up} \left|R_{m,t}\right| + \gamma_2 (1 - D^{up}) \left|R_{m,t}\right| + \gamma_3 D^{up} (R_{m,t})^2 +$$
$$\gamma_4 (1 - D^{up}) \left(R_{m,t}\right)^2 + \varepsilon_t$$

(Equation 3.4)

$R_{m,t}$ is the cross-sectional average market return at time t, all the shares are equally weighted, and the $R_{m,t}^2$ is going to capture the non-linear relationship, $D^{up}$is the dummy variable with value 1 for the days when the market return is positive and 0 when it is negative.

In this chapter, we estimate herding behaviour by fitting the standard CCK regression model in the major global stock markets based on log return calculation method. And in chapter 4, we investigate whether herding behaviour exists in the global stock markets by fitting the CCK model based on the simple return calculation method. Thus, we compare the results based on different equity return calculation methods, in particular, the Logarithmic Return and Simple Return method, both of which are very widely used in financial analysis. The mean value of the securities return calculated by using log return is smaller than using the simple return by an amount depending on the variance of the returns, but the variance is hardly influenced by the two different return calculation methods. This indicates that there is not a one-to-one relationship between the two methods and the difference will be greatest when the variance of the returns is greatest Most of the previous literature on herding used the log return calculation method in their analysis. Much of this literature found that herding was strongest in times of market turbulence which is when variance will be highest which is also when the difference between log and simple returns will be greatest. Thus, it is logical to compare herding results based on both log return and simple return calculation methods to see the extent to which they are driven by the calculation method.

The securities' log return is calculated as:

$$R_{it} = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad \text{(Equation 3.5)}$$

R_{it} *stands for the return for security i at time t*

P_t *stands for the stock price for the security I at time t*

Moreover, the simple return for security is calculated as:

$$R_{\mathrm{it}} = (\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}} - 1) * 100 \qquad \text{(Equation 3.6)}$$

R_{it} *stands for the return for security i at time t*

The data set is constructed from most of the companies in the leading indices of Denmark (OMXC-20), Finland (HEX-25), US Dow Jones Composite, Germany (DAX-30), France (CAC-40), Greece (ATHEX), Italy (FTSE-MIB), Norway (OBX), Portugal (PSI-20), Spain (IBEX-35), Sweden (OMXS-30), Hong Kong Heng SENG as well as the UK market (FTSE-100). Different indices contains different number of companies in each country. In our data sample, Denmark has 14 companies, the US has 56 companies, Finland has 19 companies, France has 34 companies, Germany has 27 companies, Greece has 47 companies, Hong Kong has 30 companies, Italy has 22 companies, Norway has 11 companies, Portugal has 10 companies, Spain has 17 companies, Sweden has 26 companies and the UK has 75 companies. These selected markets include the European, North American, and Asia markets, which contains major countries where there has been a lot of prior work on herding. Due to the different financial market policies, the Hong Kong market may be more similar to other markets compared to the China mainland financial market, and the market in Japan so the latter two markets are not covered in our study. The data sample period is from 02/Jan/2002 to 31/May/2018. The time period covers the global financial crisis and the Eurozone crisis. The time period for the global financial crisis is identified as being from Aug/2007 to Dec/2009 and the Eurozone crisis was from May/2010 to Feb/2012. The total number of observations in our data sample for each country is around 4150. As our aim is to detect the existence of herding behaviour in these selected financial markets, so we use active stock in these markets, and the results of herding behaviour existence do not affect by the survival bias.

We will test the hypothesis, which is:

H1: There is no herding behaviour within the global major stock markets during the sample period.

3.1 Full Range of Data from 02/Jan/2002 to 31/May/2018

3.1.1 Descriptive statistics results

Table 3.1.1

	variable	mean	p50	sd	variance	skewness	kurtosis	min	max	N
Denmark	$R_{m,t}$	.044824	.079958	1.21182	1.46851	-.467417	8.55016	-10.5563	7.99761	4105
	CSAD	1.2098	1.07417	.615005	.378231	3.24419	35.3323	.261331	12.504	4105
US	$R_{m,t}$	.030009	.038953	1.20649	1.45563	.14144	9.13323	-8.06138	9.54237	4132
	CSAD	.908568	.79745	.425425	.180987	2.52794	13.4162	.239378	4.90784	4132
Finland	$R_{m,t}$	.029096	.050983	1.45997	2.13152	-.07426	6.78326	-8.92102	8.93025	4124
	CSAD	1.16771	1.04695	.535559	.286823	1.83597	8.65557	.297071	5.02699	4124
France	$R_{m,t}$	.020807	.047334	1.45872	2.12787	-.084209	7.24377	-9.31602	8.91817	4202
	CSAD	1.0055	.887954	.466806	.217907	2.00715	8.57732	.30269	3.90096	4202
Germany	$R_{m,t}$	.022635	.064752	1.41664	2.00688	-.145255	7.73682	-9.02234	11.1545	4171
	CSAD	1.03381	.89293	.52707	.277803	2.33098	11.1605	.252214	5.52583	4171
Greece	$R_{m,t}$	-.01962	.073511	1.66795	2.78204	-.402569	8.74461	-15.9129	12.6811	4063
	CSAD	1.82591	1.65927	.733065	.537384	2.57838	17.2899	.547966	10.5073	4063
HK	$R_{m,t}$	.041765	.075253	1.40087	1.96245	-.112577	8.26348	-12.413	11.4602	4050
	CSAD	1.15378	1.04552	.491691	.241761	2.22905	12.3862	.31458	5.98583	4050
Italy	$R_{m,t}$	.004424	.0734	1.41339	1.99768	-.260081	6.32218	-8.56588	9.27357	4168
	CSAD	1.10248	.972056	.536711	.288059	3.63257	36.4007	.26375	9.58212	4168
Norway	$R_{m,t}$	.026429	.101438	1.83862	3.38053	-.325514	6.70776	-12.3905	10.4173	4120
	CSAD	1.50196	1.24975	.939018	.881754	2.47601	12.9371	.241345	10.65	4120
Portugal	$R_{m,t}$	.007854	.057838	1.1991	1.43784	-.357844	6.78024	-7.98493	8.74228	4194
	CSAD	1.16989	1.05155	.573614	.329033	1.63503	7.98275	.218911	5.92302	4194
Spain	$R_{m,t}$	.017445	.071006	1.31686	1.73412	-.177199	7.03014	-8.06577	9.71678	4174
	CSAD	.977813	.872125	.468243	.219251	2.41187	16.7452	.244522	7.24106	4174
Sweden	$R_{m,t}$	.030535	.069444	1.61524	2.60901	.035124	8.47388	-9.30306	13.0496	4123
	CSAD	1.01083	.870042	.507458	.257513	2.32108	13.8771	.28091	7.36813	4123
UK	$R_{m,t}$	.020814	.072211	1.18132	1.39552	-.367365	9.56934	-9.38468	7.88027	4131
	CSAD	1.09882	.949193	.532577	.283638	3.15562	19.1501	.370236	7.37284	4131

Table 3.1.1 shows the descriptive statistics for the equally weighted average market returns and the CCK measurements for each of the total thirteen

different countries, which are based on the log return calculation. We have only considered the stock of active companies. Christie and Huang (1995) and Chang et al. (2000) suggest that to test the herding effect by investigating the cross-sectional dispersion of returns that the herding effect should be compared to the level expected in a rational asset pricing model without the herding effect. Accordingly, the deviations of returns below (above) the theoretical predictions are explained as herd behaviour (anti-herd behaviour). The statistics shown in table 3.1.1 show that the mean returns of $R_{m,t}$ in all the countries other than Greece are positive during this time period. The standard deviation of $R_{m,t}$ varies between countries and is particularly high in Norway, Greece and Sweden. The minimum and maximum returns are substantial in all of the markets reflecting the times of financial turbulence in the sample period. Regarding the CASD results model, we find that the mean value of the CSAD results of 1.50196 in Norway and of 1.805907 in Greece are much higher than the other countries in our sample. Similarly, Norway has the highest standard deviation of CSAD, and Denmark and Greece have a high standard deviation of CSAD compared to the other countries where the value tends to be around 0.5. According to Chiang and Zheng (2010), within markets with similar conditions such as those in the European market, countries which have a higher standard deviation of returns may have abnormal cross-sectional variations in CSAD due to irregular fluctuations in the stock market and the statistics tend to bear this out.

3.1.2 Regression results

Table 3.1.2.1 Panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.201	0.215	0.168	0.165	0.187	0.318
	(3.20)***	(8.96)***	(7.66)***	(9.84)***	(6.23)***	(20.02)***
$R_{m,t}^2$	0.0330	0.0111	0.0112	0.0181	0.0205	0.0157
	(1.60)	(1.64)	(2.02)**	(4.72)***	(2.67)***	(5.46)***
_cons	0.987	0.709	0.969	0.797	0.805	1.406
	(35.94)***	(58.07)***	(68.70)***	(73.66)***	(49.16)***	(103.13)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.174	0.309	0.290	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.1 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.229	0.179	0.322	0.311	0.177	0.173	0.263
	(8.72)***	(6.77)***	(11.05)***	(14.93)***	(11.24)***	(8.05)***	(9.17)***
$R_{m,t}^2$	0.00988	0.0219	0.000902	0.00505	0.0175	0.00747	0.0268
	(1.40)	(2.90)***	(0.17)	(0.98)	(4.08)***	(1.68)*	(3.16)***
_cons	0.903	0.878	1.074	0.895	0.782	0.796	0.850
	(61.89)***	(61.45)***	(47.45)***	(69.47)***	(76.85)***	(55.49)***	(65.85)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.299	0.256	0.197	0.230	0.245	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.1 panel A gives the robust estimation results calculated with log returns for each country corresponding with the regression equation 3.2. For robustness checks. Table 3.1.2.1 panel B in the Appendix employs standard regression. The robust regression is designed to overcome some limitations of traditional and non-parametric methods, when data are contaminated with outliers or influential observations, and it can also be used to detect influential observations. Within the sample period from 02/Jan/2002 to 31/May/2018, under this regression model, the coefficients of $|R_{m,t}|$are highly significant and positive for all the 13 countries. It shows a positive relationship between the CSAD and the market return in the different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return. In order to capture herding in a market, we need to get a significantly negative coefficient of the squared market return. According to the results, we can find out that Finland, France, Germany, Greece, Italy, Spain and UK have significantly positive coefficient of squared market return, which is indicative of anti-herding existing in these stock market. This means that the investors in the market do not follow or even contradict with other market participants investment decision and trading based on their own thoughts. The results do not give any support for herding which is surprising given the theoretical arguments in favour of herding and the fact that prior empirical work has shown evidence of herding in some of these markets.

Table 3.1.2.2 Panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00255	-0.00850	0.0122	0.0118	0.00789	0.00791
	(-0.21)	(-1.19)	(1.76)*	(2.09)**	(1.01)	(0.97)
$\lvert R_{m,t}\rvert$	0.201	0.214	0.169	0.167	0.188	0.317
	(3.24)***	(9.14)***	(7.71)***	(9.95)***	(6.16)***	(19.59)***
$R_{m,t}^2$	0.0328	0.0116	0.0111	0.0179	0.0204	0.0160
	(1.62)	(1.76)*	(2.00)**	(4.74)***	(2.60)***	(5.35)***
_cons	0.987	0.710	0.968	0.795	0.804	1.406
	(35.87)***	(59.32)***	(68.79)***	(73.61)***	(48.95)***	(102.62)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.175	0.310	0.291	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.2 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0246	0.00883	0.00669	0.0298	0.0127	0.00702	0.00344
	(3.33)***	(1.05)	(0.62)	(3.80)***	(1.79)*	(1.10)	(0.37)
$\lvert R_{m,t}\rvert$	0.229	0.179	0.321	0.310	0.178	0.175	0.263
	(9.07)***	(6.65)***	(11.09)***	(15.57)***	(11.52)***	(8.06)***	(9.30)***
$R_{m,t}^2$	0.0101	0.0223	0.00122	0.00684	0.0175	0.00721	0.0270
	(1.49)	(2.89)***	(0.23)	(1.47)	(4.22)***	(1.59)	(3.26)***
_cons	0.902	0.878	1.074	0.894	0.780	0.795	0.850
	(63.73)***	(60.43)***	(47.53)***	(70.38)***	(77.05)***	(55.37)***	(66.04)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.304	0.257	0.197	0.234	0.246	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.2 panel A shows the robust results under equation 3, and table 3.1.2.2 panel B in the Appendix shows the results when standard regression is applied. The variable average market return $R_{m,t}$ is added into the model, which can model asymmetric investor behaviour under different market conditions. $R_{m,t}$ is positive and significant for 5 countries giving some evidence that herding is less likely when the market is increasing in these markets. This finding is broadly in accord with the literature with tends to associate more herding with severe market falls. Overall, however, the results are quite similar to those in Table 3.1.2.1. The coefficients of $|R_{m,t}|$are highly significant and positive for all the thirteen countries. The stock markets in Finland, Germany, Italy, Spain, France and Greece have a significantly positive coefficient of squared market return $R_{m,t}^2$, which is indicative of anti-herding behaviour in the market. The rest of the countries have an insignificant value of the coefficient of squared market return $R_{m,t}^2$. None of the countries have a significant negative coefficient of $R_{m,t}^2$ so again there is no evidence of herding.

Table 3.1.2.3 Panel A Robust Regression in rising and falling market condition

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.213	0.207	0.171	0.172	0.196	0.330
	$(5.17)^{***}$	$(7.85)^{***}$	$(6.25)^{***}$	$(8.79)^{***}$	$(5.04)^{***}$	$(12.92)^{***}$
$(1 - D^{up})\|R_{m,t}\|$	0.196	0.217	0.171	0.164	0.179	0.308
	$(2.49)^{**}$	$(9.85)^{***}$	$(7.66)^{***}$	$(8.51)^{***}$	$(8.25)^{***}$	$(17.38)^{***}$
$D^{up}(R_{m,t})^2$	0.0275	0.0109	0.0143	0.0200	0.0204	0.0148
	$(2.02)^{**}$	(1.33)	$(1.77)^{*}$	$(4.14)^{***}$	$(1.73)^{*}$	$(2.29)^{**}$
$(1 - D^{up})(R_{m,t})^2$	0.0354	0.0132	0.00680	0.0153	0.0205	0.0165
	(1.27)	$(1.97)^{**}$	(1.21)	$(3.21)^{***}$	$(4.46)^{***}$	$(5.73)^{***}$
_cons	0.985	0.711	0.967	0.795	0.804	1.405
	$(41.16)^{***}$	$(63.34)^{***}$	$(69.17)^{***}$	$(73.88)^{***}$	$(52.45)^{***}$	$(95.77)^{***}$
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.176	0.311	0.290	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.3 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.242	0.169	0.332	0.334	0.178	0.184	0.243
	$(7.25)^{***}$	$(5.46)^{***}$	$(11.01)^{***}$	$(15.41)^{***}$	$(10.37)^{***}$	$(7.64)^{***}$	$(9.22)^{***}$
$(1 - D^{up})\|R_{m,t}\|$	0.214	0.189	0.311	0.285	0.184	0.162	0.272
	$(8.59)^{***}$	$(5.22)^{***}$	$(8.69)^{***}$	$(11.23)^{***}$	$(9.02)^{***}$	$(8.44)^{***}$	$(8.54)^{***}$
$D^{up}(R_{m,t})^2$	0.0137	0.0288	0.000121	0.00897	0.0221	0.00664	0.0348
	(1.30)	$(2.78)^{***}$	(0.02)	$(1.94)^{*}$	$(5.00)^{***}$	(1.19)	$(4.66)^{***}$
$(1 - D^{up})(R_{m,t})^2$	0.00686	0.0162	0.00196	0.00498	0.0113	0.00855	0.0227
	(1.03)	(1.47)	(0.26)	(0.70)	$(1.66)^{*}$	$(2.21)^{**}$	$(2.15)^{**}$
_cons	0.903	0.878	1.073	0.894	0.779	0.796	0.852
	$(63.68)^{***}$	$(57.75)^{***}$	$(48.02)^{***}$	$(70.34)^{***}$	$(76.48)^{***}$	$(60.29)^{***}$	$(72.93)^{***}$
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.304	0.258	0.197	0.234	0.246	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.3 panel A and Table 3.1.2.3 panel B in the Appendix investigate whether the market has herding behaviour in rising and falling market conditions based on the log return calculation method, and Table 3.1.2.3 panel A applies the robust regression. According to the robust regression results, the coefficients of the absolute average market return under rising market conditions $\mathrm{D}^{\mathrm{up}}\left|\mathrm{R}_{\mathrm{m,t}}\right|$ and the coefficient of the absolute average market return under falling market conditions $(1-\mathrm{D}^{\mathrm{up}})\left|\mathrm{R}_{\mathrm{m,t}}\right|$ are highly significant and positive for all the countries in our data sample. This shows a positive relationship between the CSAD results and the market return in different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return. Only Denmark, Italy, Spain, France, Greece and the UK have a significantly positive coefficient of the rising market condition $D^{up}(R_{m,t})^2$, and Germany, Sweden, US, France, Greece and the UK have a significantly positive coefficient of the falling market condition $(1-D^{up})\left(R_{m,t}\right)^2$, this indicates that these countries under these specific market conditions do not have herding behaviour, but have anti-herding behaviour in their markets. For other countries and different market conditions, we do not have enough evidence to show whether there is herding behaviour in the market, they have neither herding nor anti-herding behaviour in their markets under both rising and falling market conditions The results do not give any support for the prior empirical work that has shown evidence of herding is more likely to be present under falling market conditions

Table 3.1.2.4 Panel A Robust regression with larger log positive return

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.523	0.436	0.303	0.317	0.397	0.456
	(5.78)***	(7.02)***	(3.66)***	(5.77)***	(4.53)***	(8.73)***
$R_{m,t}^2$	-0.0186	-0.0166	-0.00279	0.00152	-0.00281	0.000989
	(-1.08)	(-1.61)	(-0.20)	(0.20)	(-0.20)	(0.16)
_cons	0.631	0.416	0.792	0.600	0.518	1.208
	(6.98)***	(6.47)***	(8.04)***	(8.61)***	(5.12)***	(15.04)***
N	876	811	813	798	831	774
adj. R^2	0.248	0.366	0.232	0.366	0.325	0.424

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.4 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.406	0.344	0.503	0.328	0.270	0.423	0.418
	(5.98)***	(5.05)***	(5.37)***	(5.41)***	(6.22)***	(10.04)***	(6.09)***
$R_{m,t}^2$	-0.00474	0.00265	-0.0192	0.00765	0.0100	-0.0161	0.00861
	(-0.41)	(0.25)	(-1.87)*	(0.95)	(1.77)*	(-3.60)***	(0.76)
_cons	0.662	0.673	0.808	0.928	0.661	0.395	0.655
	(8.37)***	(7.92)***	(5.50)***	(12.94)***	(12.36)***	(6.45)***	(9.52)***
N	826	823	817	838	854	787	768
adj. R^2	0.352	0.265	0.148	0.182	0.308	0.363	0.401

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.4 panel A shows the robust regression results for the larger log positive returns, and table 3.1.2.4 panel B in the Appendix shows the equivalent standard regression results. We select the top 18% of the returns for the calculations, which is elected by choosing the observation larger than the mean value of the return which is larger than the mean value of the total observations. In the robust regression results, these countries will have herding behaviour in their market shown by negative coefficients of $R_{m,t}^2$. According to the results, we can see that the coefficients of the absolute average market return $|R_{m,t}|$ are highly significant and positive for all the countries in our data sample.

The results also shows a positive relationship between the CSAD results and the market return in different markets like previous results. Most countries now have negative coefficients of $R_{m,t}^2$ which gives some indication that herding may be more likely when returns are large although these coefficients are mostly not statistically significant, Sweden has a significantly negative coefficient of $R_{m,t}^2$, and Norway has a negative coefficient of squared market return which is significant at 10%. So, we can accept the null hypothesis that these two countries have herding behaviour in the larger market movements with a positive return.

Table 3.1.2.5 Panel A Robust regression with larger log negative returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.280	0.381	0.179	0.229	0.228	0.432
	(1.34)	(6.62)***	(2.86)***	(4.04)***	(3.86)***	(7.53)***
$R_{m,t}^2$	0.0257	-0.0113	0.00623	0.00662	0.0151	0.00613
	(0.60)	(-1.19)	(0.64)	(0.80)	(1.87)*	(1.11)
_cons	0.863	0.517	0.945	0.707	0.718	1.173
	(4.27)***	(8.37)***	(11.42)***	(9.43)***	(9.38)***	(11.78)***
N	716	735	725	723	730	726
adj. R^2	0.294	0.320	0.155	0.301	0.316	0.435

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.5 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.342	0.107	0.460	0.233	0.269	0.199	0.377
	(8.15)***	(0.83)	(4.14)***	(3.04)***	(4.28)***	(3.10)***	(4.75)***
$R_{m,t}^2$	-0.00655	0.0275	-0.0133	0.0126	-0.00118	0.00396	0.00966
	(-1.23)	(1.18)	(-1.09)	(0.97)	(-0.11)	(0.51)	(0.67)
_cons	0.706	0.995	0.814	0.961	0.670	0.743	0.707
	(12.05)***	(6.58)***	(4.39)***	(11.06)***	(8.42)***	(7.84)***	(8.31)***
N	707	718	720	729	705	681	664
adj. R^2	0.291	0.207	0.157	0.198	0.206	0.202	0.400

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.5 panel A and the equivalent robust results in table 3.1.2.5 panel B in the Appendix show the results for the larger log negative return regressions, which are larger market movements in falling market condition. The negative return was chosen from the bottom 16% of the full range of the data sample, which is elected by choosing the observation smaller than the mean value of the return which is smaller than the mean value of the total observations. In both tables, Norway, Spain, the US and Hong Kong have a negative coefficient of $R_{m,t}^2$, but these are all insignificant. The coefficients of the absolute average market return $|R_{m,t}|$ are highly significant and positive for most of countries excluding Denmark and Italy, which is an indicative of a positive relationship between the CSAD results and the market return in different markets which is consistent with standard asset pricing models like the CAPM. In the standard regression results, Denmark and Italy have a significantly positive coefficient of $R_{m,t}^2$, which is indicative that anti-herding exists in the market. In table 3.1.2.5, we do not capture clear evidence that herding behaviour exists in the market as none of the countries has a significant negative coefficient of $R_{m,t}^2$ although the results do not indicate high levels of anti-herding as we observe when we consider all returns.

3.1.3 Regression considering large market returns

3.1.3.1 market return larger than |0.5%|

Table 3.1.3 panel A, Robust Regression with market return larger than |0.5%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00245	-0.00547	0.0138	0.0127	0.00914	0.00766
	(-0.20)	(-0.78)	(1.98)**	(2.26)**	(1.20)	(0.95)
$\lvert R_{m,t}\rvert$	0.275	0.320	0.203	0.225	0.231	0.388
	(2.72)***	(9.01)***	(5.99)***	(9.04)***	(4.97)***	(15.83)***
$R_{m,t}^2$	0.0223	-0.00311	0.00629	0.00993	0.0147	0.00922
	(0.89)	(-0.43)	(0.91)	(2.26)**	(1.57)	(2.51)**
_cons	0.906	0.592	0.927	0.725	0.749	1.294
	(12.01)***	(20.18)***	(30.22)***	(31.02)***	(18.99)***	(47.44)***
N	2457	2396	2668	2696	2636	2762
adj. R^2	0.245	0.316	0.183	0.331	0.301	0.444

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0258	0.0105	0.00736	0.0309	0.0140	0.00927	0.00501
	(3.63)***	(1.24)	(0.68)	(3.84)***	(1.94)*	(1.48)	(0.53)
$\lvert R_{m,t}\rvert$	0.301	0.242	0.404	0.342	0.222	0.235	0.341
	(9.92)***	(5.69)***	(10.19)***	(10.01)***	(9.06)***	(8.43)***	(7.87)***
$R_{m,t}^2$	0.00161	0.0126	-0.00820	0.00146	0.0111	0.000359	0.0158
	(0.26)	(1.32)	(-1.39)	(0.22)	(2.28)**	(0.08)	(1.68)*
_cons	0.806	0.807	0.950	0.863	0.729	0.710	0.764
	(29.91)***	(23.05)***	(22.27)***	(28.29)***	(31.57)***	(26.07)***	(22.22)***
N	2584	2602	2968	2420	2524	2757	2211
adj. R^2	0.323	0.267	0.193	0.223	0.259	0.263	0.386

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.2 market return larger than |1%|

Table 3.1.3 panel B, Robust Regression with market return larger than $|1\%|$

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.00239	-0.00304	0.0162	0.0147	0.0132	0.00783
	(0.17)	(-0.40)	(2.22)**	(2.49)**	(1.70)*	(0.94)
$\lvert R_{m,t}\rvert$	0.364	0.446	0.237	0.271	0.330	0.423
	(2.38)**	(8.33)***	(4.45)***	(7.13)***	(5.02)***	(11.18)***
$R_{m,t}^2$	0.0117	-0.0183	0.00211	0.00433	0.00344	0.00621
	(0.38)	(-2.14)**	(0.24)	(0.79)	(0.32)	(1.31)
_cons	0.778	0.407	0.873	0.656	0.592	1.225
	(4.95)***	(6.66)***	(13.52)***	(13.65)***	(7.71)***	(22.45)***
N	1319	1267	1606	1578	1570	1775
adj. R^2	0.266	0.342	0.191	0.339	0.321	0.435

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0257	0.0139	0.00847	0.0327	0.0157	0.0122	0.00736
	(3.49)***	(1.51)	(0.75)	(3.78)***	(2.01)**	(1.88)*	(0.72)
$\lvert R_{m,t}\rvert$	0.366	0.238	0.461	0.305	0.254	0.323	0.413
	(9.58)***	(3.31)***	(8.20)***	(5.56)***	(6.21)***	(9.26)***	(6.14)***
$R_{m,t}^2$	-0.00498	0.0133	-0.0139	0.00700	0.00687	-0.00854	0.00711
	(-0.83)	(1.03)	(-2.00)**	(0.85)	(1.13)	(-1.94)*	(0.63)
_cons	0.699	0.815	0.848	0.907	0.684	0.557	0.657
	(14.57)***	(9.77)***	(10.83)***	(13.53)***	(13.05)***	(11.79)***	(8.41)***
N	1544	1535	2011	1326	1437	1673	1105
adj. R^2	0.321	0.234	0.173	0.197	0.252	0.283	0.388

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.3 market return larger than |2%|

Table 3.1.3 panel C, Robust Regression with market return larger than |2%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00128	0.00307	0.0185	0.0172	0.0202	0.00393
	(-0.06)	(0.29)	(2.00)**	(2.37)**	(2.05)**	(0.38)
$\lvert R_{m,t}\rvert$	0.493	0.538	0.198	0.418	0.470	0.420
	(1.59)	(4.34)***	(1.61)	(5.07)***	(3.33)***	(5.50)***
$R_{m,t}^2$	-0.000173	-0.0279	0.00541	-0.0111	-0.01000	0.00610
	(-0.00)	(-1.91)*	(0.35)	(-1.24)	(-0.60)	(0.92)
_cons	0.488	0.228	0.975	0.369	0.299	1.246
	(0.98)	(1.02)	(4.38)***	(2.35)**	(1.16)	(7.43)***
N	341	318	528	544	506	716
adj. R^2	0.274	0.283	0.173	0.336	0.324	0.388

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 panel C (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0285	0.0221	0.00712	0.0280	0.0206	0.0212	0.0103
	(3.10)***	(1.79)*	(0.53)	(2.33)**	(1.97)**	(2.74)***	(0.75)
$\lvert R_{m,t}\rvert$	0.494	0.322	0.444	-0.0817	0.273	0.465	0.747
	(7.23)***	(1.76)*	(3.63)***	(-0.55)	(2.38)**	(7.32)***	(4.94)***
$R_{m,t}^2$	-0.0158	0.00430	-0.0127	0.0497	0.00440	-0.0205	-0.0259
	(-2.39)**	(0.18)	(-1.10)	(3.11)***	(0.38)	(-3.59)***	(-1.57)
_cons	0.414	0.647	0.899	1.639	0.661	0.222	-0.0366
	(2.93)***	(2.04)**	(3.55)***	(5.75)***	(2.98)***	(1.68)*	(-0.13)
N	513	534	837	364	434	623	330
adj. R^2	0.327	0.226	0.111	0.170	0.230	0.269	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.4 market return larger than |3%|

Table 3.1.3 panel D, Robust Regression with market return larger than |3%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00820	0.00958	0.0222	0.0181	0.0263	0.00674
	(-0.26)	(0.69)	(1.85)*	(2.01)**	(1.93)*	(0.49)
$\|R_{m,t}\|$	0.886	0.770	0.386	0.632	0.740	0.373
	(2.02)**	(2.98)***	(1.33)	(3.57)***	(2.76)***	(2.53)**
$R_{m,t}^2$	-0.0337	-0.0481	-0.0106	-0.0295	-0.0327	0.00884
	(-0.68)	(-1.99)**	(-0.37)	(-1.85)*	(-1.34)	(0.88)
_cons	-0.510	-0.354	0.468	-0.191	-0.389	1.409
	(-0.52)	(-0.55)	(0.67)	(-0.44)	(-0.57)	(3.31)***
N	112	113	204	222	174	278
adj. R^2	0.236	0.188	0.202	0.330	0.288	0.397

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 panel D (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0258	0.0276	0.0111	0.0168	0.0251	0.0233	0.00415
	(2.02)**	(1.46)	(0.67)	(1.08)	(1.68)*	(2.34)**	(0.22)
$\|R_{m,t}\|$	0.779	0.457	0.651	0.140	0.545	0.516	1.124
	(5.30)***	(1.21)	(2.97)***	(0.45)	(1.83)*	(4.94)***	(3.08)***
$R_{m,t}^2$	-0.0355	-0.00670	-0.0282	0.0306	-0.0190	-0.0244	-0.0596
	(-3.54)***	(-0.17)	(-1.64)	(1.11)	(-0.70)	(-3.11)***	(-1.89)*
_cons	-0.425	0.272	0.299	1.035	-0.0607	0.0801	-0.955
	(-1.01)	(0.32)	(0.51)	(1.30)	(-0.08)	(0.28)	(-1.03)
N	164	197	356	110	150	260	129
adj. R^2	0.380	0.172	0.093	0.313	0.215	0.195	0.308

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.5 market return larger than |4%|

Table 3.1.3 panel E, Robust Regression with market return larger than |4%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00902	0.0166	0.0323	0.0153	0.0300	0.00632
	(-0.18)	(0.99)	(1.96)*	(1.37)	(1.85)*	(0.35)
$\|R_{m,t}\|$	0.259	0.587	1.172	0.851	1.028	0.414
	(0.23)	(1.09)	(1.69)*	(2.36)**	(2.36)**	(1.70)*
$R_{m,t}^2$	0.00956	-0.0356	-0.0748	-0.0451	-0.0524	0.00693
	(0.11)	(-0.85)	(-1.30)	(-1.60)	(-1.56)	(0.47)
_cons	1.596	0.250	-1.772	-0.923	-1.361	1.218
	(0.45)	(0.15)	(-0.90)	(-0.85)	(-1.01)	(1.47)
N	46	49	86	86	81	121
adj. R^2	0.046	0.039	0.210	0.324	0.262	0.419

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 panel E (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0320	0.0402	0.00443	0.0440	0.0335	0.0237	-0.0255
	(2.03)**	(1.52)	(0.21)	(1.99)*	(1.52)	(1.86)*	(-0.97)
$\|R_{m,t}\|$	1.253	0.314	0.530	0.484	-0.125	0.711	2.720
	(3.90)***	(0.41)	(1.16)	(0.64)	(-0.21)	(3.75)***	(2.65)**
$R_{m,t}^2$	-0.0653	0.00589	-0.0206	0.000648	0.0302	-0.0369	-0.180
	(-3.28)***	(0.09)	(-0.66)	(0.01)	(0.68)	(-3.15)***	(-2.29)**
_cons	-2.058	0.649	0.730	0.160	2.091	-0.600	-5.950
	(-1.90)*	(0.30)	(0.48)	(0.07)	(1.07)	(-0.87)	(-1.93)*
N	62	86	180	34	56	121	40
adj. R^2	0.410	0.098	0.031	0.459	0.064	0.150	0.353

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.6 market return larger than |5%|

Table 3.1.3 panel F, Robust Regression with market return larger than |5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.145	0.0140	0.0199	0.0203	0.0383	-0.0101
	(-1.07)	(0.74)	(0.83)	(1.64)	(2.16)**	(-0.41)
$\|R_{m,t}\|$	4.569	0.349	1.087	2.210	2.276	-0.122
	(0.92)	(0.30)	(0.67)	(2.79)***	(3.04)***	(-0.27)
$R_{m,t}^2$	-0.272	-0.0213	-0.0679	-0.139	-0.134	0.0325
	(-0.86)	(-0.27)	(-0.56)	(-2.53)**	(-2.82)***	(1.44)
_cons	-14.44	1.225	-1.514	-5.679	-5.836	3.594
	(-0.79)	(0.30)	(-0.29)	(-2.05)**	(-2.09)**	(1.83)*
N	18	23	37	40	38	58
adj. R^2	0.081	-0.113	-0.006	0.363	0.335	0.326

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 panel F (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0308	0.0265	-0.0126	0.0143	0.0477	0.0302	-0.0439
	(1.52)	(0.79)	(-0.53)	(0.62)	(1.90)*	(2.23)**	(-1.11)
$\|R_{m,t}\|$	1.358	2.052	1.545	-0.494	-0.695	1.100	3.697
	(1.96)*	(1.32)	(2.56)**	(-0.25)	(-0.74)	(3.67)***	(1.63)
$R_{m,t}^2$	-0.0720	-0.115	-0.0811	0.0766	0.0691	-0.0586	-0.251
	(-1.82)*	(-1.05)	(-2.21)**	(0.54)	(1.12)	(-3.56)***	(-1.52)
_cons	-2.392	-5.371	-3.318	3.142	4.061	-2.238	-9.196
	(-0.90)	(-1.02)	(-1.46)	(0.47)	(1.17)	(-1.79)*	(-1.24)
N	28	30	85	14	29	57	21
adj. R^2	0.205	0.165	0.055	0.412	0.135	0.241	0.137

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.7 market return larger than |3%| in rising and falling market condition

Table 3.1.3 Panel G Standard regression in rising and falling market condition **with market return larger than |3%|**

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.426	0.845	0.409	0.632	0.740	0.439
	(2.79)***	(3.47)***	(1.39)	(3.39)***	(2.98)***	(2.97)***
$(1 - D^{up})\|R_{m,t}\|$	1.114	0.888	0.363	0.627	0.648	0.378
	(2.25)**	(3.59)***	(1.35)	(3.55)***	(2.75)***	(2.62)***
$D^{up}(R_{m,t})^2$	-0.108	-0.0520	-0.0107	-0.0264	-0.0321	0.000755
	(-2.10)**	(-2.27)**	(-0.34)	(-1.51)	(-1.41)	(0.07)
$(1 - D^{up})(R_{m,t})^2$	-0.0421	-0.0648	-0.0105	-0.0325	-0.0245	0.00947
	(-0.75)	(-2.67)***	(-0.43)	(-1.99)**	(-1.17)	(1.07)
_cons	-1.322	-0.567	0.469	-0.183	-0.278	1.334
	(-1.12)	(-0.94)	(0.70)	(-0.41)	(-0.45)	(3.17)***
N	112	113	204	222	174	278
adj. R^2	0.262	0.183	0.198	0.328	0.285	0.397

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 Panel G (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.794	0.476	0.741	0.184	0.638	0.524	1.211
	(5.29)***	(1.26)	(3.14)***	(0.54)	(2.25)**	(4.37)***	(2.57)**
$(1 - D^{up})\|R_{m,t}\|$	0.756	0.334	0.639	0.181	0.705	0.461	1.157
	(4.94)***	(0.78)	(2.76)***	(0.48)	(2.23)**	(3.06)***	(2.82)***
$D^{up}(R_{m,t})^2$	-0.0338	-0.0112	-0.0392	0.0300	-0.0199	-0.0238	-0.0705
	(-2.62)***	(-0.33)	(-1.97)**	(1.04)	(-0.83)	(-2.88)***	(-1.52)
$(1 - D^{up})(R_{m,t})^2$	-0.0363	0.00711	-0.0250	0.0234	-0.0443	-0.0207	-0.0612
	(-3.48)***	(0.14)	(-1.33)	(0.63)	(-1.44)	(-1.44)	(-1.85)*
_cons	-0.418	0.403	0.208	0.932	-0.355	0.136	-1.089
	(-0.99)	(0.45)	(0.34)	(1.06)	(-0.49)	(0.39)	(-1.00)
N	164	197	356	110	150	260	129
adj. R^2	0.376	0.171	0.093	0.307	0.217	0.192	0.303

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.3.8 market return larger than |4%| in rising and falling market condition

Table 3.1.3 Panel H Standard regression in rising and falling market condition **with market return larger than |4%|**

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.904	0.571	1.193	0.832	0.930	0.551
	(1.04)	(1.04)	(1.88)*	(2.20)**	(2.08)**	(2.21)**
$(1-D^{up})\|R_{m,t}\|$	1.218	0.516	1.009	0.865	0.767	0.456
	(0.77)	(0.86)	(1.58)	(2.38)**	(1.50)	(1.89)*
$D^{up}(R_{m,t})^2$	-0.167	-0.0335	-0.0787	-0.0397	-0.0462	-0.00651
	(-1.08)	(-0.81)	(-1.47)	(-1.28)	(-1.45)	(-0.42)
$(1-D^{up})(R_{m,t})^2$	-0.0460	-0.0297	-0.0584	-0.0502	-0.0287	0.00608
	(-0.42)	(-0.61)	(-1.14)	(-1.76)*	(-0.70)	(0.46)
_cons	-1.820	0.365	-1.573	-0.928	-0.852	0.955
	(-0.36)	(0.21)	(-0.86)	(-0.84)	(-0.57)	(1.14)
N	46	49	86	86	81	121
adj. R^2	0.111	0.017	0.210	0.319	0.259	0.419

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.3 Panel H (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	1.336	0.335	0.632	0.275	0.124	0.742	2.674
	(4.26)***	(0.48)	(1.28)	(0.38)	(0.21)	(3.82)***	(1.95)*
$(1-D^{up})\|R_{m,t}\|$	1.229	-0.101	0.548	-0.0168	0.195	0.701	2.733
	(3.94)***	(-0.12)	(1.15)	(-0.02)	(0.30)	(3.10)***	(2.19)**
$D^{up}(R_{m,t})^2$	-0.0708	-0.00906	-0.0314	0.0131	0.0182	-0.0373	-0.178
	(-3.70)***	(-0.17)	(-0.88)	(0.23)	(0.42)	(-3.25)***	(-1.53)
$(1-D^{up})(R_{m,t})^2$	-0.0642	0.0561	-0.0196	0.0495	-0.00559	-0.0382	-0.180
	(-3.31)***	(0.68)	(-0.60)	(0.80)	(-0.11)	(-2.00)**	(-1.97)*
_cons	-2.144	1.174	0.556	1.148	1.261	-0.630	-5.908
	(-2.03)**	(0.54)	(0.35)	(0.53)	(0.65)	(-0.90)	(-1.53)
N	62	86	180	34	56	121	40
adj. R^2	0.402	0.124	0.027	0.466	0.051	0.143	0.335

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The theoretical literature hypotheses that herding behavior is more likely to exist in periods with larger absolute market return. We have also proposed that the effects of a less than perfect fit of the CAPM model will distort the standard CCK for herding in favor of finding anti-herding and this effect is primarily associated with periods of relatively low absolute market returns. Thus, we expect concentrating on larger market returns to show more evidence of herding. In this section, we have tested for herding behaviour with market returns larger than |0.5%|, |1%|, |2%| and |3%| using the standard regression model. The results shown in the various panels in Table 3.1.3 are strongly supportive of our expectations. We can find out that the coefficients of the $\mathrm{R_{m,t}}$ are significant and positive for 4 countries with the market return is larger than |0.5%|, this increases to 7 countries when the market return is larger than |2%| and reduces to only 2 countries when the market return is larger than |5%|, which giving some evidence that herding is less likely when the market return become larger and more positive in these markets which is consistent with some of the prior literature. The coefficients of $|R_{m,t}|$are highly significant and positive for all the thirteen countries when the market return larger than |0.5%| and |1%|, this shows a positive relationship between the CSAD and the market return in the different markets which is consistent with standard asset pricing models. Then there are only 4 countries having significantly a positive coefficient of $|R_{m,t}|$ with market return larger than |5%|. This is not consistent with standard asset pricing models but it could be that the smaller number of observations means that finding statistical significance is less likely. As we progress from panel A to panel F the number of countries with significantly negative coefficients of squared market returns, which is indicative of herding, progressively increases from 0 in panel A to 5 in panel F. Furthermore, if just the signs of the coefficients are considered, only 2 are negative in panel A whereas 11 are negative in panel D, and 10 in panel F. There is a corresponding pattern for positive coefficients of squared market returns. If we consider the number of significant positive coefficients which are associated with anti-herding these reduce from 4 in panel A to 0 in panel F. If we further consider the normal CCK test on all the data shown in Table 3.1.2.1 all the coefficients are positive, 8 of them at a significant level. This is an important finding as we can clearly see that the likely of finding herding as opposed to anti-herding increases with the size of market movements. When we consider rising and falling market condition, the coefficients of the absolute average market return under rising market conditions $D^{up}\left|R_{m,t}\right|$ are significantly positive for 10 countries with market returns larger than |3%|, and reduces to 5 countries when market return larger than |4%|. Also, the coefficient of the absolute average market return under falling market conditions $(1 - D^{up})\left|R_{m,t}\right|$ are highly significant and positive for 10 countries with market return larger than |3%|, then reduces to 4 countries when market return larger than |4%|. This tends to show a positive relationship between the CSAD results and the market return in different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return although statistical significance may be mitigated by less data for regressions associated with large price movements. With market returns larger than |3%|, we have found Denmark, US, Hong Kong, Norway and Sweden have clear evidence of herding behaviour in rising market condition, shown as significantly negative coefficient of squared market returns. At the same time, US, France and Hong Kong have significantly negative coefficient of squared market return in falling market condition, which means the existence of herding behaviour in these stock markets, and the UK also has herding behaviour which is significant at the 10% level. Under market condition with market return larger than |4%| in rising and falling market condition, Hong Kong and Sweden have clear evidence of herding behaviour in falling market condition. Also, France and UK have herding behaviour in their stock market significant at the 10% level. This finding is broadly consistent with the literature that tends to associate more herding with severe market declines. However, with higher absolute market return selected in our data sample, we have less observation in the data sample, so we may have some bias when we detect herding in these stock markets. When we consider the results shown in the table 3.1.2.3, with the full range of data in rising and falling market conditions, we find anti-herding in most of the countries. Thus, we can confirm that there is more herding behaviour when we have larger price movements in the stock market.

3.1.4 Larger market movements based on a proportion of the data condition

3.1.4.1 Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

Regression results by using CCK method

Table 3.1.4, panel A Robust Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00286	-0.00604	0.0142	0.0136	0.00834	0.00774
	(-0.23)	(-0.85)	(2.00)**	(2.38)**	(1.08)	(0.94)
$\lvert R_{m,t}\rvert$	0.294	0.345	0.193	0.246	0.258	0.401
	(2.59)***	(8.71)***	(4.45)***	(8.18)***	(4.58)***	(12.31)***
$R_{m,t}^2$	0.0199	-0.00625	0.00745	0.00727	0.0116	0.00806
	(0.75)	(-0.83)	(0.93)	(1.51)	(1.13)	(1.91)*
_cons	0.881	0.558	0.942	0.694	0.710	1.272
	(9.46)***	(15.46)***	(20.24)***	(21.27)***	(12.59)***	(28.78)***
N	2052	2066	2062	2102	2086	2032
adj. R^2	0.252	0.319	0.176	0.340	0.300	0.431

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.4 panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0253	0.0121	0.00862	0.0323	0.0137	0.0103	0.00450
	(3.54)***	(1.39)	(0.77)	(3.99)***	(1.86)*	(1.64)	(0.48)
$\lvert R_{m,t}\rvert$	0.332	0.251	0.454	0.316	0.226	0.293	0.346
	(9.86)***	(4.82)***	(8.32)***	(8.52)***	(7.88)***	(9.45)***	(7.71)***
$R_{m,t}^2$	-0.00166	0.0114	-0.0133	0.00522	0.0104	-0.00551	0.0151
	(-0.27)	(1.07)	(-1.94)*	(0.79)	(2.03)**	(-1.28)	(1.58)
_cons	0.757	0.795	0.862	0.895	0.723	0.613	0.757
	(21.35)***	(15.90)***	(11.54)***	(24.85)***	(23.86)***	(16.62)***	(20.48)***
N	2026	2083	2060	2098	2088	2062	2066
adj. R^2	0.327	0.257	0.175	0.213	0.256	0.284	0.389

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.4.2 Largest 10% (10% of absolute value (above 5% and 5% below 0))

Regression results by using CCK based on the Normal regression method

Table 3.1.4 panel B, Robust Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.00469	0.00486	0.0189	0.0177	0.0209	0.00414
	(0.24)	(0.50)	(1.90)*	(2.26)**	(2.01)**	(0.35)
$\|R_{m,t}\|$	0.404	0.506	0.133	0.492	0.532	0.434
	(1.38)	(4.65)***	(0.85)	(4.85)***	(3.45)***	(3.90)***
$R_{m,t}^2$	0.00816	-0.0252	0.0116	-0.0179	-0.0154	0.00525
	(0.19)	(-1.88)*	(0.64)	(-1.74)*	(-0.89)	(0.62)
_cons	0.688	0.305	1.123	0.195	0.149	1.201
	(1.53)	(1.65)*	(3.62)***	(0.92)	(0.50)	(4.24)***
N	410	414	412	420	418	406
adj. R^2	0.265	0.277	0.158	0.329	0.331	0.420

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.4 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0291	0.0251	0.00978	0.0276	0.0193	0.0242	0.0135
	(2.93)***	(1.76)*	(0.62)	(2.37)**	(1.82)*	(2.77)***	(1.06)
$\|R_{m,t}\|$	0.457	0.370	0.628	0.105	0.278	0.495	0.640
	(5.53)***	(1.61)	(3.13)***	(0.85)	(2.40)**	(5.90)***	(5.24)***
$R_{m,t}^2$	-0.0130	-0.000246	-0.0267	0.0305	0.00384	-0.0229	-0.0156
	(-1.72)*	(-0.01)	(-1.65)*	(2.24)**	(0.32)	(-3.33)***	(-1.07)
_cons	0.511	0.538	0.372	1.248	0.651	0.144	0.199
	(2.78)***	(1.25)	(0.72)	(5.46)***	(2.90)***	(0.71)	(0.93)
N	406	416	412	420	418	412	414
adj. R^2	0.302	0.221	0.099	0.185	0.226	0.228	0.389

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.4.3 Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

Regression results by using CCK based on the Normal regression method

Table 3.1.4 panel C, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00189	0.0153	0.0243	0.0206	0.0233	0.00344
	(-0.08)	(1.31)	(2.06)**	(2.24)**	(1.77)*	(0.23)
$\|R_{m,t}\|$	0.713	0.727	0.476	0.631	0.862	0.325
	(1.92)*	(4.51)***	(1.75)*	(3.33)***	(4.08)***	(1.90)*
$R_{m,t}^2$	-0.0189	-0.0452	-0.0183	-0.0294	-0.0417	0.0114
	(-0.39)	(-2.62)***	(-0.69)	(-1.74)*	(-2.12)**	(1.04)
_cons	-0.0676	-0.226	0.226	-0.190	-0.759	1.592
	(-0.10)	(-0.67)	(0.35)	(-0.40)	(-1.49)	(3.02)***
N	206	208	206	210	208	204
adj. R^2	0.295	0.277	0.216	0.321	0.345	0.396

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.4 panel C (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0309	0.0281	0.00263	0.0339	0.0236	0.0301	0.0116
	(2.65)***	(1.43)	(0.13)	(2.53)**	(1.78)*	(2.80)***	(0.75)
$\|R_{m,t}\|$	0.715	0.157	0.611	0.00393	0.342	0.651	0.964
	(5.92)***	(0.39)	(1.70)*	(0.02)	(1.65)	(5.69)***	(4.34)***
$R_{m,t}^2$	-0.0312	0.0186	-0.0257	0.0419	-0.00158	-0.0336	-0.0454
	(-3.62)***	(0.44)	(-1.01)	(2.12)**	(-0.08)	(-4.18)***	(-2.15)**
_cons	-0.230	1.092	0.426	1.434	0.479	-0.366	-0.554
	(-0.70)	(1.22)	(0.37)	(3.41)***	(1.02)	(-1.06)	(-1.11)
N	202	208	206	210	208	206	206
adj. R^2	0.380	0.138	0.048	0.238	0.212	0.212	0.355

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.4.4 Largest 3% (3% of absolute value)

Regression results by using CCK based on the Normal regression method

Table 3.1.4 panel D, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00627	0.00912	0.0271	0.0297	0.0274	0.00616
	(-0.21)	(0.67)	(1.85)*	(2.80)***	(1.85)*	(0.34)
$\|R_{m,t}\|$	0.940	0.802	1.045	0.608	0.563	0.411
	(2.26)**	(3.39)***	(2.13)**	(2.25)**	(1.57)	(1.70)*
$R_{m,t}^2$	-0.0378	-0.0506	-0.0646	-0.0278	-0.0202	0.00709
	(-0.78)	(-2.23)**	(-1.51)	(-1.23)	(-0.64)	(0.48)
_cons	-0.666	-0.450	-1.401	-0.117	0.182	1.231
	(-0.75)	(-0.79)	(-1.06)	(-0.16)	(0.19)	(1.50)
N	123	123	123	126	125	122
adj. R^2	0.261	0.214	0.249	0.316	0.233	0.420

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.4 panel D (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0263	0.0360	0.000987	0.0203	0.0306	0.0253	0.00816
	(1.93)*	(1.54)	(0.05)	(1.34)	(1.90)*	(1.98)**	(0.46)
$\|R_{m,t}\|$	0.872	0.323	0.490	-0.0623	0.364	0.680	1.265
	(4.33)***	(0.67)	(0.82)	(-0.23)	(1.10)	(3.65)***	(3.66)***
$R_{m,t}^2$	-0.0416	0.00521	-0.0179	0.0482	-0.00445	-0.0352	-0.0708
	(-3.18)***	(0.11)	(-0.46)	(1.95)*	(-0.16)	(-3.04)***	(-2.36)**
_cons	-0.726	0.618	0.856	1.573	0.460	-0.475	-1.353
	(-1.17)	(0.53)	(0.40)	(2.38)**	(0.55)	(-0.70)	(-1.56)
N	122	125	124	126	125	124	124
adj. R^2	0.364	0.145	0.020	0.288	0.175	0.143	0.361

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.4.5 Largest 2% (2% of absolute value)

Regression results by using CCK based on the Normal regression method

Table 3.1.4 panel E, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00641	0.0223	0.0324	0.0139	0.0306	0.00379
	(-0.18)	(1.50)	(1.90)*	(1.21)	(1.91)*	(0.17)
$\lvert R_{m,t}\rvert$	0.756	0.772	1.174	0.913	0.979	0.120
	(1.41)	(2.53)**	(1.58)	(2.42)**	(2.29)**	(0.38)
$R_{m,t}^2$	-0.0237	-0.0492	-0.0751	-0.0496	-0.0492	0.0215
	(-0.44)	(-1.80)*	(-1.23)	(-1.70)*	(-1.47)	(1.26)
_cons	-0.128	-0.344	-1.780	-1.126	-1.189	2.478
	(-0.09)	(-0.42)	(-0.83)	(-0.98)	(-0.91)	(1.99)*
N	82	82	82	84	83	81
adj. R^2	0.174	0.162	0.198	0.326	0.260	0.348

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.4 panel E (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0248	0.0416	-0.0132	0.0234	0.0310	0.0296	0.00460
	(1.70)*	(1.53)	(-0.55)	(1.38)	(1.64)	(2.36)**	(0.22)
$\lvert R_{m,t}\rvert$	1.220	0.129	1.553	0.550	0.560	0.907	1.593
	(4.63)***	(0.16)	(2.42)**	(1.25)	(1.39)	(4.35)***	(3.17)***
$R_{m,t}^2$	-0.0634	0.0197	-0.0816	-0.00442	-0.0196	-0.0483	-0.0968
	(-3.85)***	(0.28)	(-2.12)**	(-0.12)	(-0.58)	(-4.01)***	(-2.33)**
_cons	-1.933	1.234	-3.351	-0.0621	-0.139	-1.394	-2.311
	(-2.25)**	(0.53)	(-1.36)	(-0.05)	(-0.13)	(-1.72)*	(-1.71)*
N	81	83	82	84	83	82	83
adj. R^2	0.421	0.091	0.047	0.365	0.158	0.236	0.368

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.4.6 Largest 3% (3% of absolute value) in rising and falling market condition

Regression results by using CCK based on the Normal regression method

Table 3.1.4 panel F, Robust Regression

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.479	0.876	1.057	0.678	0.489	0.544
	(3.17)***	(3.86)***	(2.28)**	(2.53)**	(1.52)	(2.20)**
$(1-D^{up})\|R_{m,t}\|$	1.170	0.921	0.957	0.557	0.337	0.451
	(2.57)**	(3.94)***	(2.09)**	(2.07)**	(1.01)	(1.88)*
$D^{up}(R_{m,t})^2$	-0.112	-0.0543	-0.0654	-0.0339	-0.0158	-0.00603
	(-2.35)**	(-2.49)**	(-1.56)	(-1.49)	(-0.58)	(-0.39)
$(1-D^{up})(R_{m,t})^2$	-0.0464	-0.0678	-0.0570	-0.0230	0.00187	0.00634
	(-0.86)	(-2.88)***	(-1.48)	(-1.00)	(0.07)	(0.48)
_cons	-1.480	-0.657	-1.295	-0.143	0.581	0.980
	(-1.42)	(-1.20)	(-1.04)	(-0.19)	(0.64)	(1.19)
N	123	123	123	126	125	122
adj. R^2	0.287	0.211	0.245	0.314	0.233	0.420

Table 3.1.4 Panel F (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.891	0.265	0.586	-0.0509	0.457	0.687	1.429
	(4.44)***	(0.55)	(0.93)	(-0.18)	(1.33)	(3.48)***	(3.39)***
$(1-D^{up})\|R_{m,t}\|$	0.846	-0.0396	0.518	-0.106	0.473	0.621	1.329
	(4.12)***	(-0.07)	(0.83)	(-0.33)	(1.21)	(2.63)***	(3.49)***
$D^{up}(R_{m,t})^2$	-0.0406	0.000601	-0.0275	0.0481	-0.00667	-0.0343	-0.0911
	(-2.73)***	(0.01)	(-0.64)	(1.98)*	(-0.24)	(-2.95)***	(-2.19)**
$(1-D^{up})(R_{m,t})^2$	-0.0419	0.0459	-0.0179	0.0512	-0.0221	-0.0318	-0.0741
	(-3.09)***	(0.72)	(-0.44)	(1.58)	(-0.60)	(-1.59)	(-2.37)**
_cons	-0.718	1.195	0.669	1.611	0.210	-0.400	-1.610
	(-1.17)	(0.93)	(0.31)	(2.22)**	(0.23)	(-0.56)	(-1.64)
N	122	125	124	126	125	124	124
adj. R^2	0.358	0.157	0.013	0.282	0.171	0.136	0.359

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.1.4.7 Largest 2% (2% of absolute value) in rising and falling market condition

Regression results by using CCK based on the Normal regression method

Table 3.1.4 panel G, Robust Regression

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.590	0.722	1.186	0.900	0.874	0.278
	(2.16)**	(2.34)**	(1.74)*	(2.31)**	(2.04)**	(0.76)
$(1 - D^{up})\|R_{m,t}\|$	1.158	0.624	0.994	0.952	0.701	0.187
	(1.73)*	(1.78)*	(1.44)	(2.48)**	(1.44)	(0.56)
$D^{up}(R_{m,t})^2$	-0.128	-0.0446	-0.0784	-0.0440	-0.0426	0.00778
	(-1.84)*	(-1.69)*	(-1.39)	(-1.39)	(-1.37)	(0.37)
$(1 - D^{up})(R_{m,t})^2$	-0.0434	-0.0344	-0.0569	-0.0570	-0.0235	0.0194
	(-0.69)	(-1.05)	(-1.03)	(-1.90)*	(-0.60)	(1.18)
_cons	-1.548	-0.103	-1.537	-1.185	-0.648	2.105
	(-0.85)	(-0.12)	(-0.77)	(-1.02)	(-0.46)	(1.57)
N	82	82	82	84	83	81
adj. R^2	0.215	0.154	0.198	0.324	0.259	0.343

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.4 Panel G (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	1.248	0.128	1.520	0.608	0.689	0.882	1.828
	(4.70)***	(0.17)	(2.16)**	(1.34)	(1.74)*	(3.11)***	(3.18)***
$(1 - D^{up})\|R_{m,t}\|$	1.196	-0.342	1.560	0.596	0.758	0.782	1.697
	(4.57)***	(-0.38)	(2.35)**	(1.32)	(1.71)*	(2.13)**	(3.15)***
$D^{up}(R_{m,t})^2$	-0.0637	0.00518	-0.0797	-0.00556	-0.0230	-0.0456	-0.125
	(-3.64)***	(0.09)	(-1.74)*	(-0.15)	(-0.73)	(-2.96)***	(-2.34)**
$(1 - D^{up})(R_{m,t})^2$	-0.0633	0.0757	-0.0815	-0.0128	-0.0476	-0.0393	-0.102
	(-3.78)***	(0.87)	(-2.11)**	(-0.30)	(-1.15)	(-1.38)	(-2.41)**
_cons	-1.938	1.880	-3.312	-0.192	-0.550	-1.163	-2.702
	(-2.28)**	(0.80)	(-1.28)	(-0.17)	(-0.50)	(-1.00)	(-1.85)*
N	81	83	82	84	83	82	83
adj. R^2	0.413	0.122	0.035	0.357	0.154	0.227	0.367

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

According to the results based on different proportion of the observations from panel A to panel E, we can find out that the coefficients of the $R_{m,t}$ is significant and positive for 4 countries with the largest 50% of the absolute market return and reduce to only 1 country with largest 2% of the absolute market return, which giving some evidence that herding is less likely when the market return is increasing in these markets although again we need to be aware that the amount of data decreases as the returns get larger. The coefficients of $|R_{m,t}|$are highly significant and positive for all the thirteen countries when we select the largest 50% of absolute market returns, it shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 7 countries with significantly positive coefficients of $|R_{m,t}|$ in the sample of the largest 2% of the absolute market return. In panel F and G, the coefficients of the absolute average market return under rising market conditions $D^{up}|R_{m,t}|$ are significantly positive for 8 countries with samples based on the largest 3% and 2% of the absolute market return. Also, the coefficient of the absolute average market return under falling market conditions $(1 - D^{up})|R_{m,t}|$ are highly significant and positive for 8 countries when we select the 3% of absolute market returns, then reduces to 5 countries when we select the largest 2% of absolute market returns. Overall, we see a positive relationship between the CSAD results and the market return in different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return although statistical significance may be somewhat compromised for the smallest data sets. From the results shown in table 3.1.4 panel A, which is based on the largest 50% of returns in absolute terms, we find little evidence herding or anti-herding behaviour. Norway has a negative coefficient of squared market return which is only significant at the 10% level giving some indication of herding. Spain has a positive coefficient which is significant at the 5% level giving an indication of anti-herding. Table 3.1.4

panel B shows the results associated with the largest 10% of observations in absolute terms. We capture some evidence of herding behaviour in a number of the markets. Sweden has a highly significantly negative coefficient of squared market return, and US, France, Hong Kong and Norway have negative coefficients which are significant at 10% level. There is little evidence of anti-herding with just Portugal having a significantly positive coefficient of squared market returns. Table 3.1.4 panel C shows the results associated with the largest 5% of observations in absolute terms. The results shown in table 3.1.4 panel C indicate that US, Germany, Hong Kong, Sweden and UK, have got herding behaviour as shown by significantly negative coefficients on the squared market return variable. Only Portugal shows any indication of anti-herding behaviour as shown by the significantly positive coefficient of the squared market return. In panel D and panel E, we do not see any anti-herding behaviour in the stock markets. In panel D, the results indicates that US, Hong Kong, Sweden and UK have herding behaviour as shown by significantly negative coefficients on the squared market return variable. In panel E, Hong Kong, Norway, Sweden and UK have clear evidence of herding behaviour. Considering different proportion of market return in absolute value, when selected the largest |3%| of the observations, Denmark, US, Hong Kong, Sweden and UK have herding behaviour in rising market condition, shown by significantly negative coefficient of squared market return in rising market condition. In falling market condition, the US, Hong Kong and UK have clear evidence of herding behaviour presence in their stock markets. While when we select the largest 2% of the absolute value of market return, we capture clear evidence of herding in Hong Kong, Sweden and UK stock markets in rising market condition. Also, herding behaviour in Denmark, US and Norway are significant at 10% level. In falling market condition, Hong Kong, Norway and UK have significant herding behaviour in their stock market, and herding in France is significant at 10% level.

Overall, according to our results, for the full range of data, by using the standard CCK model, we have captured clear evidence that anti-herding exists in the markets of Finland, France, Germany, Greece, Italy, Spain and the UK. There is also clear evidence of anti-herding behaviour in Denmark, France, Greece, Italy, Spain and the UK in rising market conditions, and anti-herding behaviour also exists in the US, France, Germany, Greece, Sweden and UK in falling market conditions. Other countries do not have significant evidence of the presence of herding or anti-herding in their markets. Considering the larger price movements, the results shown in the various panels in Table 3.1.4 are strongly supportive of our expectations that larger market returns will be associated with greater herding. As the sample period is from 02/Jan/2002 to 31/May/2018, it covers around 16 years in the global market, and it may not accurately detect herding behaviour if it changes over time. So, we divide the current sample period equally into two parts, which is good for comparing the market performance over two decades. The first sub-period is from 02/Jan/2002 to 30/Dec/2011 is called time period 1; the second period is from 02/Jan/2012 to 31/May/2018 is called time period 2. Time period 1 covers the global financial crisis in 2008, and we can find the influence of the crisis on the market in terms of herding behaviour, and in time period 2 we can detect whether herding behaviour exists in the stock market after the financial crisis.

3.2 First time period from 02/Jan/2002 to 30/Dec/2011

3.2.1 Descriptive statistic results

Table 3.2.1 shows the descriptive statistics for the CSAD measurement and equally weighted market returns of the total thirteen different countries in the first sub time period from 02/Jan/2002 to 30/Dec/2011. The return calculation method is based on the log return method. The statistics shown in table 3.2.1 show that the mean returns of $R_{m,t}$ in all the countries other than Greece and Italy are positive during this time period, which indicates a positive performance in their stock market during our first time period. The standard deviation of $R_{m,t}$ varies between countries and is particularly high in Norway and Sweden. The minimum and maximum returns are substantial in all of the markets reflecting the times of financial turbulence in the sample period. Regarding the CASD results model, we find that the mean value of the CSAD results of 1.76188 in Norway and of 1.62505 in Greece are much higher than the other countries in our sample. Similarly, Norway has the highest standard deviation of CSAD, which is 1.06162, and Denmark, Germany and UK also have a high standard deviation of CSAD compared to the other countries where the value tends to be around 0.5. According to Chiang and Zheng (2010), within markets with similar conditions such as those in the Europe, countries which have a higher standard deviation of returns may have abnormal cross-sectional variations in CSAD due to irregular fluctuations in the stock market and the statistics tend to bear this out.

3.2.2 Regression Results

Table 3.2.2.1 in the Appendix, panel A (with robust regression results) and table 3.2.2.1 panel B (with standard regression results) shows the results based on the log return method in time period 1 and using the regression in equation 3.2. In the robust regression results shown in table 3.2.2.1 panel A, the coefficients of $|R_{m,t}|$are highly significant and positive for all the thirteen countries. It shows a positive relationship between the CSAD and the market return in the different markets. Only Italy, France and Greece have a significantly positive coefficient of $R_{m,t}^2$, which is indicative of existence of anti-herding behaviour in the market, other countries in our data sample have neither significant negative nor significant positive coefficients of squared market return, from which we can confirm that these countries do not have herding behaviour or anti-herding behaviour in their market.

Table 3.2.2.2 in the Appendix, panel A (with robust regression results) and table 3.2.2.2 panel B (with standard regression results) shows the regression results from equation 3.3. In panel A with robust regression results, the coefficient of $\mathrm{R_{m,t}}$ is positive and significant for 5 countries giving some evidence that herding is less likely when the market return is increasing in these sectors. This finding is broadly in accord with the literature with tends to associate more herding with severe market falls. The coefficients of $|R_{m,t}|$are highly significant and positive for all the 13 countries. We find that only Italy, France, Greece and the UK have significantly positive coefficients of $R_{m,t}^2$, which confirms that there is anti-herding behaviour in their stock markets. We do not capture any clear evidence of herding in other countries.

Table 3.2.2.3 in the Appendix, panel A (with figures from robust regressions) and panel B shows the results calculated by the log return method under rising and falling market conditions during the sample time period 1 using equation

3.4. In table 3.2.2.3 panel A with robust regression results, the results show that Italy, Portugal, Spain, France and the UK have a significantly positive coefficient of $D^{up}(R_{m,t})^2$ which indicates that in rising market conditions, there is anti-herding in these markets, and only Greece has anti-herding in both rising and falling market conditions shown by a significantly positive coefficient of squared market return.

Table 3.2.2.4 in the Appendix, panel A and panel B shows the regression results of the top 18% largest positive log returns in the sample time period 1 by using equation 3.2. In panel A with robust regression results, Norway, Sweden and the US still have a significantly negative coefficient of $R_{m,t}^2$, and Denmark also has evidence of herding which is significant at the 10% level, which indicates that these countries have herding behaviour in strongly rising market condition in time period 1.

Table 3.2.2.5 in the Appendix, panel A and panel B shows the regression results of the bottom 16% of negative log returns in the sample time period 1 by using equation 3.2. In panel A with the robust regression results, these countries also have a negative coefficient of $R_{m,t}^2$, both US and Hong Kong are significant at the 10% level, thus these two countries have modest evidence of herding behaviour in market conditions associated with large falls during time period 1.

In our first time period from 2002 to 2011, many markets show evidence of anti-herding as they have positive coefficients of $R_{m,t}^2$. Under equation 3.2, we find Greece and Italy have significant evidence of anti-herding in their markets, and under equation 3.3, we find Greece and UK have clear evidence of anti-herding in their markets. In rising market conditions, evidence of anti-herding exists in the markets of France, Greece, Italy, Portugal, Spain and the UK. However, in falling market conditions, only Greece has evidence of anti-herding behaviour so it does seem anti-herding seems less likely in falling markets which is consistent with the research findings in the literature that herding is most likely to be seen in falling markets. Other countries do not have evidence of either herding or anti-herding under different market conditions. We have captured evidence that herding behaviour exists in the US, Norway and Sweden markets under the rising market conditions with larger movements. Some evidence of herding exists in Denmark, with significance at the 10% level. Greece and Spain have clear evidence of anti-herding. Other countries have evidence of neither herding nor anti-herding. Also, when there are larger movements in falling market conditions, there is moderate evidence of the presence of herding behaviour in the US and Hong Kong markets with significance at the10% level. There is no evidence that herding or anti-herding exists in the markets of other countries. We find consistently with most of the prior research that herding is more likely to present in the market when there are larger price movements.

3.3 Second time Period from 02/Jan/2012 to 31/May/2018

3.3.1 Descriptive statistic results

Table 3.3.1 in the Appendix shows the descriptive statistics for the CSAD measurement and equally weighted market return for the different countries, which are based on the log return calculation in time period 2. The statistics show that the mean returns of $R_{m,t}$ in all the countries are positive, which indicates a positive performance in these stock markets during our second time period. The standard deviation of $R_{m,t}$ varies between countries and is particularly high in Greece. Also, the minimum and maximum returns are substantial in all of the markets reflecting the times of financial turbulence in the sample period. Regarding the CASD results model, we find that the mean value of the CSAD results of 2.14584 in Greece is much higher than for the other countries in our sample. Similarly, Greece also has the highest standard deviation of CSAD, which is 0.888963. According to Chiang and Zheng (2010), within markets with similar conditions, such as those in Europe, countries with higher return standard deviations may have abnormal cross-sectional changes in CSAD due to irregular stock market fluctuations, as the statistics tend to show.

3.3.2 Regression results

Table 3.3.2.1 in the Appendix, panel A (with robust regression results) and panel B show the results of the regression using equation 3.2 based on log returns in time period 2. In panel A with robust regression results, these countries still have a significantly positive coefficient of $R_{m,t}^2$, which indicates that these countries have anti-herding behaviour. We also find that in the US, Finland, Germany, Norway, Portugal and Sweden, there are no indications of either herding or anti-herding behaviour.

Table 3.3.2.2 in the Appendix, panel A (with robust regression results) and panel B show the herding estimation results using equation 3.3 based on the log returns calculation method during the second time period. In panel A, with the robust results, Denmark, France, Greece, Hong Kong, Italy, Portugal, Spain and UK have clear evidence of the presence of anti-herding in their stock markets shown by significantly positive coefficients of squared market return. Also, the US market has evidence of anti-herding behaviour with significance at the10% level. There is no evidence or either herding or anti-herding in Finland, Germany, Norway and Sweden.

Using equation 3.4. Table 3.3.2.3 in the Appendix, panel A (with robust regression results) and 3.3.2.3 panel B shows the regression results in rising and falling market conditions based on the log return calculation method in time period 2. In the robust results, Italy, Spain, France, Greece, Hong Kong and the UK have a significantly positive coefficient of both rising $D^{up}(R_{m,t})^2$ and falling market $(1 - D^{up})\left(R_{m,t}\right)^2$ terms. Denmark have a significantly positive value of the coefficient of $(1 - D^{up})\left(R_{m,t}\right)^2$, and coefficient in Portugal is significant at 10% level. Sweden and the US has a significantly positive value of the coefficient of $D^{up}(R_{m,t})^2$. Norway and Sweden have negative coefficients of $(1-D^{up})\left(R_{m,t}\right)^2$ but they are insignificant.

Table 3.3.2.4 in the Appendix, panel A (with robust regression results) and panel B shows the regression results for larger positive returns based on the log return method. In panel A and panel B, we fit equation 3.2 to estimate the herding behaviour. According to the results, we can see that all thirteen countries in our data sample do not have either significantly positive or significantly negative coefficients of squared market return, which means that neither herding nor anti-herding behaviour is evident in their stock markets under market conditions associated with larger positive market returns.

Table 3.3.2.5 in the Appendix, panel A (with robust regression results) and panel B shows the larger negative log return regression results based on equation 3.2 in time period 2. In panel A with robust results, we find that Sweden has modest evidence of herding behaviour with a significantly negative coefficient of $R^2_{m,t}$ at the 10% level. Denmark, Hong Kong, Italy, Spain and UK have significantly positive coefficients of squared market return, which is indicative of anti-herding. There is neither herding behaviour nor anti-herding behaviour in the UK, Finland, France, Germany, Greece, Norway and Portugal markets under market conditions associated with larger negative movements.

Within the second time period from 2012 to 2018, there is clear evidence of anti-herding behaviour in many of the markets around the world. Using equation 3.2, we see that Denmark, France, Greece, Hong Kong, Italy, Spain and UK have evidence of anti-herding. Under equation 3.3, Denmark, France, Greece, Hong Kong, Italy, Portugal, Spain and UK have clear evidence of anti-herding. In rising market conditions, the US, France, Greece, Hong Kong, Italy, Spain, Sweden and the UK have evidence that anti-herding is present, and in falling market conditions, Denmark, France, Greece, Hong Kong, Italy, Spain and UK have clear evidence of anti-herding. We detect modest evidence of herding behaviour in Sweden with larger price movement in falling market conditions, shown by a negative coefficient of squared market return which is significant at the 10% level. As a result, by using the CCK model based on the log return calculation method, we can capture evidence of herding mainly when the market has large movements, such as, in periods of market turmoil.

3.4 Conclusion

In this chapter, we fit the standard CCK regression model to estimate the herding behaviour based on the log return calculation method in major world markets. Also, we divide our whole data sample into two sub samples to have a better view of whether there is herding behaviour in different time periods. With the full range of data, we have captured evidence of anti-herding behaviour in most of the countries in our data sample, shown by a significantly positive coefficient of $R_{m,t}^2$. We also consider the situation when the market has larger price movements, in this case we have detected the existence of herding behaviour in some of the countries. Along with the increase in the absolute average market return, there tends to be more herding behaviour present in the market, which is in accordance with the prior research that the herding behaviour is more likely to be presented in the market when the market has larger price movements. Also, herding can be asymmetric as during rising market conditions and falling market conditions, we might have different levels of dispersion. We have found that we have more evidence of herding behaviour under rising market conditions.

During the first sample period from 2002 to 2011, we have captured evidence of anti-herding in some of the countries using the standard CCK model, and other countries have neither herding nor anti-herding behaviour in their markets. The period covers the financial crisis and we have detected more herding behaviour when the market is suffering turmoil, which is consistent with the prior literature that the herding behaviour is more likely to present when the market has larger price movements. In the second time period, which is the post-crisis period, we also captured evidence of anti-herding in most of the countries in our data sample. This can be driven by overconfidence, or excessive flights to quality. We have generally captured little evidence of herding behaviour in the stock markets. Although, there has been the presence of herding behaviour in some emerging markets when the market has larger price movements. This is in accordance with the theoretical predictions that herding behaviour is less likely to exist when price movements tend to be smaller as seen in the post-crisis stock market in different countries.

4.0 Empirical Study 2 – Worldwide Herding Results (Simple Returns)

Log return and simple return are most widely used calculation methods when we need return calculations. There are theoretical and empirical differences between the properties of returns calculated using the logarithmic rate of return and those calculated using the simple rate of return. For example, the mean value of returns calculated using the log return calculation method is less than the mean value calculated using the simple return method by an amount related to the variance of returns. At the same time, the variance is very little affected by the different return calculation method (Hudson and Gregoriou, 2015). This means that the difference between the results of the two approaches will be greatest when return variance is greatest which is also when we might expect herding to be strong. So it is interesting to compare tests for herding based on the two different return calculation methods.

The simple return for security i is calculated as:

$$R_{\mathrm{it}} = (\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}} - 1) * 100 \qquad \text{(Equation 4.1)}$$

R_{it} stands for the return for security i at time t

4.1 Review of the Properties of Logarithmic returns and Simple returns

Logarithmic returns are also known as continuously compounded returns, which means that for non-random processes, the frequency of compounding interest is not important when using log returns and returns across assets can be compared more easily (Hudson and Gregoriou, 2015). By using the log return in conjunction with a normal return distribution, security prices can effectively be prevented from becoming negative. Also, it provides a simple way to analyse multi-period returns. The logarithm returns of securities tend to be relevant when the security price follows a geometric Brownian motion. Nevertheless, there are still some unwanted features of the log return. Within a particular time period, the log return does not measure the change in wealth of investors directly. The difference between the average log return and simple return in a given period depends on the variance of the returns and the expected average simple returns. The calculation result of logarithmic returns usually are close to simple returns. As the average logarithmic returns are related to the mean and variance of simple returns, there can be no one-to-one relationship between average logarithmic returns and simple average returns (Hudson, 2010). A particular average logarithmic return may equate to a combination of mean and variance based on the calculation of simple return. We assume that based on the different securities return calculation methods, and using the CSAD to detect herding the herding behaviour detected may not occur at the same level for a selected market in a particular time period. In this chapter we will test the hypothesis that there is no difference between the results based on the different security return calculation methods.

4.1.1 Comparison between log and simple returns for Herding

In our thesis we compare the herding results based on the Logarithmic Return and Simple Return equity return calculation methods both of which are very widely used in financial analysis. There can be significant empirical differences between results calculated using the two methods (Hudson, 20100; Hudson and Gregoriou, 2015). In theoretical terms, the mean value of the securities return calculated by using log return is smaller than using the simple return by an amount depending on the variance of the returns, but the variance is hardly influenced by the two different return calculation methods. This indicates that there is not a one-to-one relationship between the two methods and the difference will be greatest when the variance of the returns is greatest (Hudson and Gregoriou, 2015).

Most of the previous literature on herding used the log return calculation method in their analysis. Much of this literature found that herding was strongest in times of market turbulence which is when variance will be highest which is also when the difference between log and simple returns will be greatest. Thus, in intuitive terms, it is logical to compare herding results based on both log return and simple return calculation methods to see the extent to which they are driven by the calculation method. We also outline a more formal analysis of the issue below:

The securities' log return is calculated as:

$$R_{Lit} = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad \text{(Equation 4.2)}$$

R_{Lit} stands for the log return for security i at time t

P_t stands for the stock price for the security I at time t

Moreover, the simple return for security is calculated as:

$$R_{\mathrm{Sit}} = (\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}} - 1) * 100 \qquad \text{(Equation 4.3)}$$

R_{Sit} stands for the simple return for security i at time t

We can now consider the effect of the different return methods on the standard CCK method used to detect herding. This method was introduced by Chang et al. (2000). The formula is as follows:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \qquad \text{(Equation 4.4)}$$

R_{it} stands for the return for security i at time t, generally it is not specified if this a log or simple return.

$R_{mt}$is the average market return at time t (equally weighted)

Now we can consider some desirable properties of a herding measure and how they are affected by the return calculation method.

Effect of a Change in the dispersion of returns

Initially, it is desirable that different measures of herding should not give different results for a given increase in the dispersion (variance) of the returns of the securities in the market under investigation if there is no indication that the securities are more prone to move together.

For simplicity, we can investigate this situation assuming that the overall market return is zero at time t.

If we use simple returns. $R_{Smt} = 0$

$CSAD_S = \frac{1}{N}\sum_{i=1}^{N}|R_{Sit} - R_{Smt}| = \frac{1}{N}\sum_{i=1}^{N}|R_{Sit}|$ (Equation 4.5)

Now if the price movements of all the securities in the market on day t change by a factor k, $CSAD_S$ will also change by a factor k so there is no indication of any change in herding.

If we use log returns.

$$CSAD_L = \frac{1}{N}\sum_{i=1}^{N}|R_{Lit} - R_{Lmt}|$$

From Equations (2) and (3)

$R_{Lit} = Ln(R_{Sit} + 1)$

$$CSAD_L = \frac{1}{N}\sum_{i=1}^{N}|Ln(R_{Sit} + 1) \quad - Ln(R_{Smt} + 1) \quad |$$

But $R_{Smt} = 0$

Thus

$Ln(R_{Smt} + 1) = 0$

So

$$CSAD_L = \frac{1}{N}\sum_{i=1}^{N}|Ln(R_{Sit} + 1) \quad |$$

For demonstration assume N =2

As $R_{Smt} = 0$

$R_{S1t} = -R_{S2t}$

Say

$R_{S1t} \geq 0$

Now

$CSAD_S = \frac{1}{2}\sum_{i=1}^{2}|R_{Sit}| = \frac{1}{2}\{|R_{S1t}| + |-R_{S1t}|\} = |R_{S1t}|$

Now

$$CSAD_L = \frac{1}{N}\sum_{i=1}^{2}|Ln(R_{Sit}+1)\ \ | = \frac{1}{2}\{|Ln(R_{S1t}+1)| + |Ln(-R_{S1t}+1)|\}$$

But by Taylors Expansion

$$Ln(R_{S1t}+1) \approx R_{S1t} - \frac{{R_{S1t}}^2}{2} + \frac{{R_{S1t}}^3}{3} - \frac{{R_{S1t}}^4}{4} + \frac{{R_{S1t}}^5}{5} \dots\dots$$

$$Ln(-R_{S1t}+1) \approx -R_{S1t} - \frac{{R_{S1t}}^2}{2} - \frac{{R_{S1t}}^3}{3} - \frac{{R_{S1t}}^4}{4} - \frac{{R_{S1t}}^5}{5} \dots\dots$$

$$|Ln(R_{S1t}+1)| \approx |R_{S1t}| - \left|\frac{{R_{S1t}}^2}{2}\right| + \left|\frac{{R_{S1t}}^3}{3}\right| - \left|\frac{{R_{S1t}}^4}{4}\right| + \left|\frac{{R_{S1t}}^5}{5}\right| \dots\dots$$

$$|Ln(-R_{S1t}+1)| \approx |R_{S1t}| + \left|\frac{{R_{S1t}}^2}{2}\right| + \left|\frac{{R_{S1t}}^3}{3}\right| + \left|\frac{{R_{S1t}}^4}{4}\right| + \left|\frac{{R_{S1t}}^5}{5}\right| \dots\dots$$

Therefore, if we neglect powers greater than 5

$$CSAD_L = \frac{1}{2}\left\{\begin{array}{c} |R_{S1t}| - \left|\frac{{R_{S1t}}^2}{2}\right| + \left|\frac{{R_{S1t}}^3}{3}\right| - \left|\frac{{R_{S1t}}^4}{4}\right| + \left|\frac{{R_{S1t}}^5}{5}\right| \\ +|R_{S1t}| + \left|\frac{{R_{S1t}}^2}{2}\right| + \left|\frac{{R_{S1t}}^3}{3}\right| + \left|\frac{{R_{S1t}}^4}{4}\right| + \left|\frac{{R_{S1t}}^5}{5}\right| \end{array}\right\}$$

$$CSAD_L = \frac{1}{2}\left\{2|R_{S1t}| + 2\left|\frac{{R_{S1t}}^3}{3}\right| + 2\left|\frac{{R_{S1t}}^5}{5}\right|\right\} = |R_{S1t}| + \left|\frac{{R_{S1t}}^3}{3}\right| + \left|\frac{{R_{S1t}}^5}{5}\right|$$

$$CSAD_L = \frac{1}{2}\left\{2|R_{S1t}| + 2\left|\frac{{R_{S1t}}^3}{3}\right| + 2\left|\frac{{R_{S1t}}^5}{5}\right|\right\} = CSAD_S + \left|\frac{{R_{S1t}}^3}{3}\right| + \left|\frac{{R_{S1t}}^5}{5}\right|$$

Thus $CSAD_L > CSAD_S$ and the difference is a non-linearly increasing function of the dispersion of returns.

Now in the literature herding is negatively related to $CSAD$ so, ceteris parabus. as the market becomes more volatile herding is more likely to be found if simple returns are used.

The table below gives numerical examples confirming our results. As the market becomes more volatile $CSAD_L$ progressively increases more than $CSAD_S$ and proportionately more than the increase in return dispersion.

Table 4.1.1 showing numerically how $CSAD_S$ and $CSAD_L$ change in response to increasing dispersion of portfolio returns for a portfolio of two assets and a constant simple mean return of zero.							
Portfolio	Asset	P_t	P_{t+1}	R_S	R_L	$CSAD_S$	$CSAD_L$
1	1	100	100.01	0.0001	1E-04		
	2	100	99.99	-0.0001	-0.0001		
	Mean			0	-5E-09	0.0001	0.0001
2	1	100	100.1	0.001	0.001		
	2	100	99.9	-0.001	-0.001		
	Mean			0	-5E-07	0.001	0.001
3	1	100	101	0.01	0.00995		
	2	100	99	-0.01	-0.01005		
	Mean			0	-5E-05	0.01	0.01
4	1	100	110	0.1	0.09531		
	2	100	90	-0.1	-0.10536		
	Mean			0	-0.00503	0.1	0.100335
5	1	100	120	0.2	0.182322		
	2	100	80	-0.2	-0.22314		
	Mean			0	-0.02041	0.2	0.202733
6	1	100	130	0.3	0.262364		
	2	100	70	-0.3	-0.35667		
	Mean			0	-0.04716	0.3	0.30952
7	1	100	140	0.4	0.336472		
	2	100	60	-0.4	-0.51083		
	Mean			0	-0.08718	0.4	0.423649
8	1	100	150	0.5	0.405465		
	2	100	50	-0.5	-0.69315		
	Mean			0	-0.14384	0.5	0.549306
9	1	100	160	0.6	0.470004		
	2	100	40	-0.6	-0.91629		
	Mean			0	-0.22314	0.6	0.693147

4.1.2 Comparison between log and simple returns when the Size and Direction of Market Returns changes.

Another desirable property of the measure of herding is that it should not be non-linearly affected by the size of the market price movements if the propensity of the securities to move together (herd) is unchanged. Indeed, investigating whether there is a non-linear relationship between the CSAD measure and market returns is the basis of the standard CCK test.

Say market returns increase by different amounts but the spread of returns is constant we can consider how herding measures based on different return calculations alter.

For demonstration we can consider the case with two assets.

Say the dispersion of returns stays constant at 2δ.

Further assume returns are R_{Smt} where $R_{Smt} \geq 0$

$CSAD_S = \frac{1}{2}\{|R_{S1t} - R_{Smt}| + |R_{S2t} - R_{Smt}|\}$

Now

$R_{S1t} = R_{Smt} + \delta$

$R_{S2t} = R_{Smt} - \delta$

$$CSAD_S = \frac{1}{2}\{|R_{S1t} + \delta - R_{Smt}| + |R_{S1t} - \delta - R_{Smt}|\}$$

$$= \frac{1}{2}\{|R_{Smt} + \delta - R_{Smt}| + |R_{Smt} - \delta - R_{Smt}|\}$$

$$= \frac{1}{2}\{|\delta| + |-\delta|\}$$

$= \delta$ where is independent of R_{Smt}

Now consider $CSAD_L$

$$CSAD_S = \frac{1}{2}\{|R_{L1t} - R_{Lmt}| + |R_{L2t} - R_{Lmt}|\}$$

$$= \frac{1}{2}\{|Ln(R_{S1t}+1) - Ln(R_{Smt}+1)| + |Ln(R_{S2t}+1) - Ln(R_{Lmt}+1)|\}$$
$$= \frac{1}{2}\left\{\left|Ln\left\{\frac{(R_{Smt}+\delta+1)}{(R_{Smt}+1)}\right\}\right| + \left|Ln\left\{\frac{(R_{Smt}-\delta+1)}{(R_{Smt}+1)}\right\}\right|\right\}$$
$$= \frac{1}{2}\left\{\left|Ln\left\{1+\frac{\delta}{(R_{Smt}+1)}\right\}\right| + \left|Ln\left\{1+\frac{-\delta}{(R_{Smt}+1)}\right\}\right|\right\}$$

Can expand terms using the Taylor expansion

$$Ln\left\{1+\frac{\delta}{(R_{Smt}+1)}\right\} \approx \frac{\delta}{(R_{Smt}+1)} - \left(\frac{\delta}{(R_{Smt}+1)}\right)^2 + \ldots. < \delta \qquad \text{(Equation 4.6)}$$

Similarly

$$Ln\left\{1-\frac{\delta}{(R_{Smt}+1)}\right\} \approx -\frac{\delta}{(R_{Smt}+1)} - \left(\frac{\delta}{(R_{Smt}+1)}\right)^2 - \ldots\ldots < -\delta \qquad \text{(Equation 4.7)}$$

Thus

$$CSAD_L < \frac{1}{2}\{|\delta| + |-\delta|\} = \delta$$

From Equation 1 and Equation 2 we can also see that $CSAD_L$ is decreasing in R_{Smt}

In summary,

$CSAD_L < CSAD_S$ and the difference between the two measures will increase as portfolio returns increase so, ceteris paribus, herding is more likely to be detected using log returns when the market is increasing.

By symmetry we can see that if $R_{Smt} < 0$

$CSAD_L > \delta$ and $CSAD_L$ is increasing in R_{Smt} so

$CSAD_L > CSAD_S$ and the difference between the two measures will increase as portfolio returns increase so, ceteris paribus, herding is more likely to be detected using simple returns when the market is decreasing.

The tables below give numerical illustrations of our findings.

Table 4.1.2 showing numerically how $CSAD_S$ and $CSAD_L$ change in response to increasing positive portfolio returns for a portfolio of two assets.							
Portfolio	Asset	Pt	Pt+1	RS	RL	CSADS	CSADL
1	1	100	120	0.2	0.182322		
	2	100	80	-0.2	-0.22314		
	Portfolio			0	-0.02041	0.2	0.202733
2	1	100	130	0.3	0.262364		
	2	100	90	-0.1	-0.10536		
	Portfolio			0.1	0.078502	0.2	0.183862
3	1	100	140	0.4	0.336472		
	2	100	100	0	0		
	Portfolio			0.2	0.168236	0.2	0.168236
4	1	100	150	0.5	0.405465		
	2	100	110	0.1	0.09531		
	Portfolio			0.3	0.250388	0.2	0.155077
5	1	100	160	0.6	0.470004		
	2	100	120	0.2	0.182322		
	Portfolio			0.4	0.326163	0.2	0.143841

Table 4.1.3 showing numerically how $CSAD_S$ and $CSAD_L$ change in response to increasing negative portfolio returns for a portfolio of two assets.							
Portfolio	Asset	Pt	Pt+1	RS	RL	CSADS	CSADL
1	1	100	120	0.2	0.182322		
	2	100	80	-0.2	-0.22314		
	Portfolio			0	-0.02041	0.2	0.202733
2	1	100	110	0.1	0.09531		
	2	100	70	-0.3	-0.35667		
	Portfolio			-0.1	-0.13068	0.2	0.225993
3	1	100	100	0	0		
	2	100	60	-0.4	-0.51083		
	Portfolio			-0.2	-0.25541	0.2	0.255413
4	1	100	90	-0.1	-0.10536		
	2	100	50	-0.5	-0.69315		
	Portfolio			-0.3	-0.39925	0.2	0.293893
5	1	100	80	-0.2	-0.22314		
	2	100	40	-0.6	-0.91629		
	Portfolio			-0.4	-0.56972	0.2	0.346574

We can consider the implications of the above findings for the standard tests for herding using the CCK approach. Now this approach regresses $CSAD_t$ as the dependent variable on various functions of market return $r_{m,t}$. The basic principle is that if there is no herding there should be a linear relationship between the two variables. From the above findings we can deduce that, ceteris paribus, $CSAD_s$ will increase less than $CSAD_L$ as volatility increases. Thus, in times of high volatility using simple returns is more likely to cause the CCK approach to indicate herding. However, herding is less likely to be detected with simple returns when the market is increasing so on occasion these two effects will act in opposition. In addition, the size and significance of the parameters in fitted regressions will be affected by the features of the total data set under investigation, the exact sequence of the observations, so it is difficult to know how well theoretical deductions such as those derived above will hold in practice on real market data. In a sense, this is ultimately an empirical issue. Given this, we can propose several hypotheses to test based on our theoretical deductions:

Hypothesis 1: Using simple instead of log returns will often change the conclusion about whether herding or anti-herding is present in a particular financial market.
Hypothesis 2: As the market becomes more volatile, the conclusion that herding (anti-herding) is present is more(less) likely if simple returns are used.
Hypothesis 3: When the market decreases, the conclusion that herding(anti-herding) is present is more(less) likely if simple returns are used.

In the remainder of the chapter we initially present descriptive statistics using simple returns followed by individual regression results for the various regression already presented in chapter 3 but using simple returns in this chapter.

After discussing the findings of the individual regressions we present final conclusions.

4.2 Full Range of Data from 02/Jan/2002 to 31/May/2018

4.2.1 Descriptive statistics results (Simple Returns)

Table 4.2.1

	variable	mean	p50	sd	variance	skewness	kurtosis	min	max	N
Denmark	$R_{m,t}$	.069696	.090726	1.20643	1.45547	-.235139	8.05749	-9.93637	8.38672	4105
	CSAD	1.21065	1.07644	.602222	.362671	2.30226	13.1517	.260639	7.97629	4105
US	$R_{m,t}$	.047245	.044848	1.20915	1.46205	.335807	9.62743	-7.69683	10.0664	4132
	CSAD	.908986	.798041	.427024	.18235	2.58384	13.9994	.24053	5.0172	4132
Finland	$R_{m,t}$	.053756	.062068	1.46356	2.14202	.075664	6.91546	-8.46355	9.37088	4124
	CSAD	1.17074	1.04929	.557217	.310491	2.83592	27.2095	.296394	10.5227	4124
France	$R_{m,t}$	.042586	.054839	1.45982	2.13108	.089238	7.38497	-8.84619	9.38817	4202
	CSAD	1.00639	.888284	.469604	.220528	2.06904	9.13229	.303672	4.19721	4202
Germany	$R_{m,t}$	.045037	.07073	1.41719	2.00844	.048563	7.98371	-8.52537	11.8836	4171
	CSAD	1.03473	.893245	.529025	.279868	2.36927	11.5692	.252528	5.55287	4171
Greece	$R_{m,t}$	.032309	.099215	1.66244	2.76371	-.109756	8.16414	-14.0175	13.8705	4063
	CSAD	1.82756	1.66307	.725082	.525744	2.35086	13.9779	.5503	8.79345	4063
HK	$R_{m,t}$	.066823	.083805	1.40287	1.96804	.086724	8.32132	-11.5609	12.2546	4050
	CSAD	1.15651	1.04731	.495203	.245226	2.247	12.6116	.316465	6.30263	4050
Italy	$R_{m,t}$	.028636	.087724	1.41354	1.99808	-.094872	6.39855	-8.14261	9.82029	4168
	CSAD	1.10372	.974755	.551834	.304521	5.02139	77.6325	.263621	13.5428	4168
Norway	$R_{m,t}$	.064272	.116481	1.86264	3.46941	-.232011	7.09096	-11.9357	11.1138	4120
	CSAD	1.5208	1.25041	1.07142	1.14794	4.84758	52.9637	.240526	16.9689	4120
Portugal	$R_{m,t}$	.029709	.067502	1.19824	1.43577	-.206582	6.8201	-7.55258	9.39527	4194
	CSAD	1.17161	1.05143	.578229	.334349	1.69435	8.36541	.219376	5.49308	4194
Spain	$R_{m,t}$	.036884	.077401	1.31646	1.73308	-.019096	7.20029	-7.69075	10.3766	4174
	CSAD	.97829	.873102	.465578	.216763	2.15877	11.9851	.244674	5.48169	4174
Sweden	$R_{m,t}$	.055766	.078644	1.61765	2.61679	.255453	8.99496	-8.82834	14.0028	4123
	CSAD	1.01093	.871083	.505825	.255859	2.14055	10.2453	.282288	5.2127	4123
UK	$R_{m,t}$	.04287	.080248	1.1798	1.39192	-.125118	9.38827	-8.79727	8.34741	4131
	CSAD	1.09861	.954173	.527464	.278218	3.00741	16.9033	.370533	6.69368	4131

Table 4.2.1 presents the descriptive statistics for the equally weighted average market return and the CSAD measurements for each of the total thirteen different countries based on the simple return calculation method. Based on the simple return calculation method, we find that the mean returns of $R_{m,t}$ in all the countries are positive during this time period, which indicates a positive performance in their stock markets. The standard deviation of $R_{m,t}$ varies between countries and is particularly high in Greece and Sweden. Also, the minimum and maximum returns are substantial in all of the markets reflecting the times of financial turbulence in the sample period. Regarding the CASD results model, we find that the mean value of the CSAD results of 1.82756 in Greece is much higher than the other countries in our sample. Similarly, Greece also has the highest standard deviation of CSAD, which is 0.725082. Comparing the descriptive statistics results with the results calculated based on the log return method, we can find out that the average market return calculated based on simple return method is larger than when calculated based on log return, and the range between the minimum and maximum is smaller than when based on the log return. Also, we see that the mean CSAD values and average market returns in the table are slightly higher than were calculated using the log return method. The mean value of CSAD is highest in the countries of Norway and Greece, and the standard deviation of CSAD in Norway is 1.071422, almost twice as high as in the other countries. Those countries that have larger CSAD results may have herding behaviour during the sample period. Denmark and Greece have a similar standard deviation to the results based on the log return method.

If we compare the results to those in Table 3.1.1 for log returns, as expected, the variances for each country are very similar and the mean returns for simple returns are larger. If we consider the max and min returns for each country the simple returns are larger than the log returns and the difference is quite substantial. The CSAD figures are quite similar for each country regardless of whether they are calculated using log or simple returns.

4.2.2 Regression Results

Table 4.2.2.1 Panel A, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t} \rvert$	0.237	0.218	0.162	0.160	0.188	0.318
	(6.55)***	(9.03)***	(6.72)***	(9.54)***	(5.77)***	(18.40)***
$R_{m,t}^2$	0.0215	0.0108	0.0150	0.0196	0.0202	0.0154
	(1.92)*	(1.59)	(2.28)**	(5.07)***	(2.42)**	(4.50)***
_cons	0.974	0.708	0.969	0.799	0.805	1.407
	(53.71)***	(58.08)***	(65.37)***	(73.91)***	(45.46)***	(99.89)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.206	0.286	0.182	0.315	0.293	0.422

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.1 Panel A,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t} \rvert$	0.224	0.146	0.195	0.317	0.174	0.173	0.255
	(8.32)***	(3.64)***	(2.89)***	(14.86)***	(11.38)***	(8.12)***	(9.64)***
$R_{m,t}^2$	0.0118	0.0320	0.0347	0.00458	0.0181	0.00748	0.0282
	(1.61)	(2.49)**	(2.20)**	(0.87)	(4.66)***	(1.69)*	(3.65)***
_cons	0.908	0.893	1.140	0.893	0.783	0.796	0.854
	(61.36)***	(47.78)***	(27.18)***	(68.70)***	(78.35)***	(55.86)***	(69.37)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.305	0.266	0.249	0.231	0.249	0.245	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.1 panel A shows the robust regression results under equation 3.2 based on the simple return calculation method, and panel B in the Appendix shows the results with standard OLS applied. We find that, the coefficients of $|R_{m,t}|$ are highly significant and positive for all the thirteen countries. It shows a positive relationship between the CSAD and the market return in the different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return. Also, Finland, France, Germany, Greece, Italy, Norway, Spain and UK have clear evidence of anti-herding behaviour, shown by significantly positive coefficients of squared market returns. Denmark and Sweden have modest evidence of anti-herding behaviour with significance at the10% level. There is no evidence of the presence of either herding or anti-herding in the markets of the US, Hong Kong and Portugal. Compared with the log return method, for both standard regression results and robust regression results which are shown in Table 3.1.2.1, we have similar results that capture evidence of anti-herding in most of the major markets. According to the robust results, there is neither the presence of herding nor anti-herding in Denmark, US, Hong Kong, Norway and Portugal based on the log return method.

Table 4.2.2.2 Panel A, Robust Regression (Simple returns)

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0216	0.00411	0.0228	0.0238	0.0200	0.0318
	(1.93)*	(0.59)	(2.58)***	(4.23)***	(2.71)***	(3.99)***
$\lvert R_{m,t}\rvert$	0.235	0.219	0.165	0.165	0.192	0.318
	(6.66)***	(9.08)***	(6.86)***	(9.82)***	(5.69)***	(16.44)***
$R_{m,t}^2$	0.0223	0.0105	0.0140	0.0185	0.0195	0.0156
	(2.03)**	(1.56)	(2.11)**	(4.86)***	(2.26)**	(3.93)***
_cons	0.973	0.707	0.967	0.796	0.802	1.406
	(54.55)***	(58.18)***	(65.40)***	(73.34)***	(44.33)***	(94.49)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.208	0.286	0.185	0.320	0.295	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.2 Panel A,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0396	0.0301	0.0107	0.0487	0.0252	0.0219	0.0192
	(5.49)***	(2.74)***	(0.61)	(6.15)***	(3.76)***	(3.70)***	(2.03)**
$\lvert R_{m,t}\rvert$	0.225	0.149	0.194	0.318	0.179	0.179	0.255
	(8.66)***	(3.67)***	(2.89)***	(16.59)***	(12.24)***	(8.09)***	(10.03)***
$R_{m,t}^2$	0.0109	0.0316	0.0351	0.00546	0.0171	0.00613	0.0284
	(1.56)	(2.43)**	(2.25)**	(1.32)	(4.84)***	(1.33)	(3.87)***
_cons	0.905	0.890	1.140	0.889	0.780	0.792	0.853
	(62.42)***	(47.46)***	(27.03)***	(70.92)***	(79.19)***	(54.13)***	(70.70)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.317	0.272	0.249	0.241	0.254	0.249	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.2 panel A presents the robust regression results based on the simple return method under the equation 3.3 regression model, and panel B in the Appendix shows the results from the standard regressions. In both tables, unlike the results based on log returns, which are shown in Table 3.1.2.2, all the coefficient of average market return $R_{m,t}$ are positive. In panel A for the robust regression results, the coefficient of $R_{m,t}$ is positive and significant for 10 countries giving some evidence that herding is less likely when the market return is increasing in these markets. This finding is broadly in accord with the literature with tends to associate more herding with severe market falls. The coefficients of $|R_{m,t}|$are highly significant and positive for all the 13 countries which is broadly in accord with standard asset pricing models. Denmark and Norway have clear evidence of anti-herding behaviour in their stock markets, shown by the significantly positive coefficients of squared market return. As a result, when estimating the existence of herding behaviour by fitting the CCK model based on the simple return calculation method, we have more chance of capturing anti-herding behaviour in the market compared with the estimation results based on the log return calculation method.

Table 4.2.2.3 Panel A Robust regression in rising and falling market condition (Simple returns)

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.246	0.224	0.188	0.183	0.212	0.353
	(6.52)***	(8.46)***	(6.73)***	(9.31)***	(5.48)***	(13.19)***
$(1-D^{up})\|R_{m,t}\|$	0.223	0.212	0.144	0.153	0.170	0.284
	(5.37)***	(9.72)***	(5.38)***	(8.08)***	(7.57)***	(15.60)***
$D^{up}(R_{m,t})^2$	0.0261	0.0102	0.0142	0.0202	0.0193	0.0148
	(1.97)**	(1.30)	(1.79)*	(4.27)***	(1.72)*	(2.27)**
$(1-D^{up})(R_{m,t})^2$	0.0187	0.0116	0.0135	0.0149	0.0199	0.0162
	(1.31)	(1.74)*	(1.41)	(3.13)***	(4.08)***	(4.66)***
_cons	0.973	0.708	0.966	0.795	0.802	1.406
	(56.46)***	(63.49)***	(67.49)***	(73.64)***	(50.60)***	(93.31)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.208	0.286	0.185	0.320	0.295	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.3 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.257	0.152	0.312	0.360	0.192	0.201	0.253
	(7.82)***	(2.76)***	(7.97)***	(16.59)***	(11.52)***	(8.30)***	(9.52)***
$(1-D^{up})\|R_{m,t}\|$	0.198	0.165	0.0881	0.280	0.183	0.157	0.255
	(7.84)***	(4.70)***	(1.00)	(10.83)***	(9.22)***	(8.11)***	(8.57)***
$D^{up}(R_{m,t})^2$	0.0133	0.0411	0.00849	0.00816	0.0216	0.00611	0.0353
	(1.35)	(2.03)**	(1.27)	(1.98)**	(5.32)***	(1.14)	(4.73)***
$(1-D^{up})(R_{m,t})^2$	0.00714	0.0172	0.0572	0.00164	0.00767	0.00620	0.0218
	(1.01)	(1.63)	(2.47)**	(0.22)	(1.28)	(1.58)	(2.15)**
_cons	0.905	0.887	1.133	0.888	0.777	0.792	0.854
	(62.90)***	(46.31)***	(30.90)***	(69.68)***	(77.36)***	(59.25)***	(74.16)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.318	0.275	0.261	0.240	0.255	0.249	0.380

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.3 panel A and panel B in the Appendix present the regression results based on the simple return calculation method, and panel A presents the robust regression results. According to the robust results, the coefficients of the absolute average market return under rising market conditions $D^{up}|R_{m,t}|$ and the coefficient of the absolute average market return under falling market conditions $(1 - D^{up})|R_{m,t}|$ are highly significant and positive for all the countries in our data sample. It shows a positive relationship between the CSAD results and the absolute market return in different markets. Denmark, Italy, Portugal, Spain, France, Greece and the UK have a significantly positive coefficient in rising market conditions. Also, Germany, France, Greece and the UK have a significantly positive coefficient in falling market conditions, and we can say these countries in specific market conditions have clear evidence of anti-herding behaviour in their stock markets. Compared with the robust results based on the log return method, in the rising market condition, we captured evidence of anti-herding behaviour in Portugal, and in a falling market, the coefficient has become insignificant in Sweden and there is some evidence of anti-herding behaviour in the US market with significance at the 10% level.

By using the full range of return data, we have not found any firm evidence of herding in the market during the sample period. Then we focus on the large price movements in the stock market, by initially using the average market returns and dividing them into the positive and negative returns, then we select the large movements in the market by using the returns higher than the positive mean value on the positive side and lower than the negative mean value on the negative side and use the equation 3.2 as the regression model.

Table 4.2.2.4 Panel A Robust regression with larger simple positive return

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.545	0.433	0.287	0.330	0.430	0.478
	(5.81)***	(6.86)***	(3.34)***	(6.09)***	(5.19)***	(9.19)***
$R_{m,t}^2$	-0.0162	-0.0138	0.00146	0.00246	-0.00418	0.00213
	(-0.94)	(-1.36)	(0.11)	(0.34)	(-0.32)	(0.37)
_cons	0.622	0.433	0.842	0.591	0.476	1.205
	(6.49)***	(6.40)***	(7.90)***	(8.45)***	(4.83)***	(14.43)***
N	885	817	815	797	829	783
adj. R^2	0.267	0.366	0.238	0.404	0.366	0.458

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.4 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.434	0.289	0.619	0.402	0.280	0.434	0.439
	(6.77)***	(2.28)**	(6.35)***	(6.65)***	(6.66)***	(10.25)***	(6.53)***
$R_{m,t}^2$	-0.00512	0.0217	-0.0246	0.000700	0.0107	-0.0146	0.00904
	(-0.50)	(0.78)	(-2.45)**	(0.09)	(2.10)**	(-3.41)***	(0.84)
_cons	0.632	0.722	0.643	0.858	0.658	0.385	0.634
	(8.15)***	(5.73)***	(4.09)***	(11.99)***	(12.26)***	(6.07)***	(9.18)***
N	824	826	816	838	852	789	766
adj. R^2	0.393	0.300	0.185	0.213	0.337	0.395	0.446

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We check the regression results based on simple returns. Table 4.2.2.4 panel A is based on the largest simple positive returns using the robust regression approach, and panel B in the Appendix shows the corresponding results based on the standard regressions. In the robust results shown in panel A, the coefficients of $|R_{m,t}|$ are highly significant and positive for all the thirteen countries. Both Norway and Sweden have a significantly negative coefficient of $R_{m,t}^2$, indicating that herding behaviour exists in the stock market. Based on this result, we can reject the no herding hypothesis and confirm that herding behaviour exists in the markets of Norway and Sweden in periods when the market is rising substantially.

Table 4.2.2.5 Panel A Robust regression with larger simple negative returns

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.373	0.359	0.167	0.220	0.218	0.381
	(4.28)***	(6.27)***	(2.43)**	(3.92)***	(3.64)***	(6.41)***
$R_{m,t}^2$	-0.00107	-0.0116	0.0113	0.00575	0.0145	0.00688
	(-0.06)	(-1.18)	(0.85)	(0.68)	(1.67)*	(1.07)
_cons	0.777	0.538	0.921	0.704	0.719	1.242
	(8.22)***	(8.93)***	(10.79)***	(9.75)***	(9.61)***	(12.35)***
N	713	739	723	719	728	723
adj. R^2	0.230	0.287	0.140	0.277	0.286	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.5 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.304	0.126	-0.225	0.226	0.289	0.183	0.349
	(6.37)***	(1.05)	(-0.76)	(2.89)***	(4.45)***	(3.19)***	(4.71)***
$R_{m,t}^2$	-0.00508	0.0228	0.0881	0.0101	-0.00824	0.00295	0.00933
	(-0.75)	(1.01)	(2.08)**	(0.73)	(-0.77)	(0.39)	(0.67)
_cons	0.749	0.941	1.702	0.953	0.641	0.753	0.731
	(11.49)***	(7.05)***	(3.99)***	(11.12)***	(8.28)***	(9.25)***	(9.44)***
N	705	713	714	723	708	690	665
adj. R^2	0.258	0.235	0.295	0.175	0.192	0.178	0.370

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.5 panel A and panel B in the Appendix show the regression results for the larger negative returns. In table panel A, with robust regression results, the coefficients of $|R_{m,t}|$are highly significant and positive for 11 countries, showing a positive relationship between the CSAD and the market return in the different markets. Only Norway has a significantly positive coefficient of $R_{m,t}^2$, meaning there is evidence of anti-herding behaviour in the stock market. As a result, there is no evidence that either herding or anti-herding behaviour exists in most of the major stock markets. Compared with the corresponding regression results based on the log return method, with larger price movements in falling market condition, we have similar results that there is no herding behaviour in most of the stock markets.

4.2.3 Regression considering large market returns

4.2.3.1 market return larger than |0.5%|

Table 4.2.3 panel A, Robust Regression with market return larger than |0.5%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0230	0.00679	0.0240	0.0251	0.0216	0.0323
	(2.08)**	(0.98)	(2.71)***	(4.47)***	(2.98)***	(4.10)***
$\lvert R_{m,t}\rvert$	0.351	0.317	0.197	0.228	0.238	0.388
	(7.08)***	(8.71)***	(5.23)***	(9.29)***	(4.74)***	(15.22)***
$R_{m,t}^2$	0.00525	-0.00259	0.00958	0.00992	0.0136	0.00839
	(0.47)	(-0.35)	(1.19)	(2.28)**	(1.35)	(2.06)**
_cons	0.846	0.595	0.930	0.718	0.743	1.300
	(20.82)***	(19.97)***	(27.76)***	(31.33)***	(17.56)***	(47.11)***
N	2460	2405	2674	2699	2645	2786
adj. R^2	0.232	0.318	0.191	0.350	0.310	0.442

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0410	0.0319	0.0106	0.0502	0.0265	0.0245	0.0217
	(5.92)***	(2.91)***	(0.60)	(6.15)***	(3.89)***	(4.15)***	(2.30)**
$\lvert R_{m,t}\rvert$	0.297	0.203	0.234	0.365	0.219	0.234	0.339
	(9.19)***	(3.33)***	(2.40)**	(11.20)***	(9.28)***	(8.40)***	(8.61)***
$R_{m,t}^2$	0.00252	0.0233	0.0306	-0.00210	0.0114	0.000195	0.0161
	(0.38)	(1.49)	(1.63)	(-0.35)	(2.63)***	(0.04)	(1.93)*
_cons	0.810	0.829	1.081	0.840	0.732	0.713	0.761
	(28.49)***	(18.50)***	(12.06)***	(28.89)***	(32.71)***	(25.90)***	(24.13)***
N	2579	2603	2979	2424	2538	2759	2208
adj. R^2	0.341	0.294	0.251	0.238	0.269	0.270	0.405

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.2 market return larger than |1%|

Table 4.2.3 panel B, Robust Regression with market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0302	0.0102	0.0275	0.0271	0.0256	0.0323
	(2.55)**	(1.35)	(2.96)***	(4.54)***	(3.37)***	(3.94)***
$\lvert R_{m,t}\rvert$	0.507	0.438	0.236	0.262	0.341	0.428
	(7.79)***	(7.92)***	(3.97)***	(6.89)***	(5.04)***	(11.39)***
$R_{m,t}^2$	-0.0141	-0.0167	0.00469	0.00585	0.00207	0.00481
	(-1.26)	(-1.88)*	(0.46)	(1.06)	(0.19)	(1.00)
_cons	0.621	0.413	0.871	0.667	0.578	1.227
	(8.29)***	(6.47)***	(12.08)***	(13.90)***	(7.27)***	(22.60)***
N	1332	1258	1609	1588	1566	1784
adj. R^2	0.259	0.340	0.194	0.352	0.329	0.431

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0410	0.0356	0.0107	0.0537	0.0289	0.0272	0.0235
	(5.72)***	(3.07)***	(0.58)	(6.05)***	(3.95)***	(4.36)***	(2.28)**
$\lvert R_{m,t}\rvert$	0.365	0.202	0.202	0.313	0.253	0.318	0.404
	(8.71)***	(2.19)**	(1.42)	(6.12)***	(6.38)***	(9.64)***	(6.42)***
$R_{m,t}^2$	-0.00430	0.0234	0.0337	0.00503	0.00713	-0.00786	0.00802
	(-0.64)	(1.21)	(1.47)	(0.69)	(1.23)	(-1.89)*	(0.78)
_cons	0.694	0.833	1.140	0.908	0.682	0.563	0.668
	(13.36)***	(8.82)***	(6.50)***	(14.17)***	(13.54)***	(12.42)***	(9.03)***
N	1540	1547	2012	1332	1430	1673	1105
adj. R^2	0.349	0.273	0.230	0.199	0.273	0.299	0.396

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.3 market return larger than |2%|

Table 4.2.3 panel C, Robust Regression with market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0366	0.0209	0.0279	0.0308	0.0348	0.0326
	(2.20)**	(2.01)**	(2.36)**	(4.15)***	(3.57)***	(3.30)***
$\lvert R_{m,t}\rvert$	0.765	0.530	0.231	0.388	0.486	0.482
	(4.77)***	(4.37)***	(1.51)	(4.62)***	(3.59)***	(6.30)***
$R_{m,t}^2$	-0.0394	-0.0261	0.00429	-0.00748	-0.0115	0.000637
	(-2.38)**	(-1.81)*	(0.24)	(-0.82)	(-0.73)	(0.09)
_cons	0.0836	0.224	0.905	0.424	0.267	1.092
	(0.26)	(1.02)	(3.19)***	(2.64)***	(1.07)	(6.82)***
N	340	315	532	544	505	714
adj. R^2	0.246	0.312	0.169	0.357	0.341	0.439

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 panel C (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0437	0.0478	0.00644	0.0495	0.0346	0.0381	0.0304
	(4.86)***	(3.08)***	(0.29)	(4.09)***	(3.52)***	(5.04)***	(2.24)**
$\lvert R_{m,t}\rvert$	0.478	0.202	0.0329	0.0990	0.184	0.424	0.749
	(6.38)***	(1.04)	(0.12)	(0.80)	(2.04)**	(7.54)***	(4.60)***
$R_{m,t}^2$	-0.0140	0.0229	0.0477	0.0290	0.0134	-0.0168	-0.0268
	(-1.79)*	(0.81)	(1.42)	(2.21)**	(1.52)	(-3.32)***	(-1.55)
_cons	0.448	0.843	1.550	1.300	0.841	0.310	-0.0417
	(3.00)***	(2.59)***	(3.00)***	(5.50)***	(4.72)***	(2.57)**	(-0.13)
N	512	537	847	367	440	627	321
adj. R^2	0.357	0.231	0.198	0.206	0.257	0.296	0.390

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.4 market return larger than |3%|

Table 4.2.3 panel D, Robust Regression with market return larger than |3%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0275	0.0311	0.0311	0.0341	0.0405	0.0346
	(1.16)	(2.29)**	(1.96)*	(3.58)***	(3.15)***	(2.61)***
$\|R_{m,t}\|$	1.569	0.770	0.757	0.489	0.899	0.476
	(3.70)***	(3.17)***	(1.99)**	(2.50)**	(4.64)***	(3.12)***
$R_{m,t}^2$	-0.109	-0.0459	-0.0407	-0.0166	-0.0433	0.00111
	(-3.02)***	(-2.01)**	(-1.17)	(-0.95)	(-2.46)**	(0.10)
_cons	-1.933	-0.420	-0.486	0.183	-0.899	1.112
	(-1.82)*	(-0.70)	(-0.53)	(0.37)	(-1.88)*	(2.63)***
N	109	112	204	221	183	278
adj. R^2	0.240	0.268	0.192	0.340	0.405	0.412

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 panel D (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0450	0.0537	-0.00575	0.0429	0.0384	0.0424	0.0295
	(3.68)***	(2.27)**	(-0.20)	(2.70)***	(2.76)***	(4.34)***	(1.69)*
$\|R_{m,t}\|$	0.767	0.436	-0.0899	0.212	0.236	0.442	1.423
	(5.56)***	(1.07)	(-0.17)	(0.73)	(1.10)	(4.16)***	(3.76)***
$R_{m,t}^2$	-0.0343	0.00238	0.0562	0.0220	0.00904	-0.0185	-0.0866
	(-3.52)***	(0.06)	(1.12)	(0.88)	(0.51)	(-2.39)**	(-2.56)**
_cons	-0.397	0.237	1.935	0.901	0.702	0.273	-1.711
	(-1.02)	(0.24)	(1.50)	(1.23)	(1.25)	(0.88)	(-1.86)*
N	167	199	379	108	149	260	126
adj. R^2	0.424	0.221	0.182	0.402	0.276	0.252	0.382

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.5 market return larger than |4%|

Table 4.2.3 panel E, Robust Regression with market return larger than |4%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0335	0.0385	0.0317	0.0374	0.0470	0.0375
	(0.89)	(2.19)**	(1.36)	(3.13)***	(2.77)***	(2.10)**
$\lvert R_{m,t}\rvert$	1.833	0.261	1.691	0.683	0.848	0.437
	(1.50)	(0.55)	(2.15)**	(1.88)*	(2.30)**	(1.55)
$R_{m,t}^2$	-0.129	-0.0121	-0.114	-0.0315	-0.0399	0.00345
	(-1.39)	(-0.33)	(-1.79)*	(-1.10)	(-1.42)	(0.19)
_cons	-2.758	1.322	-3.237	-0.420	-0.736	1.241
	(-0.75)	(0.90)	(-1.47)	(-0.39)	(-0.63)	(1.30)
N	43	49	91	83	80	121
adj. R^2	0.055	0.107	0.125	0.426	0.274	0.372

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 panel E (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0500	0.0718	-0.0331	0.0562	0.0544	0.0487	0.0267
	(3.42)***	(1.93)*	(-0.86)	(2.41)**	(2.96)***	(4.11)***	(1.10)
$\lvert R_{m,t}\rvert$	1.482	2.076	-0.0275	0.592	0.185	0.662	1.353
	(5.16)***	(1.60)	(-0.02)	(1.07)	(0.52)	(4.59)***	(1.25)
$R_{m,t}^2$	-0.0790	-0.124	0.0519	-0.0115	0.0111	-0.0326	-0.0815
	(-4.64)***	(-1.30)	(0.61)	(-0.27)	(0.41)	(-3.76)***	(-0.94)
_cons	-2.900	-4.743	1.706	-0.0407	0.913	-0.474	-1.485
	(-2.96)***	(-1.21)	(0.50)	(-0.02)	(0.87)	(-0.91)	(-0.47)
N	62	85	178	34	60	121	46
adj. R^2	0.528	0.219	0.171	0.501	0.346	0.299	0.216

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.6 market return larger than |5%|

Table 4.2.3 panel F, Robust Regression with market return larger than |5%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0481	0.0435	0.0200	0.0364	0.0503	0.0340
	(0.79)	(2.38)**	(0.57)	(2.90)***	(3.00)***	(1.46)
$\lvert R_{m,t}\rvert$	-0.911	1.102	-1.188	2.138	2.397	0.0100
	(-0.44)	(1.48)	(-0.55)	(2.65)**	(5.11)***	(0.02)
$R_{m,t}^2$	0.0572	-0.0678	0.0869	-0.132	-0.133	0.0257
	(0.40)	(-1.31)	(0.57)	(-2.36)**	(-4.80)***	(0.90)
_cons	6.874	-1.654	6.754	-5.530	-6.689	3.055
	(0.96)	(-0.63)	(0.90)	(-1.96)*	(-3.68)***	(1.49)
N	18	23	38	41	37	56
adj. R^2	-0.163	0.178	-0.073	0.513	0.558	0.333

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 panel F (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0628	0.103	-0.0680	0.0617	0.0636	0.0512	-0.000365
	(3.36)***	(1.49)	(-1.32)	(1.78)	(2.39)**	(3.36)***	(-0.01)
$\lvert R_{m,t}\rvert$	1.788	6.184	0.770	0.881	-0.746	0.896	2.358
	(2.51)**	(1.65)	(0.35)	(0.70)	(-0.91)	(3.20)***	(0.88)
$R_{m,t}^2$	-0.0963	-0.408	0.00524	-0.0321	0.0700	-0.0452	-0.157
	(-2.44)**	(-1.55)	(0.04)	(-0.37)	(1.37)	(-3.19)***	(-0.79)
_cons	-4.177	-18.94	-1.556	-1.019	4.364	-1.465	-4.641
	(-1.47)	(-1.53)	(-0.20)	(-0.23)	(1.37)	(-1.18)	(-0.54)
N	24	31	92	14	28	59	21
adj. R^2	0.413	0.169	0.171	0.535	0.253	0.312	-0.044

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.7 market return larger than |3%| in rising and falling market condition

Table 4.2.3 Panel G Standard regression in rising and falling market condition with market return larger than |3%|

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.718	0.881	0.783	0.539	0.972	0.526
	(3.47)***	(3.40)***	(2.18)**	(2.69)***	(4.86)***	(3.87)***
$(1-D^{up})\|R_{m,t}\|$	1.569	0.890	0.710	0.526	0.929	0.423
	(3.68)***	(3.00)***	(2.00)**	(2.59)**	(4.49)***	(2.83)***
$D^{up}(R_{m,t})^2$	-0.126	-0.0510	-0.0405	-0.0161	-0.0448	-0.00204
	(-2.61)**	(-2.21)**	(-1.18)	(-0.90)	(-2.53)**	(-0.23)
$(1-D^{up})(R_{m,t})^2$	-0.107	-0.0662	-0.0383	-0.0273	-0.0523	0.00404
	(-3.38)***	(-2.19)**	(-1.25)	(-1.42)	(-2.55)**	(0.36)
_cons	-2.107	-0.667	-0.463	0.0921	-1.014	1.120
	(-1.84)*	(-0.98)	(-0.53)	(0.18)	(-2.05)**	(2.78)***
N	109	112	204	221	183	278
adj. R^2	0.237	0.265	0.188	0.340	0.402	0.411

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 Panel G (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.804	0.547	0.277	0.178	0.423	0.487	1.436
	(5.55)***	(1.12)	(0.66)	(0.50)	(1.85)*	(4.04)***	(3.54)***
$(1-D^{up})\|R_{m,t}\|$	0.761	0.520	-0.210	0.0388	0.498	0.404	1.394
	(4.92)***	(0.92)	(-0.41)	(0.09)	(1.91)*	(2.84)***	(3.65)***
$D^{up}(R_{m,t})^2$	-0.0315	0.000682	0.00134	0.0265	0.000905	-0.0186	-0.0842
	(-2.72)***	(0.02)	(0.04)	(0.95)	(0.05)	(-2.30)**	(-2.17)**
$(1-D^{up})(R_{m,t})^2$	-0.0404	-0.0166	0.0878	0.0384	-0.0312	-0.0190	-0.0876
	(-3.58)***	(-0.27)	(1.57)	(0.90)	(-1.15)	(-1.38)	(-2.67)***
_cons	-0.435	0.0155	1.609	1.139	0.197	0.266	-1.692
	(-1.05)	(0.01)	(1.41)	(1.20)	(0.32)	(0.75)	(-1.78)*
N	167	199	379	108	149	260	126
adj. R^2	0.424	0.219	0.228	0.398	0.284	0.249	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3.8 market return larger than |4%| in rising and falling market condition

Table 4.2.3 Panel H Standard regression in rising and falling market condition with market return larger than |4%|

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2 (1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4 (1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	2.614	0.261	1.785	0.773	0.810	0.512
	(1.87)*	(0.50)	(2.15)**	(2.06)**	(1.90)*	(2.01)**
$(1 - D^{up})\|R_{m,t}\|$	2.209	0.162	1.776	0.773	0.657	0.363
	(1.68)	(0.26)	(1.94)*	(1.95)*	(1.30)	(1.36)
$D^{up}(R_{m,t})^2$	-0.205	-0.00967	-0.118	-0.0334	-0.0351	-0.00232
	(-1.78)*	(-0.25)	(-1.77)*	(-1.14)	(-1.18)	(-0.16)
$(1 - D^{up})(R_{m,t})^2$	-0.148	-0.00548	-0.127	-0.0457	-0.0248	0.00870
	(-1.61)	(-0.10)	(-1.66)	(-1.41)	(-0.58)	(0.53)
_cons	-4.387	1.452	-3.474	-0.672	-0.422	1.246
	(-1.09)	(0.83)	(-1.43)	(-0.58)	(-0.29)	(1.38)
N	43	49	91	83	80	121
adj. R^2	0.073	0.087	0.116	0.423	0.266	0.371

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.3 Panel H (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	1.523	2.242	0.504	0.275	0.362	0.697	1.286
	(5.25)***	(1.36)	(0.53)	(0.43)	(0.88)	(3.81)***	(1.09)
$(1 - D^{up})\|R_{m,t}\|$	1.483	2.168	-0.119	-0.000420	0.352	0.586	1.294
	(4.78)***	(1.18)	(-0.11)	(-0.00)	(0.75)	(2.44)**	(1.14)
$D^{up}(R_{m,t})^2$	-0.0763	-0.129	-0.0175	0.0134	0.00393	-0.0319	-0.0712
	(-4.62)***	(-1.14)	(-0.27)	(0.28)	(0.13)	(-3.13)***	(-0.73)
$(1 - D^{up})(R_{m,t})^2$	-0.0855	-0.142	0.0860	0.0436	-0.0139	-0.0296	-0.0812
	(-4.16)***	(-0.88)	(0.96)	(0.70)	(-0.33)	(-1.42)	(-0.93)
_cons	-2.954	-5.089	1.051	1.204	0.462	-0.416	-1.312
	(-2.93)***	(-1.00)	(0.34)	(0.61)	(0.37)	(-0.61)	(-0.39)
N	62	85	178	34	60	121	46
adj. R^2	0.524	0.210	0.226	0.496	0.338	0.293	0.198

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We assume that herding tends to be present during periods when markets have larger movements such as in periods of financial turmoil. In this section, we detect herding behaviour based on the simple return calculation method with market returns larger than |0.5%|, |1%|, |2%|, |3%|, |4%| and |5%| using the standard regression equation 3.3. According to the results shown in table 4.2.3 panel A, we can find out that the coefficients of the $R_{m,t}$ is significant and positive for 11 countries with market returns larger than |0.5%|, the number increases to 12 countries when market returns are larger than |2%| and reduces to 6 countries with market return larger than |5%|, which giving some evidence that herding is less likely when the market return is increasing in these markets also this could be due to lack of data restricting statistical significance. The coefficients of $|R_{m,t}|$ are highly significant and positive for all the thirteen countries when the market return larger than |0.5%| and |1%|, it shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 4 countries have significantly positive coefficient of $|R_{m,t}|$ with market return larger than |5%|. Focusing on the coefficient of squared market returns, we find no evidence of herding behaviour in the market as we do not see any significantly negative coefficients. In table 4.2.3 panel B, we only see US and Sweden with evidence of herding behaviour in their market and these are only significant at the 10% level. In table 4.2.3 panel C, Denmark and Sweden show significant evidence of herding behaviour, US and Hong Kong also have herding behaviour significant at the 10% level. In the last table with market returns larger than |3%|, Denmark, US, Germany, Hong Kong, Sweden and UK show clear evidence of herding behaviour. In panel E and F, with increases of absolute average market return, we have less observation in data sample, so we may have some bias to detect herding behaviour in the stock markets. In the rising and falling market condition, the coefficients of the absolute average market return under rising market conditions $D^{up}|R_{m,t}|$ are significantly positive for 9 countries with market return larger than |3%|, the number reduces to 5 countries when market return are larger than |4%|. Also, the coefficients of the absolute average market return under falling market conditions $(1 - D^{up})|R_{m,t}|$ are highly significant and positive for 9 countries with market return larger than |3%|, then reduces to 2 countries when market return larger than |4%|. It shows a positive relationship between the CSAD results and the market return in different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return. The results for absolute market returns larger than |3%|are shown in panel G, we have found Denmark, US, Germany, Hong Kong, Sweden and UK have clear evidence of herding behaviour in rising market condition, and in the falling market condition, herding behaviour exists in the market of Denmark, US, Germany, Hong Kong and UK. Compare with results based on the log return calculation methos shown in table 3.1.3 panel G, we have more evidence of herding behaviour captured in the results based on simple return calculation method, such as Denmark in falling market condition, Germany and UK in both rising and falling market condition. With absolute market return larger than 4%, compare with the results based on log return calculation method, we also found some more evidence of herding behaviour in the market, such as Denmark, Finland have some evidence of herding behaviour in rising market condition which is significant at 10% level. From the results above, we can deduce that, with the increase of value of absolute return, herding behaviour is more likely to be detected. Also, compared with the regression results based on log return calculation method, it seems that herding behaviour has more likelihood of being detected when applying the simple return calculation method, especially when the market has larger movements.

4.2.4 Larger market movements based on a proportion of the data condition

4.2.4.1 Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

Regression results by using CCK based on the standard regression method
Table 4.2.4, panel A Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0226	0.00674	0.0259	0.0259	0.0210	0.0319
	(2.01)**	(0.96)	(2.86)***	(4.53)***	(2.85)***	(3.95)***
$\|R_{m,t}\|$	0.378	0.341	0.207	0.243	0.273	0.414
	(6.95)***	(8.45)***	(4.38)***	(8.09)***	(4.66)***	(12.41)***
$R_{m,t}^2$	0.00178	-0.00555	0.00820	0.00813	0.00961	0.00599
	(0.15)	(-0.72)	(0.91)	(1.68)*	(0.90)	(1.32)
_cons	0.811	0.562	0.916	0.696	0.689	1.255
	(16.47)***	(15.35)***	(18.42)***	(21.44)***	(11.80)***	(28.06)***
N	2052	2066	2062	2102	2086	2032
adj. R^2	0.239	0.320	0.193	0.355	0.316	0.433

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4, panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0406	0.0336	0.0107	0.0514	0.0261	0.0251	0.0213
	(5.79)***	(3.01)***	(0.58)	(6.25)***	(3.78)***	(4.18)***	(2.25)**
$\|R_{m,t}\|$	0.316	0.209	0.207	0.334	0.226	0.288	0.340
	(8.40)***	(2.86)***	(1.52)	(9.48)***	(8.13)***	(9.65)***	(8.30)***
$R_{m,t}^2$	0.000556	0.0225	0.0332	0.00225	0.0105	-0.00500	0.0160
	(0.08)	(1.31)	(1.49)	(0.38)	(2.24)**	(-1.20)	(1.88)*
_cons	0.780	0.822	1.130	0.879	0.722	0.619	0.759
	(19.76)***	(13.13)***	(6.91)***	(25.27)***	(24.57)***	(17.29)***	(22.21)***
N	2026	2084	2060	2098	2088	2062	2066
adj. R^2	0.336	0.289	0.232	0.223	0.271	0.297	0.403

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.4.2 Largest 10% (10% of absolute value (above 5% and 5% below 0))

Regression results by using CCK based on the standard regression method
Table 4.2.4 panel B, Robust Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0394	0.0196	0.0291	0.0310	0.0345	0.0315
	$(2.51)^{**}$	$(1.99)^{**}$	$(2.31)^{**}$	$(3.89)^{***}$	$(3.36)^{***}$	$(2.69)^{***}$
$\|R_{m,t}\|$	0.664	0.491	0.281	0.454	0.544	0.478
	$(4.85)^{***}$	$(4.61)^{***}$	(1.45)	$(4.38)^{***}$	$(3.73)^{***}$	$(4.14)^{***}$
$R_{m,t}^2$	-0.0298	-0.0227	-0.000248	-0.0134	-0.0163	0.000976
	$(-1.96)^{*}$	$(-1.72)^{*}$	(-0.01)	(-1.28)	(-1.01)	(0.11)
_cons	0.310	0.323	0.785	0.270	0.119	1.100
	(1.23)	$(1.79)^{*}$	$(2.02)^{**}$	(1.25)	(0.42)	$(3.78)^{***}$
N	410	414	412	420	418	406
adj. R^2	0.241	0.299	0.173	0.357	0.351	0.413

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0468	0.0487	-0.00243	0.0514	0.0349	0.0403	0.0311
	$(4.85)^{***}$	$(2.79)^{***}$	(-0.09)	$(4.34)^{***}$	$(3.49)^{***}$	$(4.71)^{***}$	$(2.44)^{**}$
$\|R_{m,t}\|$	0.462	0.242	-0.00372	0.135	0.223	0.457	0.608
	$(5.27)^{***}$	(1.05)	(-0.01)	(1.15)	$(2.37)^{**}$	$(6.16)^{***}$	$(4.73)^{***}$
$R_{m,t}^2$	-0.0129	0.0190	0.0502	0.0254	0.00974	-0.0193	-0.0132
	(-1.50)	(0.63)	(1.05)	$(2.00)^{**}$	(1.04)	$(-3.27)^{***}$	(-0.89)
_cons	0.494	0.752	1.665	1.223	0.752	0.224	0.268
	$(2.63)^{***}$	$(1.72)^{*}$	(1.42)	$(5.58)^{***}$	$(4.06)^{***}$	(1.20)	(1.16)
N	406	416	412	420	418	412	414
adj. R^2	0.349	0.224	0.189	0.196	0.266	0.274	0.383

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.4.3 Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

Regression results by using CCK based on the standard regression method

Table 4.2.4 panel C, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0343	0.0300	0.0305	0.0370	0.0399	0.0344
	(1.81)*	(2.54)**	(1.96)*	(3.83)***	(3.22)***	(2.36)**
$\|R_{m,t}\|$	1.156	0.652	0.793	0.582	0.882	0.466
	(4.90)***	(4.17)***	(2.17)**	(2.85)***	(4.86)***	(2.50)**
$R_{m,t}^2$	-0.0742	-0.0370	-0.0436	-0.0244	-0.0420	0.00179
	(-3.40)***	(-2.20)**	(-1.29)	(-1.35)	(-2.49)**	(0.14)
_cons	-0.865	-0.0672	-0.586	-0.0730	-0.850	1.137
	(-1.64)	(-0.21)	(-0.67)	(-0.14)	(-1.96)*	(2.05)**
N	206	208	206	210	208	204
adj. R^2	0.280	0.300	0.195	0.354	0.416	0.408

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4 panel C (continued)

	(1) Hong Kong	(2) Italy	(3) Norway	(4) Portugal	(5) Spain	(6) Sweden	(7) UK
$R_{m,t}$	0.0500	0.0574	-0.0250	0.0530	0.0372	0.0498	0.0310
	(4.28)***	(2.31)**	(-0.68)	(3.75)***	(2.93)***	(5.01)***	(2.08)**
$\|R_{m,t}\|$	0.643	0.325	-0.0553	0.121	0.184	0.621	1.077
	(4.84)***	(0.77)	(-0.06)	(0.66)	(1.17)	(6.14)***	(4.43)***
$R_{m,t}^2$	-0.0261	0.0114	0.0540	0.0277	0.0134	-0.0301	-0.0566
	(-2.61)***	(0.28)	(0.72)	(1.56)	(1.00)	(-4.43)***	(-2.42)**
_cons	-0.0100	0.549	1.792	1.226	0.838	-0.329	-0.826
	(-0.03)	(0.54)	(0.64)	(3.07)***	(2.20)**	(-1.06)	(-1.55)
N	202	208	206	210	208	206	206
adj. R^2	0.380	0.209	0.175	0.255	0.262	0.343	0.415

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.4.4 Largest 3% (3% of absolute value)

Regression results by using CCK based on the standard regression method

Table 4.2.4 panel D, Robust Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0255	0.0267	0.0299	0.0446	0.0462	0.0364
	(1.14)	(1.93)*	(1.44)	(4.04)***	(3.13)***	(2.05)**
$\lvert R_{m,t}\rvert$	1.608	0.633	1.503	0.620	0.699	0.467
	(4.26)***	(2.58)**	(2.32)**	(2.30)**	(2.48)**	(1.66)*
$R_{m,t}^2$	-0.112	-0.0353	-0.0996	-0.0282	-0.0297	0.00181
	(-3.41)***	(-1.53)	(-1.85)*	(-1.26)	(-1.23)	(0.10)
_cons	-2.047	-0.0203	-2.677	-0.159	-0.248	1.123
	(-2.23)**	(-0.03)	(-1.53)	(-0.21)	(-0.32)	(1.18)
N	123	123	123	126	125	122
adj. R^2	0.281	0.219	0.190	0.385	0.317	0.374

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4 panel D (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0438	0.0714	-0.0498	0.0451	0.0461	0.0493	0.0310
	(3.24)***	(2.28)**	(-1.08)	(2.77)***	(3.13)***	(4.19)***	(1.76)*
$\lvert R_{m,t}\rvert$	0.828	0.852	-0.186	-0.144	-0.0268	0.678	1.472
	(4.21)***	(1.14)	(-0.11)	(-0.48)	(-0.10)	(4.85)***	(3.83)***
$R_{m,t}^2$	-0.0383	-0.0319	0.0614	0.0513	0.0286	-0.0335	-0.0907
	(-2.97)***	(-0.53)	(0.54)	(1.88)*	(1.40)	(-3.98)***	(-2.65)***
_cons	-0.595	-0.932	2.303	1.881	1.497	-0.534	-1.846
	(-0.98)	(-0.45)	(0.42)	(2.58)**	(2.07)**	(-1.06)	(-1.96)*
N	122	125	124	126	125	124	124
adj. R^2	0.396	0.207	0.147	0.295	0.249	0.313	0.384

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.4.5 Largest 2% (2% of absolute value)

Regression results by using CCK based on the standard regression method

Table 4.2.4 panel E, Robust Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0373	0.0365	0.0309	0.0359	0.0470	0.0320
	(1.37)	(2.45)**	(1.25)	(2.98)***	(2.81)***	(1.50)
$\|R_{m,t}\|$	1.596	0.702	1.597	0.540	0.854	0.120
	(2.82)***	(2.51)**	(1.91)*	(1.40)	(2.44)**	(0.29)
$R_{m,t}^2$	-0.111	-0.0416	-0.107	-0.0209	-0.0403	0.0202
	(-2.37)**	(-1.65)	(-1.60)	(-0.69)	(-1.49)	(0.86)
_cons	-2.008	-0.192	-2.936	0.0413	-0.760	2.554
	(-1.34)	(-0.26)	(-1.24)	(0.04)	(-0.70)	(1.63)
N	82	82	82	84	83	81
adj. R^2	0.195	0.220	0.097	0.392	0.287	0.304

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4 panel E (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0450	0.0719	-0.0791	0.0408	0.0531	0.0472	0.0378
	(3.31)***	(1.88)*	(-1.43)	(2.71)***	(3.34)***	(3.60)***	(1.86)*
$\|R_{m,t}\|$	1.257	2.085	1.902	0.741	0.465	0.823	1.575
	(5.35)***	(1.52)	(0.77)	(2.51)**	(1.49)	(4.64)***	(2.79)***
$R_{m,t}^2$	-0.0653	-0.125	-0.0600	-0.0209	-0.00842	-0.0411	-0.0992
	(-4.57)***	(-1.24)	(-0.37)	(-0.85)	(-0.34)	(-4.19)***	(-2.08)**
_cons	-2.078	-4.770	-6.229	-0.585	-0.0226	-1.151	-2.128
	(-2.70)***	(-1.16)	(-0.70)	(-0.77)	(-0.03)	(-1.63)	(-1.43)
N	81	83	82	84	83	82	83
adj. R^2	0.508	0.211	0.196	0.563	0.406	0.324	0.336

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.4.6 Largest 3% (3% of absolute value) in rising and falling market condition

Regression results by using CCK based on the Normal regression method

Table 4.2.4 panel F, Robust Regression

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.723	0.744	1.589	0.664	0.683	0.540
	(3.97)***	(3.00)***	(2.43)**	(2.44)**	(2.34)**	(2.12)**
$(1 - D^{up})\|R_{m,t}\|$	1.597	0.771	1.577	0.575	0.542	0.398
	(4.26)***	(2.87)***	(2.24)**	(2.07)**	(1.68)*	(1.49)
$D^{up}(R_{m,t})^2$	-0.125	-0.0407	-0.103	-0.0282	-0.0263	-0.00363
	(-2.88)***	(-1.80)*	(-1.88)*	(-1.25)	(-1.11)	(-0.25)
$(1 - D^{up})(R_{m,t})^2$	-0.110	-0.0580	-0.112	-0.0281	-0.0173	0.00660
	(-3.86)***	(-2.11)**	(-1.88)*	(-1.16)	(-0.59)	(0.40)
_cons	-2.162	-0.280	-2.885	-0.158	-0.0251	1.121
	(-2.21)**	(-0.44)	(-1.57)	(-0.21)	(-0.03)	(1.24)
N	123	123	123	126	125	122
adj. R^2	0.278	0.217	0.184	0.380	0.312	0.373

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4 panel F (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.868	0.908	0.283	-0.238	0.118	0.707	1.496
	(4.23)***	(1.06)	(0.19)	(-0.74)	(0.40)	(3.92)***	(3.58)***
$(1 - D^{up})\|R_{m,t}\|$	0.843	0.744	-0.425	-0.439	0.109	0.591	1.441
	(3.72)***	(0.77)	(-0.26)	(-1.22)	(0.33)	(2.47)**	(3.70)***
$D^{up}(R_{m,t})^2$	-0.0353	-0.0314	-0.00669	0.0589	0.0228	-0.0325	-0.0896
	(-2.47)**	(-0.51)	(-0.07)	(2.24)**	(1.05)	(-3.24)***	(-2.25)**
$(1 - D^{up})(R_{m,t})^2$	-0.0463	-0.0271	0.106	0.0841	0.00582	-0.0295	-0.0911
	(-2.90)***	(-0.29)	(0.88)	(2.27)**	(0.18)	(-1.42)	(-2.73)***
_cons	-0.667	-0.872	2.090	2.312	1.164	-0.455	-1.836
	(-1.02)	(-0.35)	(0.40)	(2.80)***	(1.43)	(-0.67)	(-1.87)*
N	122	125	124	126	125	124	124
adj. R^2	0.397	0.201	0.203	0.296	0.246	0.307	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.4.7 Largest 2% (2% of absolute value) in rising and falling market condition

Regression results by using CCK based on the Normal regression method

Table 4.2.4 panel G, Robust Regression

$$\mathrm{CSAD}_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.893	0.773	1.715	0.641	0.821	0.193
	(3.09)***	(2.68)***	(1.89)*	(1.62)	(2.04)**	(0.48)
$(1 - D^{up})\|R_{m,t}\|$	1.625	0.727	1.720	0.656	0.671	0.0571
	(2.94)***	(2.22)**	(1.69)*	(1.60)	(1.41)	(0.15)
$D^{up}(R_{m,t})^2$	-0.145	-0.0438	-0.112	-0.0233	-0.0358	0.0148
	(-2.54)**	(-1.75)*	(-1.57)	(-0.75)	(-1.26)	(0.67)
$(1 - D^{up})(R_{m,t})^2$	-0.108	-0.0494	-0.124	-0.0379	-0.0259	0.0246
	(-2.72)***	(-1.55)	(-1.45)	(-1.13)	(-0.64)	(1.15)
_cons	-2.394	-0.303	-3.267	-0.265	-0.463	2.539
	(-1.57)	(-0.37)	(-1.20)	(-0.22)	(-0.34)	(1.66)
N	82	82	82	84	83	81
adj. R^2	0.203	0.210	0.087	0.391	0.279	0.299

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.4 panel G (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	1.297	2.246	2.500	0.859	0.625	0.900	1.658
	(5.37)***	(1.32)	(1.15)	(2.37)**	(1.73)*	(3.77)***	(2.85)***
$(1 - D^{up})\|R_{m,t}\|$	1.281	2.172	1.721	0.826	0.614	0.832	1.539
	(4.91)***	(1.15)	(0.73)	(2.02)**	(1.48)	(2.57)**	(2.67)***
$D^{up}(R_{m,t})^2$	-0.0621	-0.129	-0.139	-0.0257	-0.0146	-0.0427	-0.105
	(-4.24)***	(-1.11)	(-1.04)	(-0.90)	(-0.55)	(-3.43)***	(-2.03)**
$(1 - D^{up})(R_{m,t})^2$	-0.0740	-0.142	-0.0172	-0.0359	-0.0327	-0.0468	-0.0973
	(-4.16)***	(-0.87)	(-0.11)	(-0.85)	(-0.85)	(-1.77)*	(-2.03)**
_cons	-2.164	-5.103	-6.707	-0.827	-0.401	-1.278	-2.188
	(-2.69)***	(-0.98)	(-0.81)	(-0.87)	(-0.38)	(-1.29)	(-1.44)
N	81	83	82	84	83	82	83
adj. R^2	0.509	0.201	0.247	0.559	0.403	0.315	0.328

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

By using different proportions of observations in the datasets, we see that the coefficients of the $R_{m,t}$ is significant and positive for 11 countries with the largest 50% of the absolute market return and reduces to 7 countries with largest 2% of the absolute market return, which giving some evidence that herding is less likely when the market return is increasing in these markets. The coefficients of $|R_{m,t}|$are highly significant and positive for 12 countries when we select the largest 50% of the absolute market return, this shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 7 countries have significantly positive coefficient of $|R_{m,t}|$ with the largest 2% of the absolute market return. The coefficients of the absolute average market return under rising market conditions $D^{up}\left|R_{m,t}\right|$ are significantly positive for 9 countries with the largest 3% and 7 countries with the largest 2% of the absolute market return. Also, the coefficient of the absolute average market return under falling market conditions $(1 - D^{up})\left|R_{m,t}\right|$ are highly significant and positive for 7 countries with the largest 3% of the absolute market return, then reduce to 6 countries when we select the largest 2% of the absolute market return. It shows a positive relationship between the CSAD results and the market return in different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return. We can determine that under the condition with the largest 50% of returns in absolute value, we do not have clear evidence of herding behaviour in the stock markets. With the largest 10% returns by absolute return value, the results shown in table 4.2.4 panel B reveal that Sweden has significant evidence of herding behaviour in its stock market, and Denmark and the US markets have evidence of herding which is significant at the 10% level. In table 4.2.4 panel C, we capture significant evidence of the presence of herding behaviour in Denmark, the US, Germany, Hong Kong, Sweden and the UK. In panel D and panel E, we have got similar results, that

Denmark, Hong Kong, Sweden and UK have clear evidence of herding behaviour in their stock markets. Compared with the results using log return, the regression results using the simple return method shows the presence of more herding behaviour in the stock market, particularly during periods where the market has larger movements. Considering the rising and falling market conditions with largest 3% of the absolute value, we can observe clear evidence of herding behaviour exists in Denmark, Hong Kong, and the UK market in both rising and falling market conditions. Also, Sweden has significant herding behaviour in rising market condition, the US market have herding behaviour presents in the falling market condition and in rising market condition, herding behaviour is significant at 10% level. Portugal has significant anti-herding behaviour in both rising and falling market condition shown as significantly positive coefficient of squared market return in different market conditions. With observations selected larger than 2% of absolute value, we do not observe anti-herding in stock markets, Denmark, Hong Kong, Sweden and UK have clear evidence of herding behaviour in rising market condition, and US herding in the UK market is significant at 10% level. Denmark, Hong Kong and UK also have herding behaviour in falling market condition, and herding in Sweden is significant at the 10% level.

Similarly to the empirical results for log returns, we divide the current sample time period into two parts, the first time period is from 02/Jan/2002 to 30/Dec/2011, and is called time period 1; the second time period is from 02/Jan/2012 to 31/May/2018, and is called time period 2.

4.3 Conclusion

This chapter has the objective of considering whether using simple returns can give substantially different results from log returns when testing for herding. Logic and mathematical theory imply that this could be the case although empirical analysis is necessary to evaluate the importance of the effect in practice. We have derived three hypotheses from theory that we can check empirically. Our empirical analysis duplicates that carried out in Chapter 3 so we can directly compare results based on log and simple returns. Overall, the data sample has covered the time period from 02/Jan/2002 to 31/May/2018, as well as two different sub-periods within the sample period, time period one from 02/Jan/2002 to 30/Dec/2011 and time period two from 02/Jan/2012 to 31/May/2018. We use the standard CCK method to detect herding behaviour.

We have fitted a substantial number of regressions and the results are summarised in the two tables below. The first table shows, for each regression, the number of countries with significant findings of anti-herding and herding when log and simple returns are used. Overall, the results for the log and simple calculations are relatively similar but by no means identical. Generally, for each individual equation it is not possible to find statistically significant differences between the number of significant results for log and simple returns. By examining the results as a whole, it is possibly to see, qualitatively and quantitatively, whether there is any evidence to support our hypotheses 2 and 3. The evidence is mixed and not particularly strong statistically. For hypothesis 2, 10 out of 20 regression support the hypothesis. Working out the probability of this is difficult but can be approximated. If we assume for a regression to support the hypothesis the coefficient of one more country must become significant when simple returns are used. When we are using the 10% significant level there is say 0.1 probability of this. Now there are 13 countries so the binomial method would indicate there is a .74 probability of one of the 13 countries changing significance. Now the change has to be in a particular direction to support the hypothesis so there is about a .37 probability of such a change for each regression. Now there are 20 regressions, and the binomial regression would indicate approximately a 0.16 probability of getting 10 out of 20 changes (this assumes each regression is independent). Thus, there is some evidence to support hypothesis 2 but not at conventionally acceptable significance levels. A similar calculation for hypothesis 3 gives little support for the hypothesis.

The second table considers hypothesis 1. We can see that for nearly all of the formulae some of the tests for anti-herding or herding change significance when simple returns are used instead of log returns. In economic terms the effect is quite important with around 16.9% of tests changing significance when the return calculation method changes. In statistic terms the exact calculation of significance would be very complex but approximating the result using a simple test comparing the number of significant tests for our log and simple samples would indicate that the difference between them is significant at the 1% level[1].

To summarise, our overall findings in this chapter we can see that theoretical arguments suggest that log and simple returns are likely to often give different conclusions in tests for herding. Whilst it is difficult to predict exactly when results will differ using theoretical arguments it is certainly true that the results do frequently differ in practice. In our tests the significance of the results for particular countries has changed about 16.9% of the time which we can consider to be both economically and statistically significant.

Summary table 4.3.1 showing the number of significant results indicating either anti-herding or herding for log and simple calculations. There are a total of 13 countries examined.					
Formula	Log Number anti-herding	Log Number herding	Simple Number anti-herding	Simple Number herding	Hypothesis 2 or Hypothesis 3 supported
$CSAD_t = \alpha + \gamma_1 \lvert R_{m,t} \rvert + \gamma_2 R_{m,t}^2 + \varepsilon_t$	8 (1 at 10%)	0	10 (2 at 10%)	0	Not Applicable
$\mathrm{CSAD_t} = \alpha + \gamma_1 \mathrm{R_{m,t}} + \gamma_2 \lvert \mathrm{R_{m,t}} \rvert + \gamma_3 \mathrm{R_{m,t}^2} + \varepsilon_t$	8 (1 at 10%)	0	9	0	Not Applicable

[1] Compared equality of population proportions of 118 out of 325 and 173 out of 325. The 325 is based on 13 countries in 25 regressions. The 118 is the number of significant results when log returns are used the 173 is when the number of changed results are added on.

$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (UP Market)	9 (2 at 10%)	0	9 (2 at 10%)	0	No Support for Hypothesis 3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (DOWN Market)	7 (1 at 10%)	0	6 (1 at 10%)	0	Support for Hypothesis 3 – anti-herding is reduced
$CSAD_t = \alpha + \gamma_1\lvert R_{m,t}\rvert + \gamma_2 R_{m,t}^2 + \varepsilon_t$ (Top 18% of Returns)	1 (1 at 10%)	2 (1 at 10%)	1	2	No Support for Hypothesis 2 or Hypothesis 3
$CSAD_t = \alpha + \gamma_1\lvert R_{m,t}\rvert + \gamma_2 R_{m,t}^2 + \varepsilon_t$ (Bottom 16% of Returns)	1 (1 at 10%)	0	2 (1 at 10%)	0	No Support for Hypothesis 2 or Hypothesis 3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |0.5%|)	4 (1 at 10%)	0	4 (1 at 10%)	0	No Support for Hypothesis 2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |1%|)	0	3 (1 at 10%)	0	2 (2 at 10%)	No Support for Hypothesis 2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |2%|)	1	3 (1 at 10%)	1	4 (2 at 10%)	Support for Hypothesis 2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |3%|)	0	5 (2 at 10%)	0	6	Support for Hypothesis 2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |4%|)	0	3	0	3 (1 at 10%)	No Support for Hypothesis 2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |5%|)	0	5 (1 at 10%)	0	4	No Support for Hypothesis 2
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$	0	5 (1 at 10%)	0	6	Support for Hypothesis 2 No support for Hypothesis 3

(Market Return greater than |3%|) (UP Market)					
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1 - D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |3%|) (DOWN Market)	0	4 (2 at 10%)	0	5	Support for Hypothesis 2 Support for Hypothesis 3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1 - D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |4%|) (UP Market)	0	2	0	4 (2 at 10%)	Support for Hypothesis 2 No Support for Hypothesis 3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1 - D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |4%|) (DOWN Market)	0	4 (2 at 10%)	0	1	No Support for Hypothesis 2 No Support for Hypothesis 3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 50% of returns absolute value)	2 (1 at 10%)	1 (1 at 10%)	3 (2 at 10%)	0	No Support for Hypothesis 2 No Support for Hypothesis 3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 10% of returns absolute value)	1	5 (4 at 10%)	1	3 (2 at 5%)	No Support for Hypothesis 2 No Support for Hypothesis 3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 5% of returns absolute value)	1	6 (1 at 10%)	0	6	Support for Hypothesis 2 No Support for Hypothesis 3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 3% of returns absolute value)	1 (1 at 10%)	4	1 (1 at 10%)	5 (1 at 10%)	Support for Hypothesis 2 No Support for Hypothesis 3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 2% of returns absolute value)	0	6 (2 at 10%)	0	4	No Support for Hypothesis 2
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1 - D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$	0	5	0	7 (2 at 10%)	Support for Hypothesis 2 No Support for Hypothesis 3

(Largest 3% of returns absolute value) (UP Market)					
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (Largest 3% of returns absolute value) (DOWN Market)	0	3	1	5 (1 at 10%)	Support for Hypothesis 2 Support for Hypothesis 3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (Largest 2% of returns absolute value) (UP Market)	0	6 (3 at 10%)	0	5 (1 at 10%)	No Support for Hypothesis 2. Support for Hypothesis 3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (Largest 2% of returns absolute value) (DOWN Market)	0	5 (2 at 10%)	0	4 (1 at 10%)	No Support for Hypothesis 2. No Support for Hypothesis 3
Summary For Hypothesis 2 there are 20 sets of regressions where the hypothesis can be examined and 10 of these support the hypothesis. For Hypothesis 3 there are 16 sets of regressions where the hypothesis can be examined and 6 of these support the hypothesis					

Summary table 4.3.2 showing the number of results that have changed significance when calculation changes from log to simple		
Formula	Number of countries significant when log calculations used	Number of countries changing significance when simple calculations used
$CSAD_t = \alpha + \gamma_1\lvert R_{m,t}\rvert + \gamma_2 R^2_{m,t} + \varepsilon_t$	8	2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\lvert R_{m,t}\rvert + \gamma_3 R^2_{m,t} + \varepsilon_t$	8	3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$ (UP Market)	9	0
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1 - D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}(R_{m,t})^2 +$	7	3

$\gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$ (DOWN Market)		
$CSAD_t = \alpha + \gamma_1\|R_{m,t}\| + \gamma_2 R_{m,t}^2 + \varepsilon_t$ (Top 18% of Returns)	3	0
$CSAD_t = \alpha + \gamma_1\|R_{m,t}\| + \gamma_2 R_{m,t}^2 + \varepsilon_t$ (Bottom 16% of Returns)	1	1
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |0.5%|)	4	0
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |1%|)	3	1
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |2%|)	4	1
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |3%|)	5	3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |4%|)	3	2
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Market Return greater than |5%|)	5	1
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1-D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 +$ $\gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |3%|) (UP Market)	5	2
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1-D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 +$ $\gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |3%|) (DOWN Market)	4	3
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1-D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 +$ $\gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |4%|) (UP Market)	2	2
$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\|R_{m,t}\| + \gamma_2(1-D^{up})\|R_{m,t}\| + \gamma_3 D^{up}(R_{m,t})^2 +$ $\gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$ (Market Return greater than |4%|) (DOWN Market)	4	3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2\|R_{m,t}\| + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 50% of returns absolute value)	3	4

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \lvert R_{m,t} \rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 10% of returns absolute value)	6	4
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \lvert R_{m,t} \rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 5% of returns absolute value)	7	3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \lvert R_{m,t} \rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 3% of returns absolute value)	5	3
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \lvert R_{m,t} \rvert + \gamma_3 R_{m,t}^2 + \varepsilon_t$ (Largest 2% of returns absolute value)	6	4
$\mathrm{CSAD}_{i,t} = \alpha + \gamma_1 D^{up} \lvert R_{m,t} \rvert + \gamma_2 (1 - D^{up}) \lvert R_{m,t} \rvert + \gamma_3 D^{up} (R_{m,t})^2 +$ $\gamma_4 (1 - D^{up}) (R_{m,t})^2 + \varepsilon_t$ (Largest 3% of returns absolute value) (UP Market)	5	1
$\mathrm{CSAD}_{i,t} = \alpha + \gamma_1 D^{up} \lvert R_{m,t} \rvert + \gamma_2 (1 - D^{up}) \lvert R_{m,t} \rvert + \gamma_3 D^{up} (R_{m,t})^2 +$ $\gamma_4 (1 - D^{up}) (R_{m,t})^2 + \varepsilon_t$ (Largest 3% of returns absolute value) (DOWN Market)	3	3
$\mathrm{CSAD}_{i,t} = \alpha + \gamma_1 D^{up} \lvert R_{m,t} \rvert + \gamma_2 (1 - D^{up}) \lvert R_{m,t} \rvert + \gamma_3 D^{up} (R_{m,t})^2 +$ $\gamma_4 (1 - D^{up}) (R_{m,t})^2 + \varepsilon_t$ (Largest 2% of returns absolute value) (UP Market)	6	2
$\mathrm{CSAD}_{i,t} = \alpha + \gamma_1 D^{up} \lvert R_{m,t} \rvert + \gamma_2 (1 - D^{up}) \lvert R_{m,t} \rvert + \gamma_3 D^{up} (R_{m,t})^2 +$ $\gamma_4 (1 - D^{up}) (R_{m,t})^2 + \varepsilon_t$ (Largest 2% of returns absolute value) (DOWN Market)	5	4
Average	4.7	2.2
In summary out of 13 countries the average probability of the test for herding in a country changing significance when simple compared to log returns are used is 16.9%		

5.0 Review of CAPM and Drawbacks of the CCK method and possible methods to overcome them.

The CAPM is a very important model in the financial literature and has been used by investors to analyse stock returns and risks for many years. The purpose of this section is to emphasize the limitations of the model when used for testing for herding and the impact of error terms in the model. The section also uses simulation results to show the impact of error terms in the Cross-Departmental Absolute Deviation Model (CSAD).

5.1 Review of CAPM

Financial independence is the main factor in determining the lifestyle of individuals and organizations. Individuals and companies take various steps to obtain their desired prosperity and have to bear multiple risks. One example of this is an investment in the stock market, in which investors provide finance to companies in the form of stock investment. However, this method of achieving affluence comes with a price, particularly the risks associated with stock market returns. Investors need to create an optimal portfolio with their expected standard deviation and highest return compared to other portfolios. In order to strike a balance between the expected return and investment risk, the Capital Asset Pricing Model (CAPM) has been used by investors as a general tool for many years, and it has greatly helped investors during the decision-making process (Barberis et al., 2015).

CAPM assumes that a sector is fully competitive in the securities market and that the market is frictionless, meaning that there are no tax or transaction costs during trading. In addition, investors are short-sighted and have only one holding period; investors are limited to investing in publicly traded assets and can borrow without any risk or have their investment affected by interest rates. While the information available in the market is perfect, under perfect market efficiency, investors are able to access any information without any extra cost

and get any information they want to, also the asset returns are well distributed without too many biases and the risk of the portfolio can be minimized.
Sharpe (1965) initially introduced the CAPM, with it being developed further by Jack Treynor, John Lintner and Jan Mossin (Perold, 2004) in the 1960s. The CAPM calculates the expected return of a portfolio by adding the risk-free interest rate and the beta adjustment difference to the expected market return and the risk-free return.

$$R_{it} = R_f + \beta_i\left(R_{mt} - R_f\right) + \mu_{it} \qquad \text{(Equation 5.1)}$$

The idiosyncratic error term μ_{it} has mean zero and is independent of the excess return $\left(R_{mt} - R_f\right)$ The CAPM is extremely simple to use and is reasonably accurate in analyzing portfolio returns, making it the ideal choice for investors. CAPM covers the basic areas related to portfolio pricing and calculates investment risks by dividing the portfolio risk into two major categories, systemic and specific. CAPM can help investors mitigate investment risks without potentially reducing returns (Zabarankin et al., 2014). One of the most effective ways to reduce investment risks is to choose a portfolio that includes negatively correlated returns or ones that have no or little correlation between asset returns. The Markowitz (1959) model described that the portfolio chosen by the investor will minimize the variance of the portfolio's returns given a specific level of expected returns or maximize the expected rate of return given a specific level of variance. Systemic risk is expressed as beta (Elbannan, 2014). Beta is calculated by the using asset return covariance with the market return divided by the variance of the market return. A beta value of less than 1 means that the portfolio risk is lower than the market and vice versa. It is also assumed that all investors' preferences, expectations and market knowledge are the same, meaning that they will make informed decisions about their portfolio management. In addition, risk-free investment is available in the market, and as part of their portfolio diversification arrangements, investors will always use it.

5.1.1 Limitations of CAPM

Investors have used CAPM for many years to analyse the risks associated with investing in the stock market based on assumptions related to beta accuracy, the availability of risk-free investments and the homogeneity of all investors in the market. However, the above assumptions have been questioned by many researchers, and certain assumptions in the CAPM model have been declared incorrect (Dempsey, 2013).

One of the most obvious objections relates to investors' overall understanding of market risk and the expected return of the portfolio. Other factors include the unavailability of the risk-free rate of return, expected market returns and the value of β_i which measure the sensitivity of the asset's return to variation in the market return. In fact, it is impossible for every investor to fully grasp market trends and understand the covariance between different assets and potential assumptions, especially as these assumptions have a greater impact on the final return of a single asset or a group of assets. Furthermore, the CAPM does not take into consideration stock dividends and market prices when calculating the expected return of a portfolio (Ward and Muller, 2012).

Moreover, Banz (1981) believes that compared to medium and large organizations, smaller companies show higher or abnormal asset return potential (called the scale effect). This contradicts the assumptions used by the CAPM model, which propose a scenario in which market-based diversification and systematic risk management can predict market trends and expected returns fairly accurately. It has been suggested that other factors also contribute to market performance and return on asset portfolios. According to research conducted by Litzenberger and Ramaswamy (1982) in relation to common stocks from 1936 to 1977, there is a positive correlation between dividend yield and asset returns. In addition, the price-earnings ratio seems to have a large impact on the overall performance, namely on asset returns. However, this article does not seem to point out any shortcomings of CAPM and implies that this trend is due to market inefficiencies. In contrast, other researchers have pointed out that abnormal changes in asset returns is due to CAPM's failure to recognize the importance of the price-earnings ratio, i.e., the relationship between company returns and stock market prices. Banz (1981) suggested that gamma (a term that accounts for the company's market size) should be included in the CAPM model to eliminate this anomaly.

Reinganum (1981) also noted that the research results show that an organization's income and its size can be effectively used by analysts and investors to form a portfolio, thereby providing a more accurate investment portfolio. This idea is based on a review of the profitability of portfolios during 1976 –1977, whereby the abnormal return of the portfolio can be obtained through the analysis of the diversification of the portfolio and the analysis of the company's price-earnings ratio.

Roll (1976) highlighted that no tests could be validly conducted to verify the accuracy of CAPM or to confirm its hypothesis. Basu (1977) highlighted that the CAPM model ignores the impact of low P / E stocks. In addition, DeBondt and Thaler (1985) determined that stocks with unusually low returns in the past three years tend to provide unusually high returns in the following three years. An element which the CAPM has not covered.

There are other factors such as economic growth, rising inflation, legal and other conditions and the introduction of an enhanced regulatory framework that have not been incorporated into the CAPM. These factors may have a significant impact on individual stock returns and overall market performance. Not all stocks respond to changes in interest rates, technological progress, crime rates, etc. in a similar manner. Although these factors are critical, they are ignored in the CAPM model (Andriotto and Teti, 2014). Furthermore, the

CAPM ignores tax and transaction costs, which may become the determinants of market decisions. Carhart (1997) revealed that transaction costs, portfolio turnover rate and expense ratio have a negative impact on the short-term returns of mutual funds. Carhart also describes how investing in the best-performing stocks last year and selling the worst-performing stocks increased overall earnings by 8%. This 8% increase is accounted for by 4.6% being due to the difference between the market value and the momentum of the stocks held, 0.7% being due to changes in the expense ratio and 1% being due to transaction costs. In the short term, the successful use of the previous year's high-performance stocks to invest originates from the idea of a one-year momentum strategy (Jegadeesh & Titman, 1993). These factors are crucial for both short-term and long-term investments in the stock market. However, these factors are not included in the CAPM model, which indicates another anomaly related to the concept.

When investors use different time periods to calculate different results, problems also begin to arise, increasing the likelihood of misunderstandings in stock performance with reference to market trends. Bhandari (1988) also pointed out that the average return is related to leverage. CAPM claims that the expected excess return of an asset depends on its beta, and that the beta depends on the covariance between the return on assets and the return on the market portfolio. Most empirical studies that have used static CAPM assume that the value of β will remain constant over time, and that stock-based returns based on value-weighted portfolios can replace total wealth returns. The value of β depends on the expected return assets. The static CAPM cannot satisfactorily explain the cross-section of average stock returns. In their conditional CAPM study Jagannathan and Wang (1996) highlighted the cross-sectional changes in the average return of a large stock portfolio.

5.1.2 Critical Evaluation

The aforementioned anomalies and empirical failures in the CAPM model have led to the emergence of more complex and detailed models for determining asset pricing and returns. These models incorporate more factors, allowing them to more accurately calculate the expected return of the market, and thus aim to overcome the limitations of CAPM, especially those related to uncertainty. Therefore, researchers have proposed some theories to replace CAPM and eliminate the above limitations. The most famous model is the one proposed by Fama and French (1992). By using the earnings data collected from a large number of assets and analyzing it, factors such as the price-earnings ratio, organizational size and economic growth that are ignored in the CAPM model can be included in the multi-factor model. Also, the Fama-French five-factor model adds two factors, which are profitability and investment, as there is evidence shows that the three-factor model is insufficient for expected returns, because the three-factor model does not take the relationship between profitability and investment into consideration (Fama and French, 2015). The static CAPM model found that "the relationship between market beta and average income is stable." Similarly, the random variables also known as the error term at the end of the CAPM model equation have a significant impact on the model. The expectation of unconditional random variables is a constant parameter set by the density function and should not be affected by other factors. However, this error can affect the regression results of the expected returns calculated based on the CAPM model.

5.2 Drawbacks with the CCK method and possible methods to overcome them

As we can see from the previous empirical results, we have detected very little herding behaviour in our data sample using the traditional CCK method, only a few countries have herding behaviour in rising markets during the time sample time period, and a few more countries have herding behaviour which could be influenced by the global financial crisis. These results could be affected by the CSAD analysis method. As we mentioned above, the CSSD and CCK methods only work for markets with extreme herding behaviour, and they will tend not to detect herding behaviour when it is weak. We will initially show some drawbacks in the CCK method because of the way it interacts with the CAPM. We will then introduce some methods to deal with these drawbacks. One of these methods is the new symmetry test approach which will call symmetry cross-sectional absolute deviation (SCSAD).

The intuition behind our discussion of the drawbacks in the CCK method is that the expected properties of the CSAD jointly depend both on the degree of herding and on how well the CAPM models the returns of stocks in the market. If the CAPM is not a perfect model (that is if it contains an idiosyncratic error term), even if there is no herding, the graph of CSAD against $|R_{mt}|$ will not be a straight line but will be convex. Having said this as $|R_{mt}|$ increases, CSAD will tend towards a straight line if there is no herding present and this enables valid tests of herding to be constructed.

We show that the standard method of testing for herding is biased against finding herding as it assumes that in the case of no herding there will be a linear relationship between CSAD and $|R_{mt}|$ when the true relationship is convex.

We have:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}|$$

Or more correctly as CSAD is time varying

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}|$$

Where R_{it} follows the CAPM:

$$R_{it} = R_f + \beta_i\left(R_{mt} - R_f\right) + \mu_{it}$$

Assume $E\ [\mu_{it}] = 0$
And μ_{it} is independent of $\left(R_{mt} - R_f\right)$ and hence of R_{mt}.

Then:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}\left|R_f + \beta_i\left(R_{mt} - R_f\right) + \mu_{it} - R_{mt}\right|$$

For convenience, we can assume that R_f is sufficiently small compared to the μ_{it} and R_{mt} terms to be neglected which is reasonable for daily data particularly in a low interest rate environment. We then have:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|\beta_i.(R_{mt}) + \mu_{it} - R_{mt}|$$

$$= \frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)(R_{mt}) + \mu_{it}|$$

If we disregard μ_{it}

$$CSAD_t = \tfrac{1}{N}\textstyle\sum_{i=1}^{N}|(\beta_i - 1)(R_{mt})| \quad (+)$$

Now β_i does not depend on t or m

We can consider an exhaustive range of scenarios

If $(\beta_i - 1) \leq 0$ and $R_{mt} \leq 0$ then $|(\beta_i - 1)(R_{mt})| = (\beta_i - 1)(R_{mt})$

$= -(\beta_i - 1)|R_{mt}| = |\beta_i - 1||R_{mt}|$

If $(\beta_i - 1) \leq 0$ and $R_{mt} > 0$ then $|(\beta_i - 1)(R_{mt})| = -(\beta_i - 1)(R_{mt})$

$= -(\beta_i - 1)|R_{mt}| = |\beta_i - 1||R_{mt}|$

$$\text{If } (\beta_i - 1) > 0 \text{ and } R_{mt} > 0 \text{ then } |(\beta_i - 1)(R_{mt})| = (\beta_i - 1)(R_{mt})$$
$$= (\beta_i - 1)|R_{mt}| = |\beta_i - 1||R_{mt}|$$

$$\text{If } (\beta_i - 1) > 0 \text{ and } R_{mt} \leq 0 \text{ then } |(\beta_i - 1)(R_{mt})| = -(\beta_i - 1)(R_{mt})$$
$$= (\beta_i - 1)|R_{mt}| = |\beta_i - 1||R_{mt}|$$

Thus

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)(R_{mt})|$$

$$= |R_{mt}|\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)|$$

Thus if μ_{it} is disregarded, CSAD is directly proportional to $|R_{mt}|$. In the literature a regression testing for a linear relationship between CSAD and $|R_{mt}|$ is the standard test for herding. However, is it not generally valid to disregard μ_{it}.

If we consider

$$CSAD_t = \tfrac{1}{N}\textstyle\sum_{i=1}^{N}|(\beta_i - 1)(R_{mt}) + \mu_{it}| \quad \text{- (*)}$$

We can look at exhaustive scenarios for each element of the series on the right-hand side of the expression.

In all cases we can note that μ_{it} is independent of R_{mt}.

Scenario 1: If $(\beta_i - 1)(R_{mt}) \ \leq 0$ and $\mu_{it} \leq 0$

Then $|(\beta_i - 1)(R_{mt}) + \mu_{it}| = \ |(\beta_i - 1)(R_{mt})| + |\mu_{it}| \ \geq \ |(\beta_i - 1)(R_{mt})|$

Scenario 2: If $(\beta_i - 1)(R_{mt}) \ \leq 0$ and $\mu_{it} > 0$

If $|\mu_{it}| \ \geq 2|(\beta_i - 1)(R_{mt})|$ then $|(\beta_i - 1)(R_{mt}) + \mu_{it}| \geq \ |(\beta_i - 1)(R_{mt})|$

If $|\mu_{it}| < 2|(\beta_i - 1)(R_{mt})|$ then $|(\beta_i - 1)(R_{mt}) + \mu_{it}| \ < \ |(\beta_i - 1)(R_{mt})|$

Scenario 3: If $(\beta_i - 1)(R_{mt}) \ > 0$ and $\mu_{it} > 0$

Then $|(\beta_i - 1)(R_{mt}) + \mu_{it}| = \ |(\beta_i - 1)(R_{mt})| + |\mu_{it}| > \ |(\beta_i - 1)(R_{mt})|$

Scenario 4: If $(\beta_i - 1)(R_{mt}) \ > 0$ and $\mu_{it} \leq 0$

If $|\mu_{it}| \ \geq 2|(\beta_i - 1)(R_{mt})|$ then $|(\beta_i - 1)(R_{mt}) + \mu_{it}| \geq \ |(\beta_i - 1)(R_{mt})|$

If $|\mu_{it}| < 2|(\beta_i - 1)(R_{mt})|$ then $|(\beta_i - 1)(R_{mt}) + \mu_{it}| \ < \ |(\beta_i - 1)(R_{mt})|$

For each scenario the inequality compares the relevant element of the series in equation (*) with the equivalent element of the series in equation (+). That is, the element in the equation with the CAPM error term to the equivalent expression in the equation where the CAPM error term is ignored.

In the 1st scenario the element in the equation with the CAPM error term is larger than the equivalent element in the equation where the CAPM error term is ignored by an amount $|\mu_{it}|$. We have the condition that $\mu_{it} \leq 0$. Now if we consider expectations, $E[|\mu_{it}|] > 0$ so the expected value of the element in the equation with the CAPM error term is larger than the expected value of equivalent term in the equation where the CAPM term is ignored.

In the 2nd scenario the element in the equation with the CAPM error term is larger if $|\mu_{it}|$ is sufficient large compared to $|(\beta_i - 1)(R_{mt})|$. As β_i is a constant, the condition can be rewritten as the element in the equation with CAPM error term is larger if $|\mu_{it}|$ is sufficient large compared to $|(R_{mt})|$. We can see how this term varies with the size of $|(R_{mt})|$. As $|(R_{mt})|$ tends to become smaller, the element in the equation with the CAPM error term tends to become larger than the equivalent term in the equation where the CAPM term is ignored by an amount $|\mu_{it}|$. Now if we consider expectations, $E[|\mu_{it}|] > 0$ so, if $|(R_{mt})|$ becomes small, the expected value of the element in the equation with the CAPM error term is larger than the expected value of the equivalent term in the equation where the CAPM term is ignored. As $|(R_{mt})|$ tends to become larger, the term in the equation with the CAPM error term tends to become equal to the equivalent term in the equation where the CAPM term is ignored.

In the 3rd scenario the element in the equation with the CAPM error term is larger than the equivalent element in the equation where the CAPM error term is ignored by an amount $|\mu_{it}|$. We have the condition that $\mu_{it} > 0$. Now if we consider expectations, $E[|\mu_{it}|] > 0$ so the expected value of the element in the equation with the CAPM error term is larger than the expected value of equivalent term in the equation where the CAPM term is ignored.

In the 4th scenario the element in the equation with the CAPM error term is larger if $|\mu_{it}|$ is sufficient large compared to $|(\beta_i - 1)(R_{mt})|$. As β_i is a constant, the condition can be rewritten as the element in the equation with CAPM error term is larger if $|\mu_{it}|$ is sufficient large compared to $|(R_{mt})|$. We can see how this term varies with the size of $|(R_{mt})|$. As $|(R_{mt})|$ tends to become smaller, the element in the equation with the CAPM error term tends to become larger than the equivalent term in the equation where the CAPM term is ignored by an amount $|\mu_{it}|$. Now if we consider expectations, $E[|\mu_{it}|] > 0$ so, if $|(R_{mt})|$ becomes small, the expected value of the element in the equation with the CAPM error term is larger than the expected value of the equivalent term in the equation where the CAPM term is ignored. As $|(R_{mt})|$ tends to become larger, the term in the equation with the CAPM error term tends to become equal to the equivalent term in the equation where the CAPM term is ignored.

If we combine the findings from all the scenarios we can make conclusions about how $CSAD_t$ with the CAPM error term differs from $CSAD_t$ where the error term is ignored. First, it is clear that when the error term is introduced there is no longer expected to be a simple linear relationship between $CSAD_t$ and $|R_{mt}|$. $CSAD_t$ also depends on $|\mu_{it}|$ with is independent of $|R_{mt}|$ and on the relationship between $|\mu_{it}|$ and $|R_{mt}|$.

In the limits as $|R_{mt}|$ tends to 0.

$$CSAD_t \approx \frac{1}{N}\sum_{i=1}^{N}|\mu_{it}| > 0$$

So

$$E[CSAD_t] \approx E\,|\mu_{it}| > 0$$

And

$$\frac{\partial E[CSAD_t]}{\partial |R_{mt}|} = 0$$

Which means that if R_{mt} is small, E[CSAD] will always be positive and its size will depend on μ_{it} which is a random variable which is determined by how well the CAPM fits the data rather than by any attribute related to herding
In the limit as $|R_{mt}|$ tends to ∞.

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)(R_{mt})| + \frac{1}{N}\sum_{i=1}^{N}|\mu_{it}| \ \textit{if the sign of } \mu_{it} \textit{ is the same as } R_{mt}$$

$$= |R_{mt}|\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)| + \frac{1}{N}\sum_{i=1}^{N}|\mu_{it}| \ \textit{if the sign of } \mu_{it} \textit{ is the same as } R_{mt}$$

Now μ_{it} can be assumed to be symmetrically distributed about 0 so
$E[CSAD] = |R_{mt}|\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)| + \frac{1}{2}E\ |\mu_{it}|\ \textit{given}\ \mu_{it}\ > 0$

$$\frac{1}{2}E\ |\mu_{it}|\ \textit{given}\ \mu_{it} \textit{ is a constant is not dependent on } |R_{mt}|$$

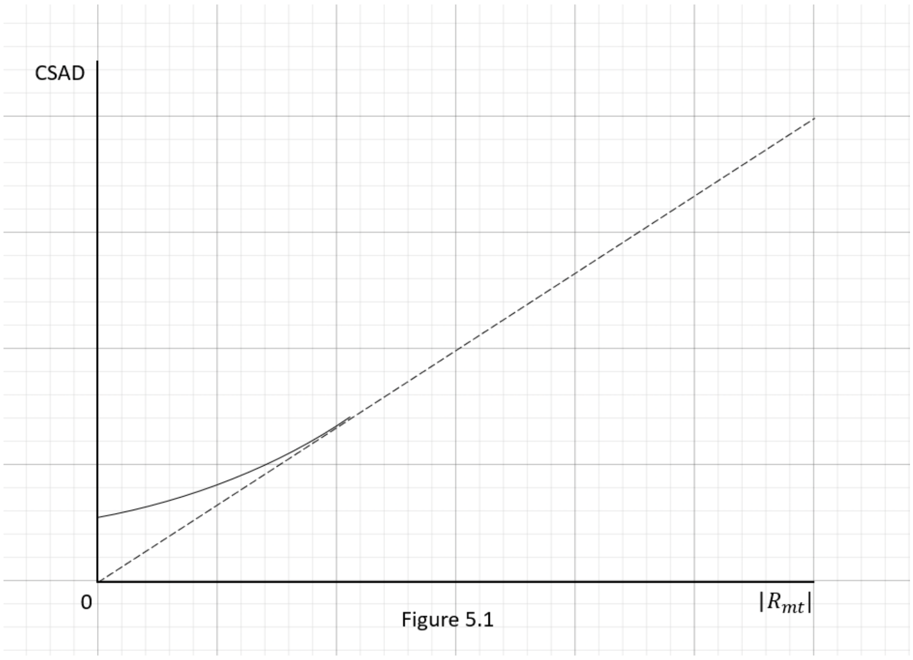
And

$$\frac{\partial E[CSAD]}{\partial |R_{mt}|} = \frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)|$$

So, given the above even if there is exactly 0 herding plotting CSAD against $|R_{mt}|$ will have a graph, as shown in figure 6.1. That is, it will have a positive value and a gradient of 0 at $|R_{mt}| = 0$ and will tend to a value of $|R_{mt}|\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)|$ plus a small constant with a gradient of $\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)|$ as $|R_{mt}|$ increases.

Clearly, this is a convex relationship graph and will be associated with a positive coefficient of a quadratic curve fitted to it. So, the standard test for herding will be highly biased against finding herding.

Figure 5.1 Relationship between the CSAD and the absolute value of market return



Horizontal axes are the absolute value of the average market return.
Vertical axes are the cross-sectional absolute deviation (CSAD).

In Figure 5.1, the dotted line shows the hypothetical relationship between the CSAD and the absolute value of market return if the CAPM model is a perfect fit with no idiosyncratic error term. And the above curved line is what will be observed if there is no herding and there is a realistic model of the CAPM with a random, non-zero, error term.

In summary, if we use regressions of CSAD on $|R_{mt}|$ to test for herding there will be issues as the test will not be solely of herding but of how well the CAPM fits the data. The standard approach in the literature assumes that if there is no herding or anti-herding (we term this zero herding), there will be a straight-line relationship between CSAD and $|R_{mt}|$ and it is not an issue if there is a significant constant term

It is fairly easy to see the rationale for the standard approach. If there is herding one can modify the CAPM as follows:

$$R_{it} = R_f + \beta(R_{mt})_i\left(R_{mt} - R_f\right) + \mu_{it}$$

The term corresponding to β_i in the normal CAPM is now a function of R_{mt}

Now in the case of herding one would see that as R_{mt} increases stocks would act more and more similarly to one another so the $\beta(R_{mt})_i$ terms will tend to 1. That is, stocks will tend to move more in line with the market as R_{mt} increases. Thus, CSAD will not increase linearly in proportion to R_{mt} . The literature assumes this can be simply captured by a negative coefficient of $R^2_{m,t}$ in the standard regressions. The problem with this rationale is that it is only necessarily true if there is no idiosyncratic error term in the modified CAPM. As we have seen, if there is an idiosyncratic error term, there will be a tendency to see a positive coefficient of $R^2_{m,t}$ independently of whether there is any herding or not. If the modified CAPM is an appropriate model and there is no idiosyncratic error term, and we neglect R_f due to its relatively small size, the regression of CSAD on $|R_{mt}|$ will still go through the origin.

To test for herding one conventionally checks whether there is a concave relationship between CSAD and $|R_{mt}|$. However, we have shown that if there is exactly zero herding there will be a convex relationship between CSAD and $|R_{mt}|$ so even if a degree of herding exists, the standard test is likely to show no evidence of herding.

We consider various solutions to this problem below:

Solution 1 – Supressing the constant term in the regression test

As discussed in the literature review, herding is expected to be most acute when there are large overall market movements. As shown above, if there is zero herding and market movements are large, we can expect the gradient of the curve between CSAD and $|R_{mt}|$ to be a straight line. For large $|R_{mt}|$, CSAD will have a value of $|R_{mt}|\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)|$ with a gradient of $\frac{1}{N}\sum_{i=1}^{N}|(\beta_i - 1)|$ if a straight line with that gradient is fitted though that point, it will go through the origin of the graph. Also, as shown above, even if there is zero herding the effect of the idiosyncratic error term in the CAPM will cause the any line fitted to the data to be convex and to have a positive constant coefficient. Thus, a reasonable way to test for herding is to adopt the standard approach in the literature but constrain the constant in the regression to be zero so that the fitted line goes through the origin of the graph. This means that less emphasis will be given to the effect of the idiosyncratic CAPM error term for small values of $|R_{mt}|$ and the shape of the fitted line will be a better test of whether herding exists.

The regression model is:

$$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \qquad \text{(Equation 5.2)}$$

This method has the advantages of both being extremely simple and not requiring any assumptions about the distribution properties of the idiosyncratic CAPM error terms other than those in the basic assumptions underlying the CAPM. This contrasts with the approach of Bohl et al (2017) which requires a set of distributional assumptions about the error terms in order to bootstrap a test statistic for the coefficient of $R_{m,t}^2$.

Solution 2 – Create a New Variable SCSAD

We can set up SCSAD as below:

SCSAD = CSAD if $R_{mt} > 0$

SCSAD = - CSAD if $R_{mt} < 0$

Now we can plot and regress SCSAD against R_{mt} (not $|R_{mt}|$).

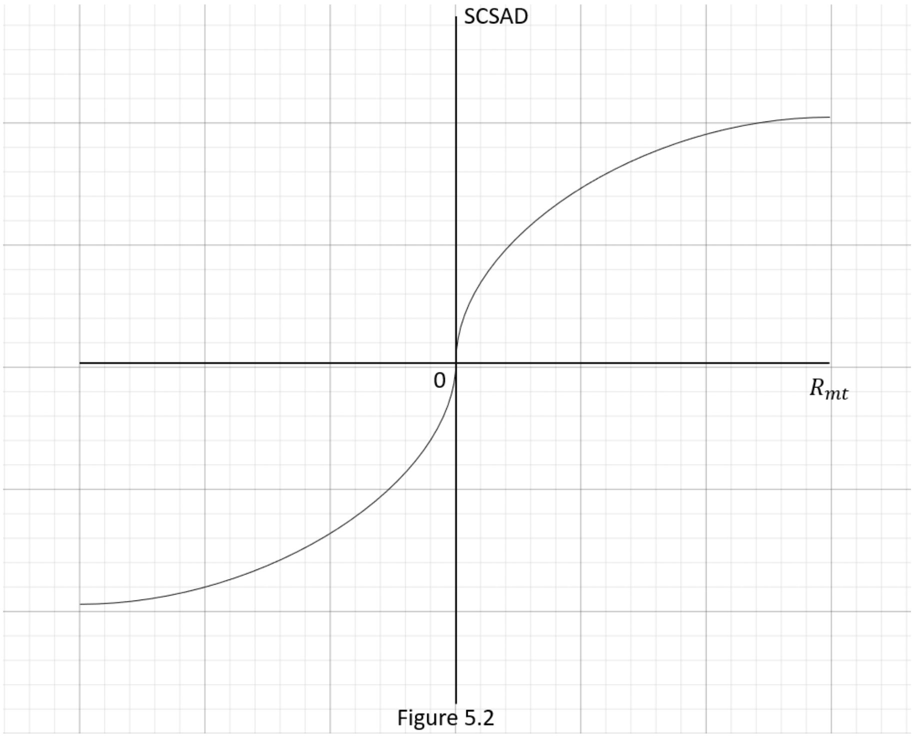
The point of SCSAD is that when R_m is close to 0 half the time SCSAD will be greater than 0 and a half the time it will be less than 0, so there will not be any systematic random distortion, and fitted lines will go through the origin. This means any fitted lines will be related to herding, not to the attributes of how well the CAPM fits.

To test for herding the curve of SCSAD should be convex if R_{mt} is positive and concave if R_{mt} is negative, as shown in Figure 5.2. The appropriate regression model for the SCSAD is:

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \varepsilon_t \qquad \text{(Equation 5.3)}$$

We need to look for a negative coefficient on the cubic term to check for herding[2].

Figure 5.2: Relationship between SCSAD and average market return



Horizontal axes are the value of the average market return.
Vertical axes are the symmetry cross-sectional absolute deviation (SCSAD).

Solution 3 – Investigating the situation given large market movements

As herding is expected to be most acute when there are large overall market movements, and the results of the tests for herding are distorted by the values of

[2] The model is primarily testing the direction of curvature of the fitted line and having an absolute return variable will not qualitatively alter this. In addition, empirically the results are very similar whether absolute market returns are included or not so for parsimony we have removed the absolute market return variable as now mentioned in the thesis.

CSAD associated with small values of $|R_{mt}|$ another viable approach is to use the normal test for herding but disregard data associated with small values of $|R_{mt}|$. This, however, gives rise to the issue of which values of $|R_{mt}|$ should appropriately be disgarded. In order to detect herding when there are large market movements, we can set up the subset in two different ways, one is to limit the minimum return such as detect herding when the market return larger than a specified value like 0.5%, 5% and 10%, or we can restrict the range of the return, for example we may limit the large market movement by using extreme value of return which accounted for 14% of the full proportion.

5.3 Market Simulation

We have constructed the market simulation to have a better clear view of the herding behaviour presence in market under different situations. Which include one market condition with zero herding and the other with significant herding behaviour exists in the market. Through the simulation with different market condition, we have compared the results by applying different herding detection methods, such as the standard CCK method and our alternative methods and observe the efficiency of different methods. For concreteness, normally when we try to detect whether the market has herding behaviour, we will need to have the whole market return and each single stock return included in the market at the same time. The measure of herding is the cross-sectional absolute deviation of returns (CSAD), introduced by Chang et al. (2000), follows the formula:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}|$$

R_{it} stands for the return for security i at time t
R_{mt} is the average market return at time t

We assume, the single security return R_{it} follows the CAPM model:

$$R_{it} = R_f + \beta_i\left(R_{mt} - R_f\right) + \mu_{it}$$

After we have the value of CSAD, we can detect herding behaviour by using the following regression model and find whether it has a significantly negative coefficient of the squared market return. Once it has, then we can confirm that the market has herding behaviour. At the same time, the results may indicate different market situations. When the squared market return has a significantly positive coefficient, we will say this situation is that anti-herding behaviour exists in the market, which stands for an underreaction to the information related to the market. When the squared market return has an insignificant coefficient, and this indicates for no herding or anti-herding in the market.

Regression model is:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \qquad \text{(Equation 5.4)}$$

5.3.1 Simulation with zero herding in market

In order to test the efficiency of different herding detection methods, we build the dataset which do not have clear evidence in this simulation market condition. If we run regressions on real world market data, it is difficult to know the proportionate extent to which the results are influenced by herding effects or by the less than perfect fit of the CAPM. We can overcome these problems by running regressions on simulated data with known properties.

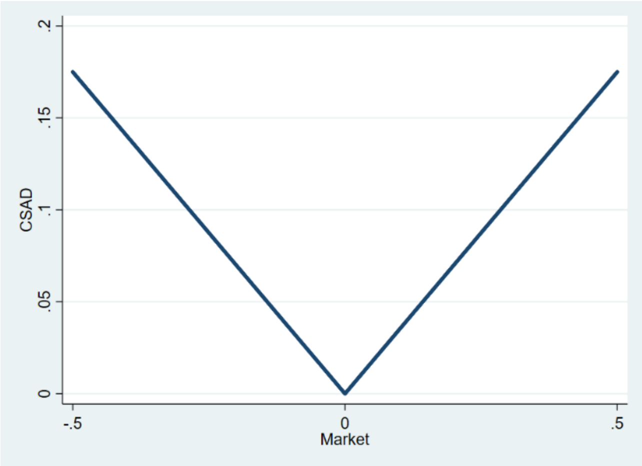
5.3.1.1 Regression under normal condition

Normal regression

We can use market simulation to see the influence of the error term on the anti-herding behaviour detected by the regression model. In order to simulate a market where there is no herding (or anti-herding) behaviour, we assume that stock returns follow the CAPM. We further assume that there are four different types of stock in the market, and the corresponding stock betas are 0.5; 0.8; 1.2

and 1.5. Then we assume for each stock beta, we have five stocks with that beta, so given the four different stock betas, we have a total of 20 stocks in the market. We consider overall market returns ranging from -0.5 to 0.5, in increments of 0.001, and thus we have total 1001 observations in each simulation. In this experiment we are aiming to observe the shape of the relationship between CSAD and $|R_{mt}|$ so it is not necessary for market returns of different sizes to occur with the same relative frequency as they would in an actual market situation. After we calculate the CSAD results, we calculate regressions of CSAD on $|R_{mt}|$ using both model 1 and equation 5.4. We have run the simulation 500 times and done the regression each time. For the simulations the CAPM is a perfect model for returns, that is, where the error term in the CAPM equation is 0. In the regressions, we always have insignificantly negative coefficients for the squared market return, and the size of the coefficient is almost zero. Thus, the standard regression used to test for herding correctly confirms that the simulated market does not have herding behaviour. In addition, we have a very small intercept value, so we can say the graph is a straight line and goes through the origin. The graph 5.3 shows the trend that supposed to be when zero herding without the influence of the random error term in the CAPM model.

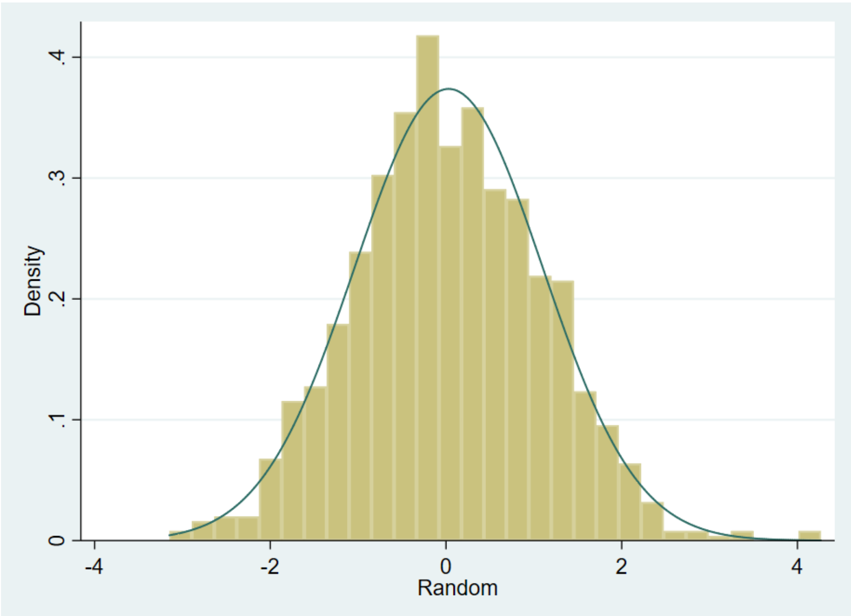
Figure 5.3: Zero herding without the influence of the random error term in the CAPM equation:



The above graph shows the regression results without the influence of the random variable in the CAPM

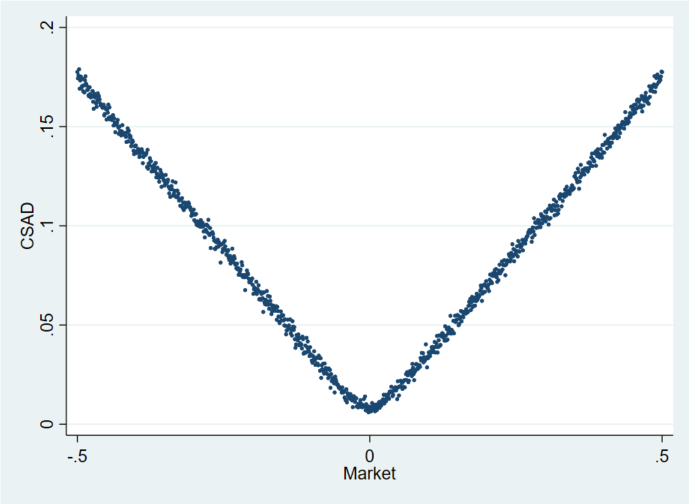
After this, we follow the formula which adds the random error variable at the end of each single stock return CAPM calculation, the random error variable is generated randomly and follows the normal distribution as shown in Figure 5.4.

Figure 5.4: Random variable distribution:



With this new dataset, we calculate the CSAD and do the regressions again. We find a significantly positive coefficient of squared market return in every regression with extremely high adj. R^2. Thus, the standard test approach indicates that the market does not have the herding behaviour but, in fact, has anti-herding behaviour. This contracts the fact that we have set up the simulations so that there is not herding behaviour. At the same time the slope of the fitted line changes with the market movement the fitted line is shown in Figure 5.5:

Figure 5.5: Zero herding influenced by the random variable:



Compared with the graph of the result without the random error variable in the CAPM formula, we find that with the market movement, the graph slope changes all the time, so the fitted line is not straight anymore; also, the fitted line has a larger intercept above the origin. This confirms our theoretical perditions. In conclusion, 100% of the regressions incorrectly indicate anti-herding in the market.

Standard regression without constant value

The mathematical meaning of a constant term is the value of the interpreted variable when the value of all explanatory variables is zero. However, in the empirical model of econometrics, this is often practically meaningless because the interpretation of the variable sometimes does not necessarily include zero, for example, human height, weight etc.. In our case, the theoretical considerations discussed above indicate that, if the CAPM is an appropriate model for individual share returns, the graph of CSAD against $|R_{mt}|$ should be a straight line through the origin. From the results of the regressions without a constant value, unlike the regression with a constant value, the large majority (73.8%) of the regression results the results show insignificant coefficient of the squared market return. This indicates that the regression correctly indicates no herding and no anti-herding. Around 26.2% of the coefficient values of the squared market return are significantly negative, this indicates that the market has herding behaviour which is an incorrect finding.

Regression with the SCSAD model

The regression model for the SCSAD is:

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t \quad \text{(Equation 5.5)}$$

By using the new regression model, we need to have a significantly negative coefficient of the cubic market return to confirm herding behaviour. for the graph of the SCSAD method, if the fitted line is straight then there having no herding behaviour. In the results, most of the cubic market coefficients are insignificant, around 14.4% of the cubic market coefficients are significantly negative, which indicates herding behaviour in the market, whereas a positive coefficient would indicate herding. The fitted scatter graph is shown as:

Figure 5.6: Zero herding under SCSAD regression:

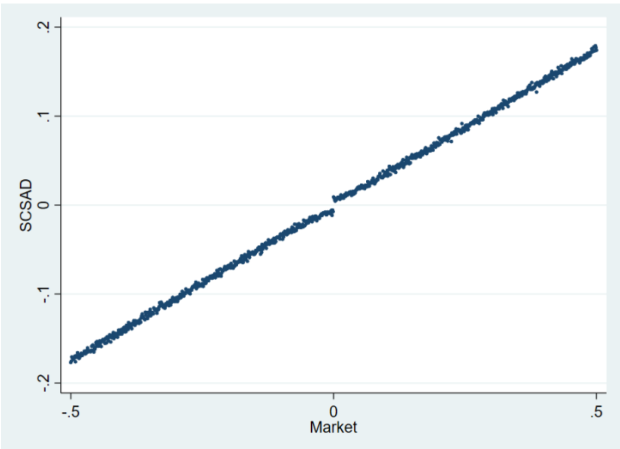


Table 5.3.1.1

Full Range Market Return	Anti-Herding	Nothing	Herding
Standard Regression	100%	0	0
Regression without constant	0	73.80%	26.20%
Cubic Regression	0	85.60%	14.40%

Table 5.3.1.1summarises the results for the simulation where there is no herding or anti-herding. The standard regression model shows 100% anti-herding as in every regression the coefficient of squared market return is significantly positive. Thus, the conclusions drawn from the standard approach are 100% incorrect. For solution 1, where the regression model does not have a constant value, 73.8% of the regressions lead to the correct conclusion that there is no herding. For solution 3, using the SCSAD regression model, and 85.6% lead to the correct conclusion. The two solutions are considerably more accurate than the standard approach although they perhaps have a slight bias towards find herding when it does not exist.

5.3.1.2 Solution 3 Investigating the situation given large market movements using Standard CCK regression

Solution 3 states that herding behaviour is more likely happen under larger market movement, we will check the herding behaviour under three market movement condition with absolute market returns larger than 0.5%, 5% and 10%. Market returns larger than 5% and 10% do not happen very often in the real market but are more common in our simulations.

In the regressions, the results are shown in Table 5.3.1.2. When absolute returns of less than 0.5% are removed 100% of the squared market returns have a significantly positive coefficient, which implies an anti-herding effect. Thus, the conclusions are almost entirely incorrect, given there is no herding or anti-herding, so removing absolute returns of this magnitude 0.5% has not been sufficient to correct the biases in the underlying method. The results are much more encouraging when there are larger thresholds for removing returns. When absolute returns of less than 5% are removed, 84.4% of the regressions correctly identify that there is neither anti-herding nor herding in the data. Similarly, when absolute returns of less than 10% are removed, we see a further modest improvement with 92.4% of the regressions correctly identifying that there is neither anti-herding nor herding.

Table 5.3.1.2

	Anti-Herding	Nothing	Herding
Market Return >= |0.5%|	100%	0	0
Market Return >= |5%|	15.4%	84.4%	0.20%
Market Return >= |10%|	3.8%	92.4%	3.8%

In conclusion from the simulation with no herding we can see that the performance of the standard regression on all the market data is extremely poor with both the regression with constant and the cubic regression performing much more accurately. When the effect of examining market returns in excess of a particular size is considered the accuracy of the approaches seems quite dependent on the return threshold. If we consider the standard regression the accuracy of the results improves as the threshold increases. The results are still very poor with a threshold of |0.5%|but quite good with a threshold of |5%| and even better with a threshold of |10%|. The regression without a constant and the cubic regression seem to offer, at best, only very modest accuracy improvements over the standard method when the larger thresholds are used.

5.3.1.3 Larger market movements based on a proportion of the data

As there is a higher possibility of detecting herding behaviour when the market exhibits extreme movement, we select some extreme proportions of returns to do the market simulation. In this section we detect herding under situations where we use proportions of the observations based on absolute return size. We investigate the largest 50% of returns by their absolute size, the largest 10% of returns by absolute size and the largest 5% of returns by absolute size.

Table 5.3.1.3

	Anti-Herding	Nothing	Herding
Largest 50% of observations	2%	94.8%	3.2%
Largest 10% of observations	3%	95.4%	1.6%
Largest 5% of observations	3.4%	94.2%	2.4%

When the largest 50% of observations examined 94.8% of the squared market returns have a significantly and insignificantly positive coefficient, which implies zero herding exists in the simulation. Thus, the conclusions are mostly correct, given there is no herding or anti-herding. The results are much better when observations are selected based on larger absolute returns. When the largest 10% of observations are examined, 95.4% of the regressions correctly identify that there is neither anti-herding nor herding in the data. Similarly, when the largest 5% of observations are examined, again 94.2% of the regressions correctly identify that there is neither anti-herding nor herding in the data.

In conclusion from the simulation with no herding we can see that the performance of the standard regression using all the simulated market data is extremely poor with both the regression with constant and the cubic regression performing much more accurately. When the effect of examining market returns in excess of a particular size is considered the accuracy of the approaches seems quite dependent on the return threshold. If we consider the standard regression the accuracy of the results improves as the threshold increases. The results are still very poor with a threshold of 0.5% but quite good with a threshold of 5% and even better with a threshold of 10%. Similarly, when a subset of returns is selected based on their absolute size the results are mostly correct when the largest 50% of absolute returns are selected but much better when the largest 10% and 5% of absolute returns are selected.

5.3.2 Simulation with herding in the market

In order to find out the effectiveness of our tests in the market, we set up a market simulation where there is definitely herding. As previously with have five different stock types with particular patterns of beta. In our simulation market returns still increase from -0.5 to 0.5 as in the previous simulation. When the market return is 0 the betas of the stock groups range from 0.95 to 1.05 (0.95, 0.975, 1.025 and 1.05). The betas then progress linearly until the betas of the different groups are all 1 when returns are -0.5 and 0.5, that is, there is perfect herding under extreme market conditions. Table 5.3.2.1.1 below shows how the betas vary. For example, in the second and third columns for stocks with a beta 0.95 when market returns are 0, as the market return increases from -0.5 to 0.5, the stock beta starts from 1 when the market return is -0.5 and decreases to 0.95 when the market return is 0 and then increases back to 1 when the market return reaches 0.5. Also, by using the market return times the stock beta and then adding a random variable which follows the normal distribution, we obtain the results shown in the third column which shows the average return of a single security in the group 1 to 5. Applying this calculation method, we can obtain the returns for each of the 20 securities.

Table 5.3.2.1.1 Herding simulation sample:

Market Return	Stocks 1-5 With Beta of 0.95 when Market Return is 0		Stocks 6-10 With Beta of 0.975 when Market Return is 0		Stocks 11-15 With Beta of 1.025 when Market Return is 0		Stocks 16-20 With Beta of 1.05 when Market Return is 0	
	Beta[1]	Return[2]	Beta[1]	Return[2]	Beta[1]	Return[2]	Beta[1]	Return[2]
-0.5	1	-0.49727	1	-0.50526	1	-0.49417	1	-0.50341
0	0.95	0.00503	0.975	0.00098	1.025	0.00432	1.05	0.00188
0.5	1	0.49754	1	0.50063	1	0.49917	1	0.49794

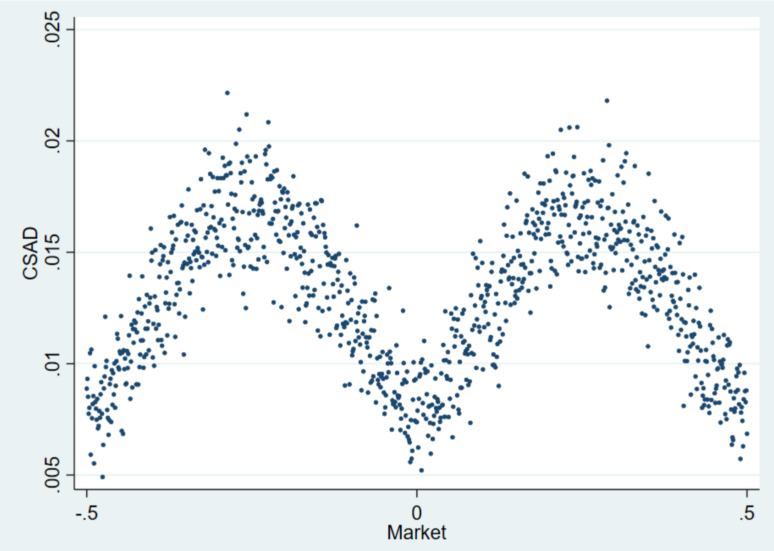
[1]Beta for the five stock portfolios associated with that Market Return.

[2]Average return for the five stock portfolios associated with that Market Return.

5.3.2.1 Regression under normal conditions

When we wish to determine whether the market has herding behaviour, we will need to find a significantly negative coefficient of squared market return in the CSAD model or a significantly negative coefficient of cubic market return in SCSAD model. Under this kind of situation, both the CCK method and SCSAD method can be used to detect herding behaviour in the market, and if we fitted the line for the CSAD market, the scatter graph would look like:

Figure: 5.7: Herding simulation under standard regression:



The graph shows the supposed trend of the return distribution that extreme herding behaviour exists in the market as was designed into the simulation.

Standard Regression Approach

In this simulation the standard CSAD regression has not enough ability to detect herding behaviour, the results show the coefficient of the squared market return is 60% significantly negative which indicates herding behaviour in the market.

Solution 1: Standard regression without constant value

When we take out the constant value in the regression model, the results meet the expectation of our solution 1. The coefficient of the squared market return become 100% significantly negative, correctly showing that the market has herding behaviour.

Solution 2: Regression with SCSAD model

When using the SCSAD regression method, we find that the coefficient of the cubic market return is 100% significantly negative, which correctly indicates the market has herding behaviour in this herding market simulation.

Table 5.3.2.1: Results from standard regression and solutions 1 and 2

Full Range Market Return	Anti-Herding	Nothing	Herding
Standard Regression	0	40%	60%
Regression without constant	0	0	100%
Cubic Regression	0	0	100%

From table 5.3.2.1 above, under the simulation where extreme herding behaviour exists, standard regression, solution 1 without a constant value and solution 3 the SCSAD cubic regression show 100% correct results, they successfully detect the herding behaviour in the market.

Solution 3

5.3.2.2 Investigating the situation given large market movements using Standard CCK regression

From the results, 100% of the squared market return still have a significantly positive coefficient, which incorrectly implies the existence of anti-herding.

In the regressions, the results are shown in Table 4.8. When we consider only absolute market return larger than 0.5%, larger than 5% as well as larger than 10% we find similar results. As the market movement is from -50% to 50%, which is unlikely to be observed in real markets, and herding are more likely to be present when the market is suffering turmoil, according to the results, under the most extreme market conditions, it is more likely to detect herding behaviour in the simulation market.

Table: 5.3.2.2

	Anti-Herding	Nothing	Herding
Market Return >= |0.5%|	0	30%	70%
Market Return >= |5.0%|	0	44%	56%
Market Return >=|10.0%|	0	74%	26%

5.3.2.3 Larger market movements based on a proportion of the data condition

In this section we detect herding under situations where we use proportions of the observations based on absolute return size. We investigate the largest 50% of returns by their absolute size, the largest 10% of returns by absolute size and the largest 5% of returns by absolute size. Our results are shown in the following table. When the largest 50% of observations examined none of the squared market returns have a significantly negative coefficient, which implies there is no herding. According to the results based on the largest 10% and 5% proportions of the observations based on absolute return size, only 4% of the regressions detect herding behaviour in the top 10% observations, and only 2% of the regression detect herding behaviour detected in top 5% observations. Still, under the extreme market condition which have larger market movements, the standard regression model could capture some evidence of herding behaviour.

Table: 5.3.2.2

	Anti-Herding	Nothing	Herding
Largest 50% of observations	4%	96%	0
Largest 10% of observations	4%	92%	4%
Largest 5% of observations	2%	96%	2%

In summary, the market simulation with zero anti-herding and herding in the market shows the differing accuracy of the prevalent herding detection approaches and our three different solution plans. When the market has no herding behaviour, the standard regression results are likely to incorrectly show anti-herding exists in the market. When market returns larger than 0.5%, 5% and 10% are considered, the standard regression produces reasonably accurate results which show that no herding exists in the market.

Under the simulation which ensures that extreme herding behaviour exists in the market, the standard regression has lost its ability to detect herding with larger proportions of the observations based on absolute return size. With market return larger than 0.5% and 5%, and 10% the standard regression results show the evidence of herding behaviour in herding simulation, but under the condition where we examine the largest 10% and 5% observations based on the absolute market return, the traditional CCK regression model cannot detect herding behaviour effectively.

6.0 Empirical Study 3 – Worldwide Herding Results using Log returns

6.1 Full range of data

Robust regression results by using CSAD based on the Log return method. Equivalent results based on the Simple return method are shown in chapter 6.0* in the Appendix.

The following tables and graph present the results of the SCSAD approach with the regression model in equation 5.4 and compare it with the results based on the traditional CCK model.

6.1.1 Normal regression

Full range of data robust regression

Table 6.1.1 panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.201	0.215	0.168	0.165	0.187	0.318
	(3.20)***	(8.96)***	(7.66)***	(9.84)***	(6.23)***	(20.02)***
$R_{m,t}^2$	0.0330	0.0111	0.0112	0.0181	0.0205	0.0157
	(1.60)	(1.64)	(2.02)**	(4.72)***	(2.67)***	(5.46)***
_cons	0.987	0.709	0.969	0.797	0.805	1.406
	(35.94)***	(58.07)***	(68.70)***	(73.66)***	(49.16)***	(103.13)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.174	0.309	0.290	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.1.1 panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.229	0.179	0.322	0.311	0.177	0.173	0.263
	(8.72)***	(6.77)***	(11.05)***	(14.93)***	(11.24)***	(8.05)***	(9.17)***
$R_{m,t}^2$	0.00988	0.0219	0.000902	0.00505	0.0175	0.00747	0.0268
	(1.40)	(2.90)***	(0.17)	(0.98)	(4.08)***	(1.68)*	(3.16)***
_cons	0.903	0.878	1.074	0.895	0.782	0.796	0.850
	(61.89)***	(61.45)***	(47.45)***	(69.47)***	(76.85)***	(55.49)***	(65.85)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.299	0.256	0.197	0.230	0.245	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Full range of data robust regression

Table 6.1.1 panel B, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00255	-0.00850	0.0122	0.0118	0.00789	0.00791
	(-0.21)	(-1.19)	(1.76)*	(2.09)**	(1.01)	(0.97)
$\|R_{m,t}\|$	0.201	0.214	0.169	0.167	0.188	0.317
	(3.24)***	(9.14)***	(7.71)***	(9.95)***	(6.16)***	(19.59)***
$R_{m,t}^2$	0.0328	0.0116	0.0111	0.0179	0.0204	0.0160
	(1.62)	(1.76)*	(2.00)**	(4.74)***	(2.60)***	(5.35)***
_cons	0.987	0.710	0.968	0.795	0.804	1.406
	(35.87)***	(59.32)***	(68.79)***	(73.61)***	(48.95)***	(102.62)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.175	0.310	0.291	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.1.1 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0246	0.00883	0.00669	0.0298	0.0127	0.00702	0.00344
	(3.33)***	(1.05)	(0.62)	(3.80)***	(1.79)*	(1.10)	(0.37)
$\|R_{m,t}\|$	0.229	0.179	0.321	0.310	0.178	0.175	0.263
	(9.07)***	(6.65)***	(11.09)***	(15.57)***	(11.52)***	(8.06)***	(9.30)***
$R_{m,t}^2$	0.0101	0.0223	0.00122	0.00684	0.0175	0.00721	0.0270
	(1.49)	(2.89)***	(0.23)	(1.47)	(4.22)***	(1.59)	(3.26)***
_cons	0.902	0.878	1.074	0.894	0.780	0.795	0.850
	(63.73)***	(60.43)***	(47.53)***	(70.38)***	(77.05)***	(55.37)***	(66.04)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.304	0.257	0.197	0.234	0.246	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Based on the results under the standard regression. In panel A, the coefficients of $|R_{m,t}|$ are highly significant and positive for all 13 countries. It shows a positive relationship between the CSAD and the market return in the different markets which is as expected in the light of asset pricing models such as CAPM which propose a positive relationship between risk and return. The coefficient of $R_{m,t}$ is positive and significant for 3 countries giving some evidence that herding is less likely when the market return is increasing in these sectors. This finding is broadly in accord with the literature with tends to associate more herding with severe market falls. The coefficients of $|R_{m,t}|$are highly significant and positive for all 13 countries. We find that Finland, France, Germany, Greece, Italy, Spain and UK have a significantly positive coefficient of squared market return under both equation 3.2 and equation 3.3, this indicates that anti-herding exists in these markets. The rest of the countries in our data sample have an insignificantly positive coefficient of squared market return, which shows that there is no herding behaviour in these markets.

6.1.2 Solution 1 Regression results without constant

Full range of data Regression results without constant

Table 6.1.2, Robust Regression without constant

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2|R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.000468	0.00934	0.0255	0.0234	0.0219	0.0128
	(-0.03)	(1.00)	(2.40)**	(2.87)***	(2.14)**	(0.94)
$\|R_{m,t}\|$	1.216	0.953	1.086	0.914	0.930	1.322
	(25.56)***	(41.04)***	(42.91)***	(50.30)***	(39.05)***	(18.49)***
$R^2_{m,t}$	-0.119	-0.0988	-0.126	-0.0912	-0.0836	-0.0875
	(-5.47)***	(-10.02)***	(-12.95)***	(-13.71)***	(-9.38)***	(-3.90)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.664	0.699	0.679	0.711	0.694	0.738

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.1.2 (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0312	0.0170	0.00755	0.0409	0.0297	0.0265	0.00521
	(2.60)***	(1.44)	(0.61)	(2.44)**	(2.55)**	(3.20)***	(0.40)
$\|R_{m,t}\|$	1.007	1.059	1.127	1.293	0.980	0.815	1.175
	(27.69)***	(31.07)***	(43.76)***	(26.52)***	(28.38)***	(36.94)***	(40.01)***
$R^2_{m,t}$	-0.0882	-0.121	-0.0949	-0.165	-0.112	-0.0693	-0.114
	(-6.26)***	(-8.82)***	(-12.69)***	(-7.19)***	(-7.79)***	(-10.11)***	(-9.24)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.714	0.695	0.661	0.696	0.692	0.677	0.703

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As mentioned above, one of the solutions to detect herding behaviour more accurately is to limit the constant in the regression to zero in order to make the fitted graph go through the origin, which can reduce the impact of the idiosyncratic error term in the CAPM when $|R_{m,t}|$ is small. Based on the results, when we force the constant to be zero, all the countries have a significantly negative coefficient of squared market return, giving significant evidence showing there is herding behaviour in these markets.

6.1.3 Solution 2 Regression results in SCSAD

Full range of data robust regression using SCSAD

Table 6.1.3, Robust Regression

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.985	0.775	0.837	0.728	0.754	1.071
	(53.50)***	(69.81)***	(56.70)***	(65.04)***	(64.43)***	(47.41)***
$R_{m,t}^2$	-0.00815	0.0106	0.00956	0.00656	0.00880	-0.00736
	(-1.07)	(2.63)***	(1.87)*	(1.89)*	(2.32)**	(-1.35)
$R_{m,t}^3$	-0.00900	-0.00865	-0.0110	-0.00758	-0.00620	-0.00402
	(-4.68)***	(-9.30)***	(-8.79)***	(-9.30)***	(-7.64)***	(-3.35)***
_cons	0.0255	-0.0152	0.000307	0.00998	0.00845	0.0997
	(1.58)	(-1.50)	(0.02)	(0.86)	(0.70)	(4.66)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.637	0.672	0.642	0.683	0.670	0.709

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.1.4 (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.806	0.819	0.893	1.003	0.769	0.650	0.953
	(61.55)***	(45.23)***	(51.77)***	(48.16)***	(42.39)***	(56.07)***	(63.92)***
$R_{m,t}^2$	0.00144	0.00772	-0.00126	0.0154	0.0114	0.00977	-0.00475
	(0.27)	(1.25)	(-0.32)	(1.59)	(1.94)*	(4.02)***	(-0.95)
$R_{m,t}^3$	-0.00515	-0.0101	-0.00656	-0.0141	-0.00954	-0.00478	-0.00917
	(-5.26)***	(-5.57)***	(-8.37)***	(-5.01)***	(-4.91)***	(-8.05)***	(-7.84)***
_cons	0.0522	0.0108	0.0425	0.0350	0.0243	0.00793	0.0383
	(3.56)***	(0.72)	(2.23)**	(2.11)**	(1.93)*	(0.68)	(3.17)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.682	0.663	0.635	0.661	0.660	0.648	0.676

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.1.3 shows the results for our solution 2 - the new SCSAD method. The results show that all the countries have a significantly negative coefficient of $R_{m,t}^3$, which means we will reject the null hypothesis, and confirm that these countries have herding behaviour in their stock markets. Also, the adjusted R^2 is much higher than in the traditional method.

6.1.4 Fitted line for CSAD based on Log returns for the full range of data

The following graphs show the fitted line for the traditional CCK approach based on the log return calculation method. The fitted lines curve in a convex way which would correspond to a positive coefficient on the $R_{m,t}^2$ term. As discussed above, one would expect this even if there is no herding. For the new SCSAD method, the line goes through the origin and curves in the opposite concave way, which indicates that there is herding behaviour; otherwise, they would be a straight line.

The scatter diagrams in Figures 6.1 to 6.13 show the distribution of CSAD results and the fitted line shows the predicted fit value based on regression results by using the CCK model. According to the regression results shown in table 6.1.1, there is no significant herding behaviour in the selected countries in the sample period, and from these figures, we can find that the fitted regression line are mostly upwards curved although some of them tend to be a straight line such as Norway and Portugal, this phenomenon indicates there has no herding behaviour in these stock markets.

Figure 6.1 to 6.13: Fitted line for CSAD results

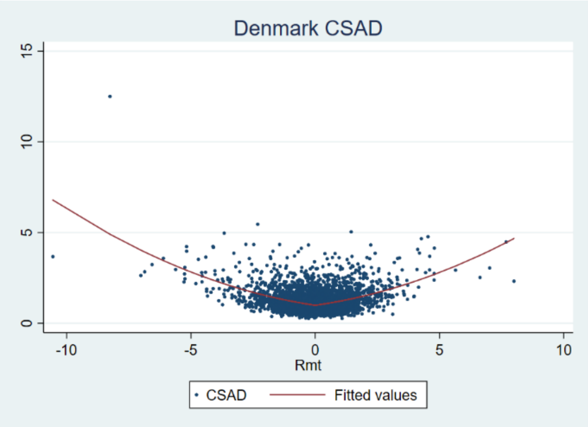


Figure 6.1

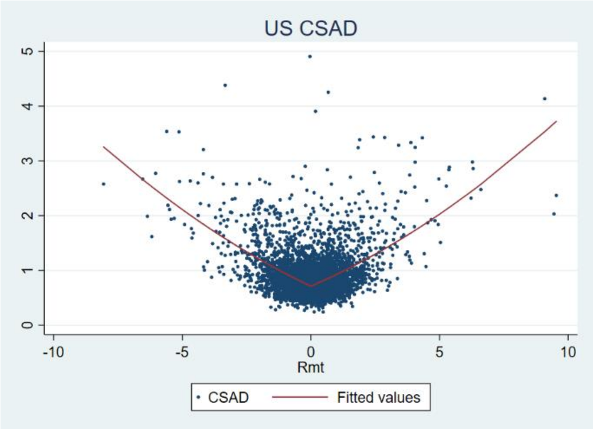


Figure 6.2

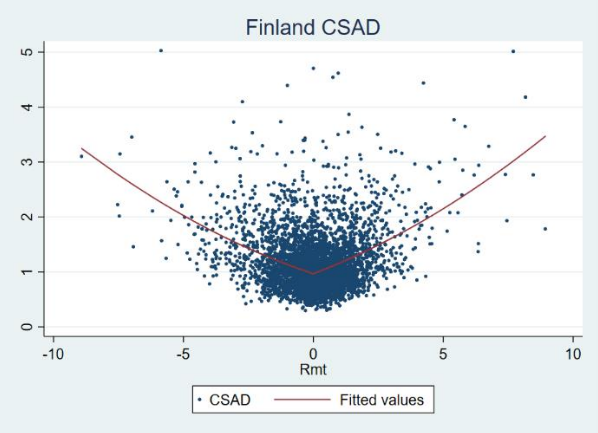


Figure 6.3

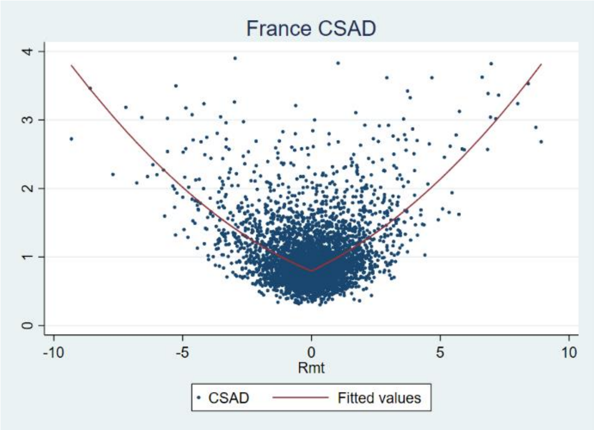


Figure 6.4

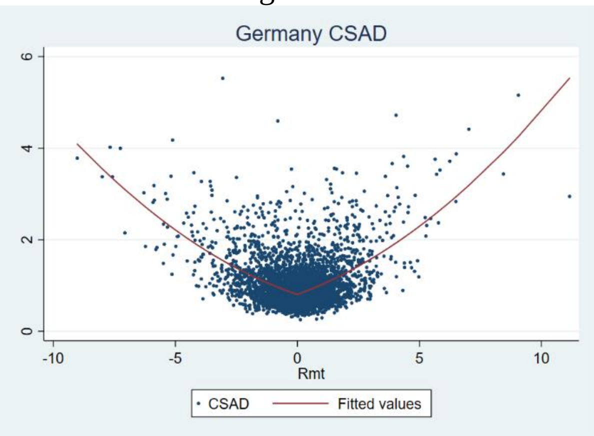


Figure 6.5

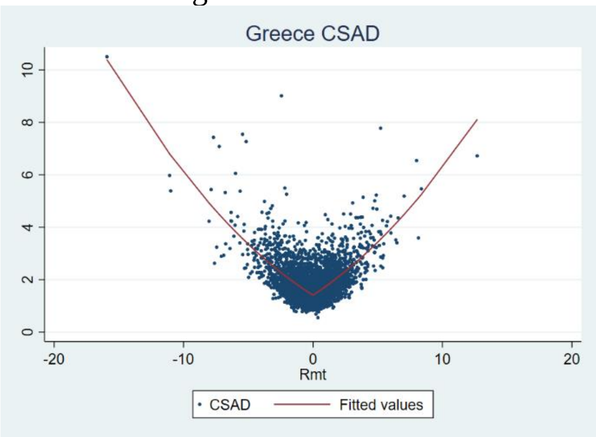


Figure 6.6

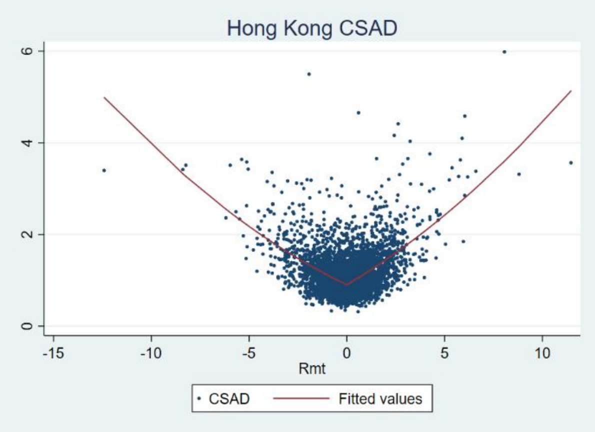


Figure 6.7

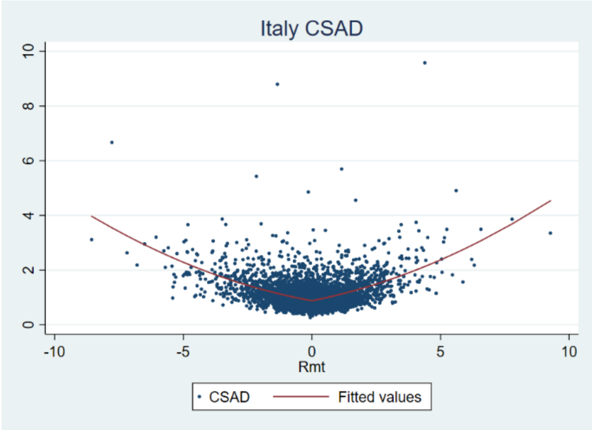


Figure 6.8

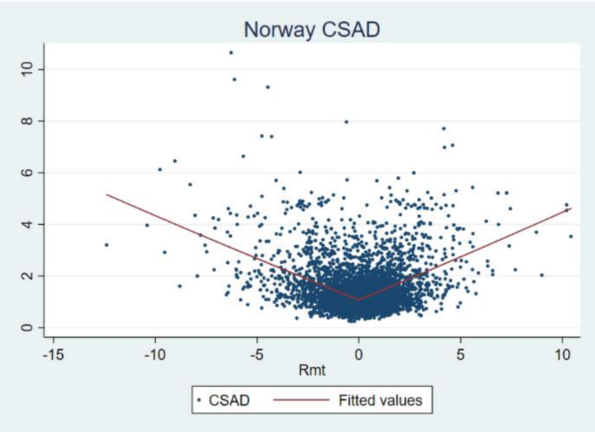


Figure 6.9

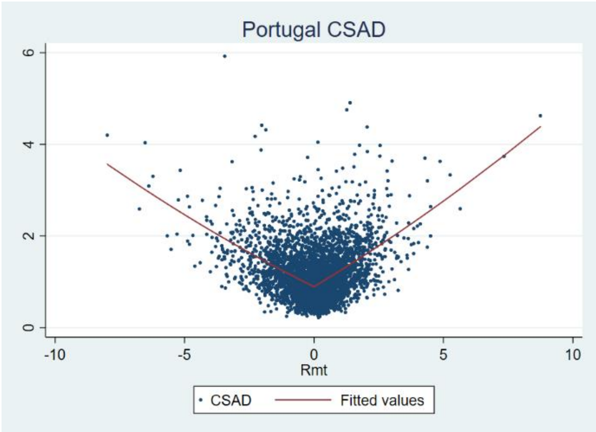


Figure 6.10

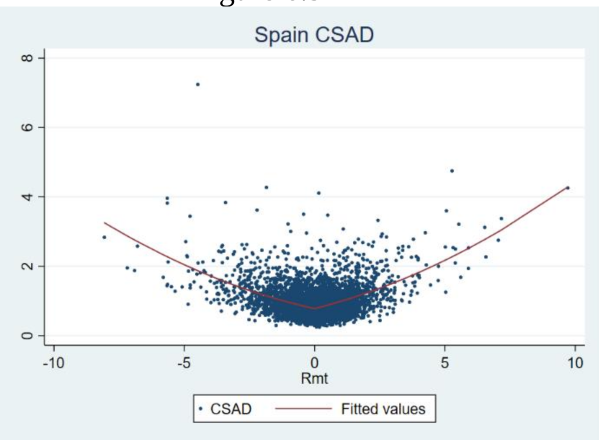


Figure 6.11

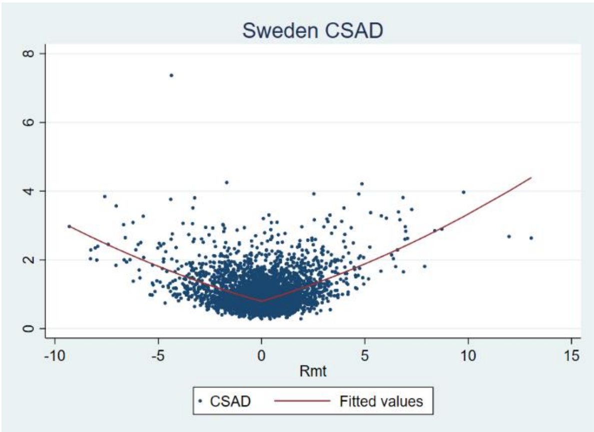


Figure 6.12

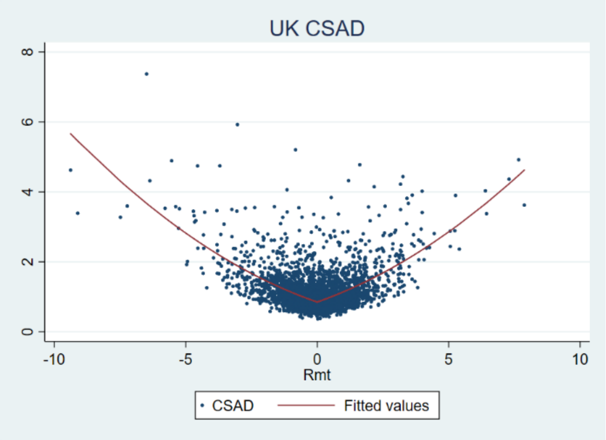


Figure 6.13

6.1.5 Fitted line for CSAD without constant based on Log returns for the full range of data

By using solution 1 regression without constant value, from the regression results shown in table 6.1.2, all countries have significantly negative coefficients of squared market returns which indicates the existence of herding behaviour in the stock markets of these countries. Also, from these figures, we can see that the predicted fitted value based on regression result using model two without constant, the regression line is curved downwards at the end of left and right side, this also indicates the herding behaviour presence in stock market.

Figure 6.14 to 6.26 Fitted line for CSAD without constant

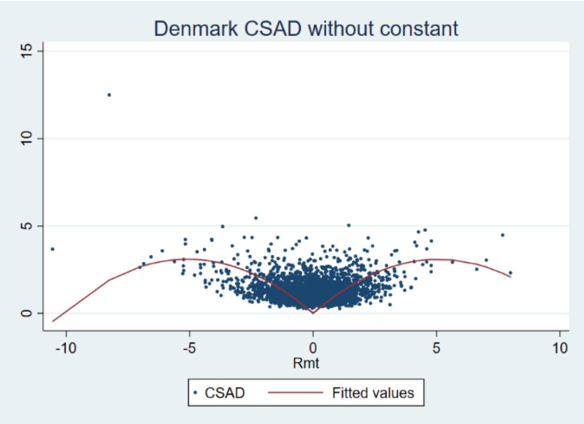


Figure 6.14

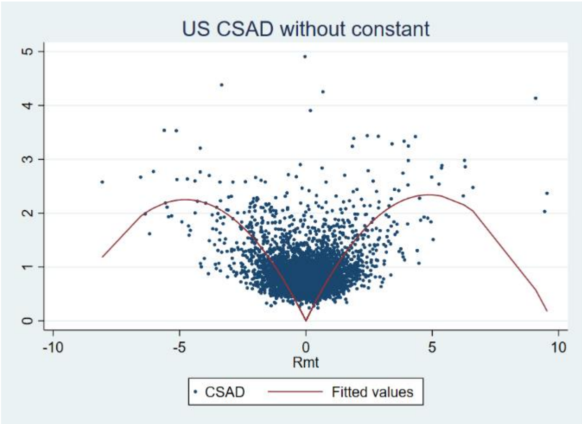
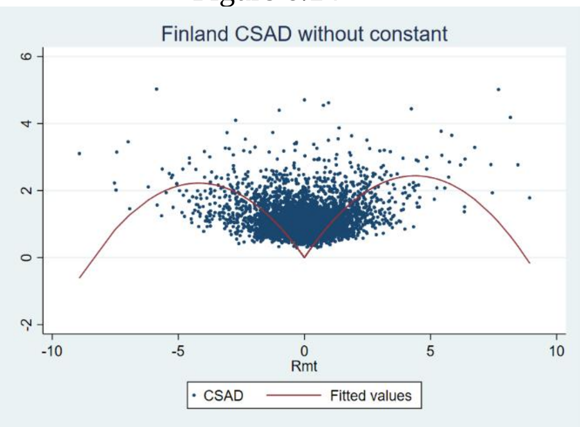


Figure 6.15



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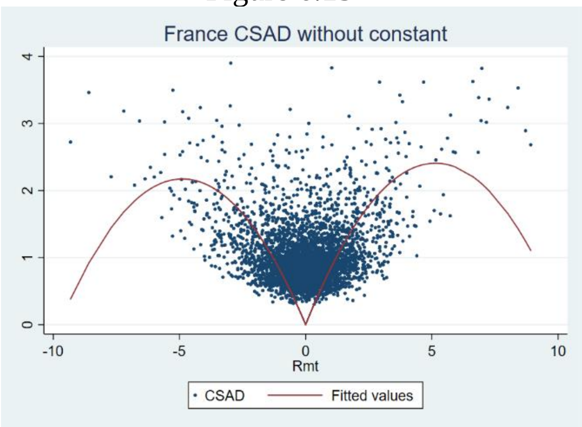

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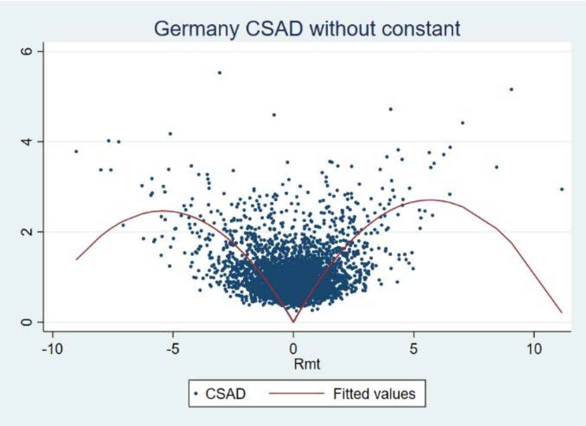


Figure 6.18

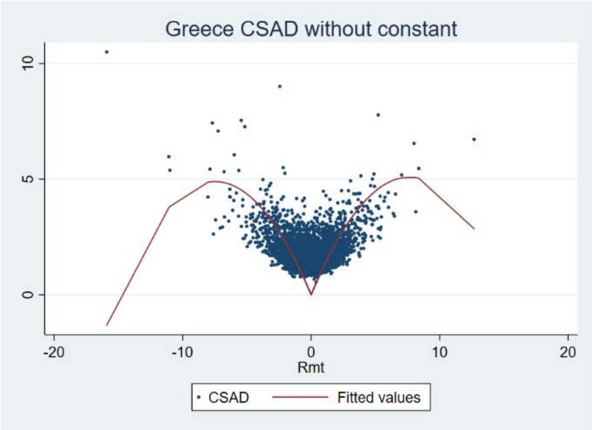


Figure 6.19

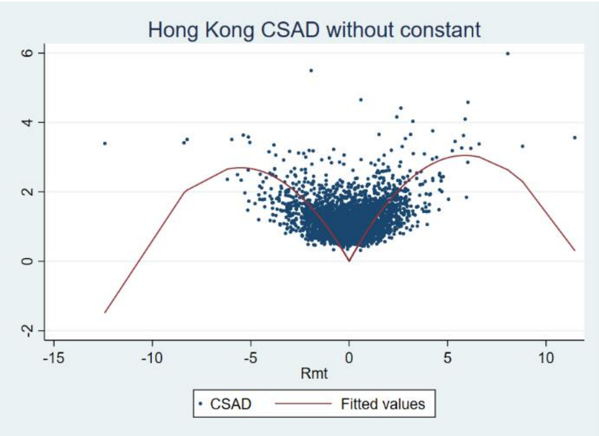


Figure 6.20

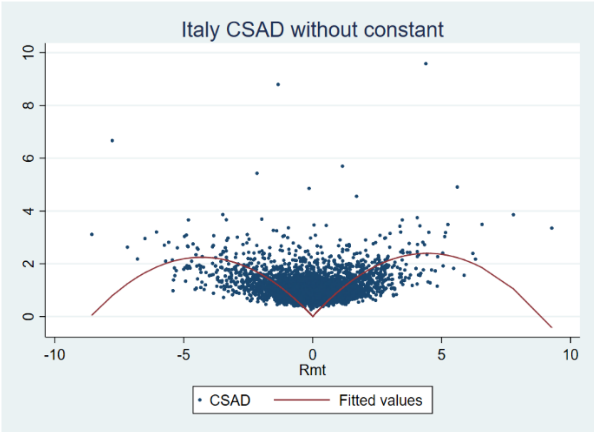


Figure 6.21

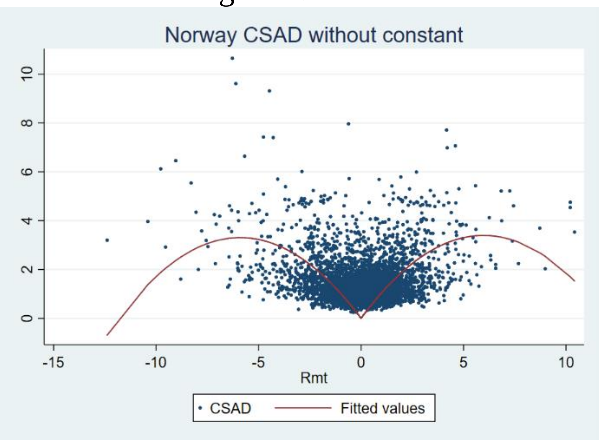
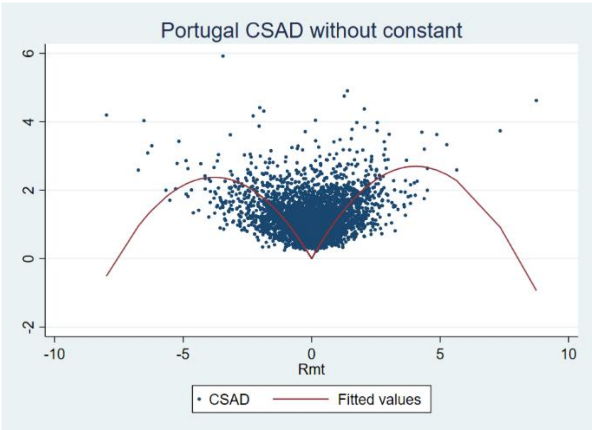


Figure 6.22



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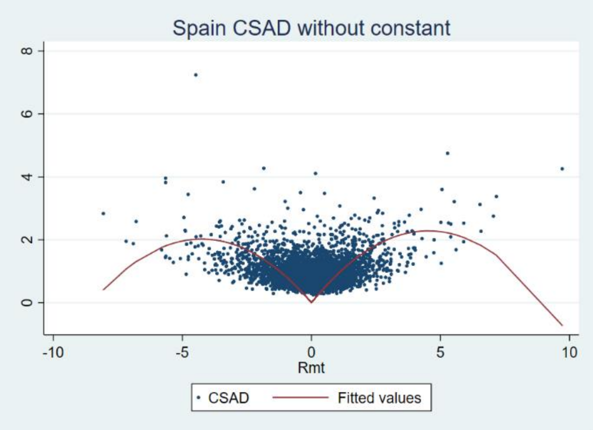


Figure 6.24

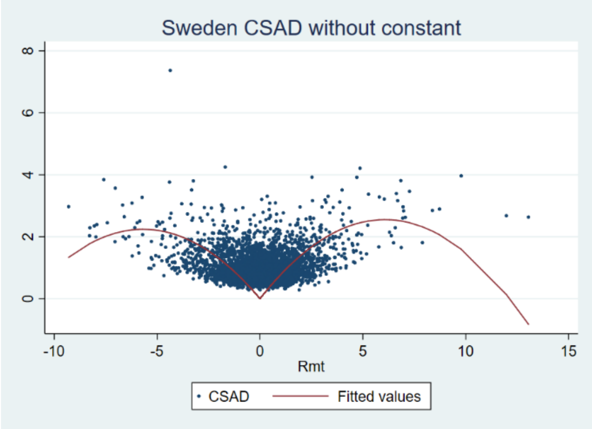


Figure 6.25

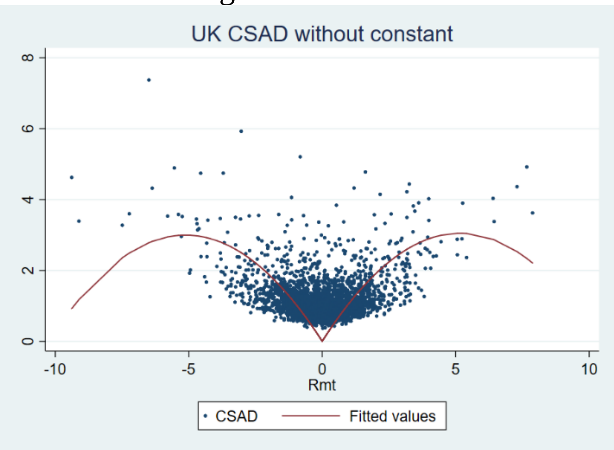


Figure 6.26

6.1.6 Fitted line for SCSAD based on Log returns for the full range of data

When we apply our new method, the solution 2 SCSAD regression model to detect the presence of herding behaviour in stock market, with the results shown in table 6.1.3 we have captured significant evidence of herding behaviour. From the figures, as we expected from the market simulation section, if there is no herding behaviour in the market, the fitted regression line should be a straight line, but the following figures shows the regression line curved into two different directions, this phenomenon indicates that herding behaviour exists in the stock market of the selected countries in our data sample.

Figure 6.27 to 6.39 Fitted line for SCSAD results

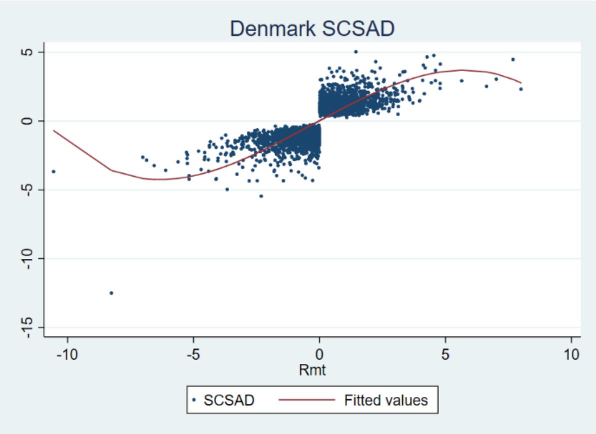
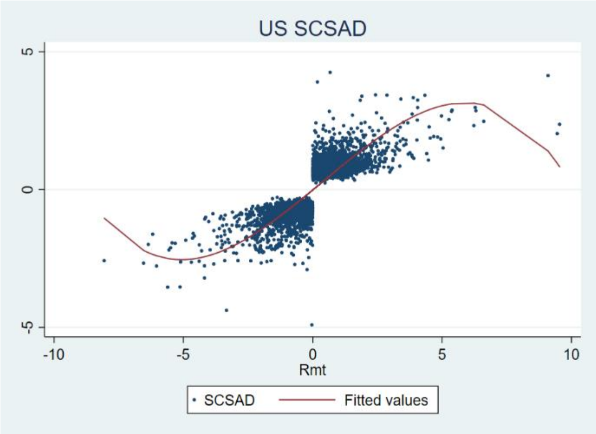


Figure 6.27



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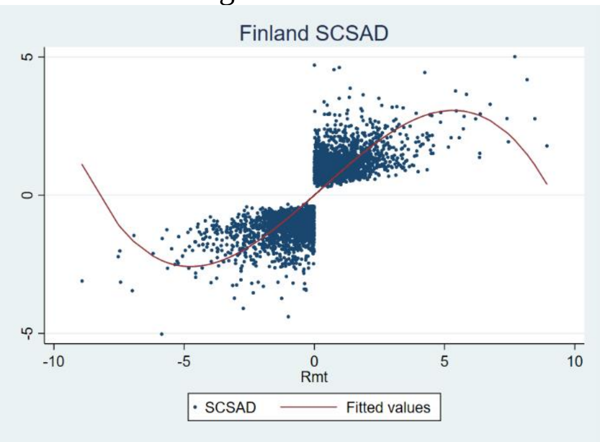

Figure 6.29

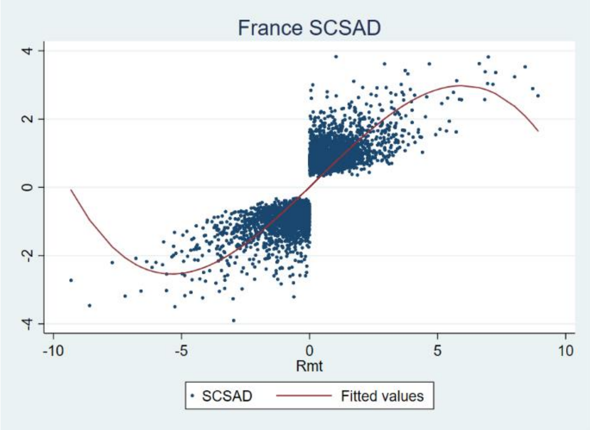

Figure 6.30

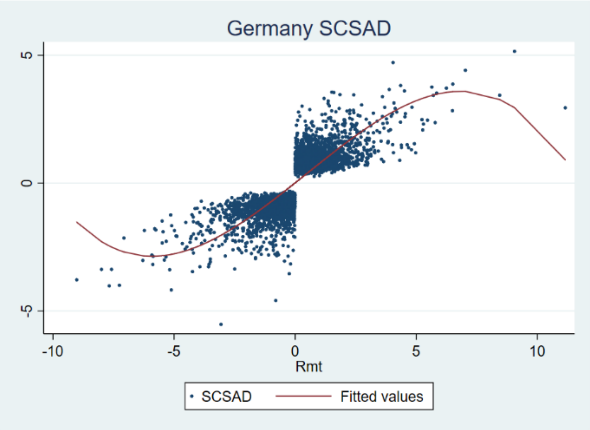

Figure 6.31

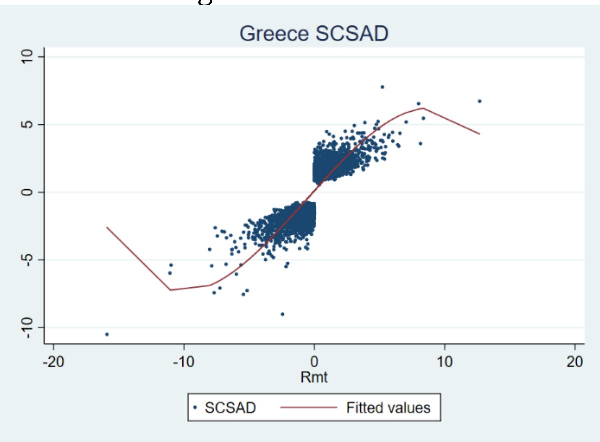

Figure 6.32

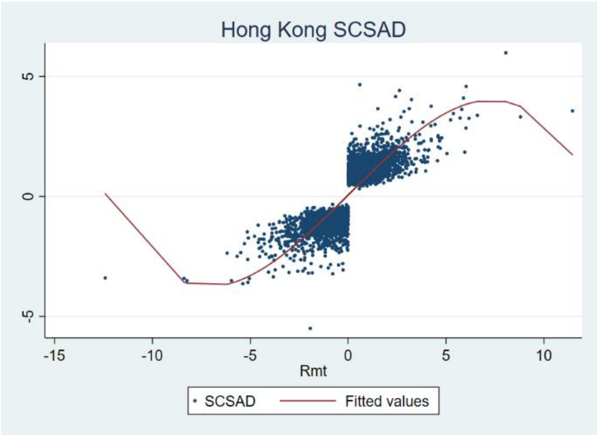

Figure 6.33

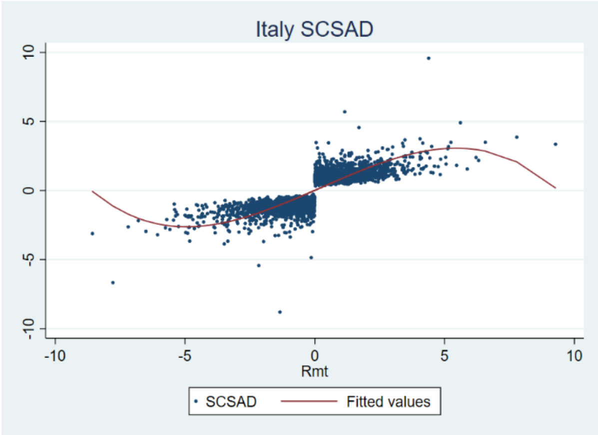

Figure 6.34

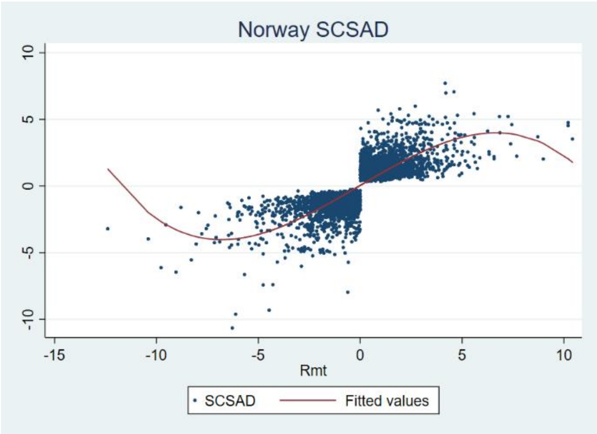

Figure 6.35

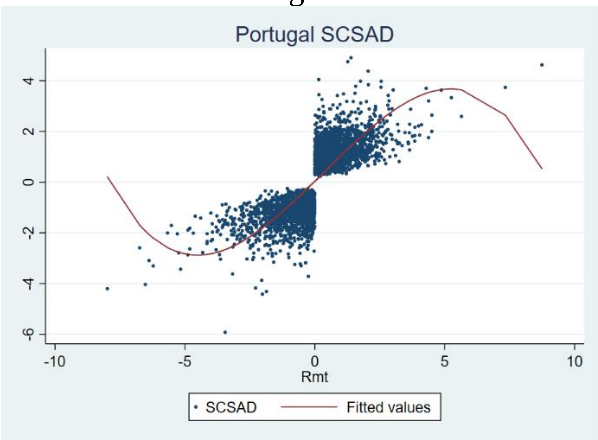

Figure 6.36

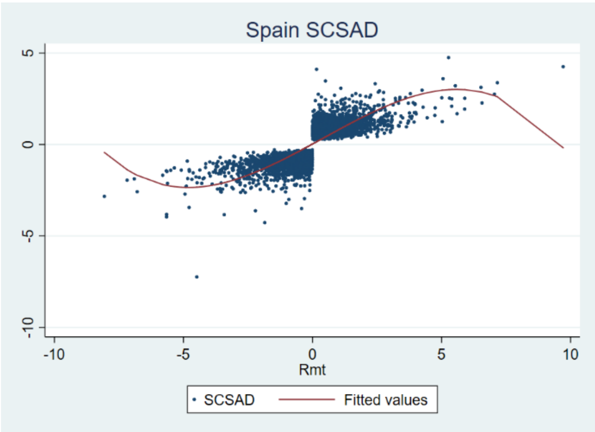

Figure 6.37

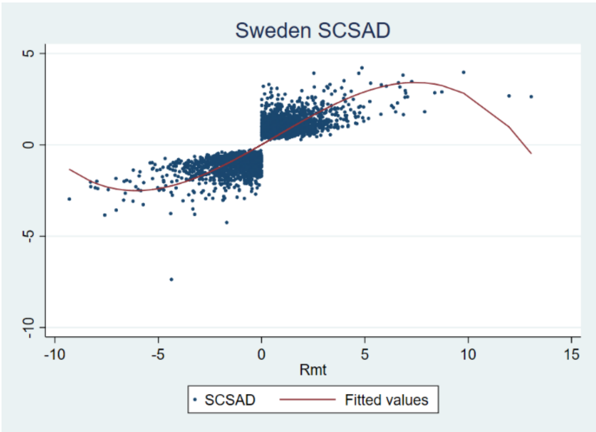

Figure 6.38

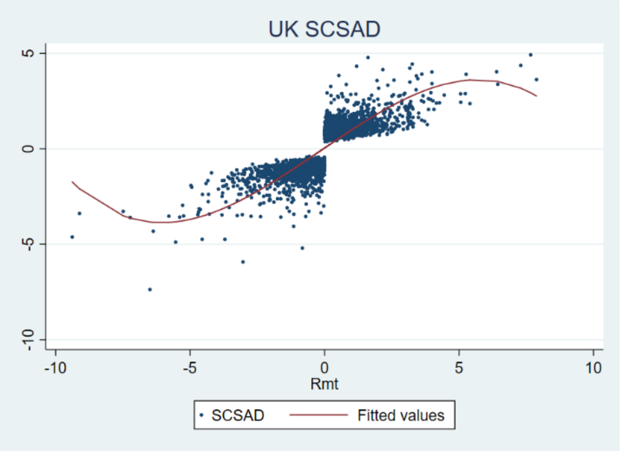

Figure 6.39

7.0 Herding behaviour in stock markets at sector level

In this chapter, we will investigate and provide robust regression results for herding detection in different sectors in the Germany, UK and France markets. We will apply the traditional CCK model and our three different methods to detect herding and compare the results. In prior literature, Gavriilidis, K et.al, (2013) using a database of Spanish funds' quarterly portfolio holdings Using both market and industry status to assess the extent to which institutional herds at the industry level are intention driven. They have shown that evidence denoting that institutional herding in the Spanish market is intentional for most sectors, manifesting itself mainly during periods when the market as a whole or the specific sector under examination has underperformed, generated rising/high volatility and exhibited rising/high volume. Gębka and Wohar, (2013) investigate the existence of herding in the global equity market, they have shown that herding does not seem to take place internationally. However, when national indices are disaggregated and different economic sectors (industries) are considered separately, some sector-specific indices reveal price patterns indicative of traders' irrationality, especially in basic materials, consumer services, and oil and gas. This can be driven by a group of investors following each other in and out of markets, overconfidence, or excessive flight to quality. These irrational patterns decline over time. Bharti and Kumar (2020) Empirically examine the herding behaviour of fast-moving consumer goods sector stocks under different market return conditions and during the global financial crisis and its aftermath in the Indian equity market. Research do not find clear evidence of the herding effect in the industry. In contrast, anti-conformity behaviour was observed at lower and median quantile values. One possible reason could be the non-cyclical nature of the industry, with investors relying more on fundamentals rather than chasing the crowd. Also, during bull and bear phases, extreme volatility, market asymmetries during and after the global financial crisis, there is no herding behaviour. Satish, B. and Padmasree, K. (2018) examine herding behaviour in the Indian stock market at the sector level and found that the herding behaviour is not exhibited in the Indian Stock Market for a long period and these results validate the presence of rational asset pricing models. Also, the study found Herding behaviour is absent during the pre-financial crisis period, crisis period and post-financial crisis period. Herding behaviour is also not present during the market is in a rising and declining state but the volatility of the stock high. Filip et.al (2015) investigated the existence of the herding behaviour of investors for the major stock markets from Central and South-Eastern Europe: Czech Republic, Poland, Hungary, Romania and Bulgaria at the sector level by using firm-level information. Focused on banking, financial, construction, energy, pharmaceutical and hotels industries. Their results have highlighted that investors herd especially during decline periods and their behaviour is different in the pre-crisis and post-crisis periods compared with the crisis period. The results have provided evidence of the herding behaviour of investors for all CEE stock markets, except Poland. Ukpong et.al (2021) provides empirical evidence on the determinants of herding in the US using both market and industry-level data. Their findings demonstrate that herding at the market level does not exist, however, some herding becomes visible at the industry level. The results also demonstrate significant evidence of anti-herding behaviour at the market and industry level.

Given that the most studies regarding the existence of herding behaviour were realized for developed stock in the US market and some emerging market such as Central and South-Eastern Europe and Indian market. It becomes obvious the need to expand the research also for western European market. In this chapter we have proposed to investigate the herding behaviour for the major stock markets in three main western European countries, which includes the UK, Germany and France markets.

7.1 Data sample

For this empirical chapter, we use daily data narrowed down to the sector level for the top three economies in Europe: Germany, France, and the UK. This can provide us with a good view of herding in different industries. We will test the hypothesis that companies are less likely to herd within particular sectors. Herding may vary between sectors in crises. For example, during the financial crisis period, financial sector companies, in particular, might have been more or less likely to herd. Also, we test whether different sectors herd more than the whole market. In order to test these hypotheses, we collect data from Bloomberg. The range of our data sample is from 03 Jan 2000 to 20 Oct 2020, this long time period has covered several important events including the global financial crisis from about March 2008 to March 2009, Brexit from June 2016 until the end of the period, and Covid-19 starting in 2020 which will have had a significant impact on the global stock market and the industries within it.

The Bloomberg database follows the S&P sectors and divides all listed companies into twelve sectors comprising Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Government, Healthcare, Industrials, Materials, Real Estate, Technology, and Utilities. As there are no listed companies in the Government sector, there are eleven relevant sectors. The Communications sector is made up of companies that provide connections for people to keep in touch. This includes providers of internet and telephone plans. It also includes social media, entertainment and interactive media and service companies. The Consumer Discretionary sector consists of business and manufacturers providing luxury goods and services which are not essential for survival. These include jewellery, premium vehicles, luxury experiences in hotels and restaurants and so on. The demand for these services and items fluctuates depending on the economic conditions facing individuals. The Consumer Staple sector generally refers to those companies which produce necessities, including food and beverages as well as producers of personal products. The Energy sector refers to those companies that explore and produce gas and oil. It also consists of companies that extract materials and companies that supply, or manufacture equipment used in the extraction process. The Financial sector includes all the companies engaged in financial services such as commercial banks, insurance companies, and investment firms as well. Companies in this industry are generally relatively stable as most of them are well-established companies. The HealthCare sector includes firms which provide health care equipment, run hospitals, manufacturer pharmaceuticals and biotechnology companies. The Industrials sector includes a wide range of companies involved in manufacture and transportation, they work in areas such as defence and aerospace, airlines, railroads and machinery. Materials industries include companies that provide the raw material needed for other sectors to function, such as chemicals, construction materials, metals and mining, and paper and forest products. Real Estate which was previously included in the Financial sector, consists of equity real estate investment trusts and real estate management and development firms. The Technology sector includes manufacturers and sellers of computer hardware, software, semiconductors and computer equipment in addition to providers of IT services. The Utilities sector includes electric and gas companies, water companies and renewable electricity producers.

7.2 Empirical results

7.2.1 Full range of data

Table 7.2.1.1 Panel A Descriptive statistics of UK sectors

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.002649	.050456	.70866	.502199	-1.42775	14.9801	5426
CSAD	1.4325	1.31651	.558632	.312069	2.26509	15.4195	5426
Communications							
$R_{m,t}$	-.022017	.024701	.895033	.801084	-.449117	6.63303	5426
CSAD	1.57428	1.37814	.808569	.653783	1.88584	9.45145	5426
Consumer Discretionary							
$R_{m,t}$	.000382	.037334	.852487	.726734	-2.17624	34.1263	5426
CSAD	1.44107	1.30852	.705412	.497607	4.34612	55.7024	5426
Consumer Staples							
$R_{m,t}$	.021389	.045604	.63424	.40226	-.665948	10.8876	5426
CSAD	1.07739	.984175	.466068	.21722	1.9497	10.7823	5426
Energy							
$R_{m,t}$	-.038762	.007179	1.71534	2.9424	-.630689	25.6354	5426
CSAD	2.2901	1.88724	1.97165	3.88741	6.57385	70.7387	5426
Financials							
$R_{m,t}$	-.000187	.044265	.886534	.785942	-.786486	12.4548	5426
CSAD	1.12319	.978857	.620468	.38498	3.11295	21.2007	5426
Health Care							
$R_{m,t}$	-.014	0	.958641	.918993	-.11819	9.39551	5426
CSAD	1.76997	1.56053	1.01763	1.03557	3.25357	28.8712	5426
Industrials							
$R_{m,t}$	.004493	.056995	.788494	.621723	-1.57851	18.8015	5426
CSAD	1.37611	1.26745	.567542	.322104	2.22045	17.1806	5426
Materials							
$R_{m,t}$	-.009458	.017499	1.07662	1.15911	-.53015	8.95969	5426
CSAD	1.96034	1.78169	.978265	.957002	3.11221	29.054	5426
Real Estate							
$R_{m,t}$	.000919	.03317	.998564	.99713	-1.23942	18.408	5426
CSAD	1.13945	.994781	.666295	.443949	3.10588	26.907	5426
Technology							
$R_{m,t}$	-.012231	.028006	.958278	.918297	-.78819	12.4253	5426
CSAD	1.76669	1.55382	.959671	.920969	3.35022	34.1881	5426
Utilities							
$R_{m,t}$	.008665	.024089	.974352	.949362	-.299713	17.1896	5426
CSAD	.90797	.78227	.686868	.471787	10.3338	217.251	5426

Table 7.2.1.1 Panel B Descriptive statistics of German and France sectors

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.00348	.030283	.788374	.621533	-.713039	8.89318	5426
CSAD	1.88718	1.77828	.647251	.418934	1.17267	8.81659	5426
Communications							
$R_{m,t}$	-.025549	.013401	1.16712	1.36217	-.146736	12.9533	5426
CSAD	2.00424	1.76996	1.1417	1.30348	6.08655	99.2408	5426
Consumer Discretionary							
$R_{m,t}$	-.002473	.023687	.988079	.9763	-.536116	9.02097	5426
CSAD	1.96342	1.711	1.07642	1.15868	2.53132	12.4779	5426
Consumer Staples							
$R_{m,t}$	.012478	.018204	.682771	.466176	-.296176	6.36544	5426
CSAD	1.21667	1.11994	.5241	.27468	2.05957	14.5428	5426
Energy							
$R_{m,t}$	-.033646	.003386	1.62003	2.62451	-.156218	8.13735	5426
CSAD	2.19308	1.82506	1.56215	2.44032	4.36796	50.5322	5426
Financials							
$R_{m,t}$	-.012393	.019329	1.00887	1.01783	-.461285	18.3792	5426
CSAD	1.90641	1.72718	1.02414	1.04885	6.50206	119.015	5426
Health Care							
$R_{m,t}$	.009543	.035748	1.06819	1.14103	-.23336	9.66686	5426
CSAD	1.9958	1.78303	1.03514	1.07151	3.10347	26.2107	5426
Industrials							
$R_{m,t}$	.000212	.031629	.958086	.917929	-.431123	7.11103	5426
CSAD	2.00789	1.85529	.889888	.7919	2.19356	14.2501	5426
Materials							
$R_{m,t}$	.008777	.035316	1.23032	1.51369	-.243066	18.4373	5426
CSAD	1.7348	1.44105	1.59394	2.54064	6.36897	51.7873	5426
Real Estate							
$R_{m,t}$	-.003463	0	1.37749	1.89748	.041953	45.9118	5426
CSAD	2.37995	1.9916	2.11582	4.47669	7.10505	80.4946	5426
Technology							
$R_{m,t}$	-.011085	.026597	1.18231	1.39785	-.413067	7.97017	5426
CSAD	2.26252	2.04379	1.00667	1.01338	2.02647	12.9094	5426
Utilities							
$R_{m,t}$	.016557	.014726	.841651	.708376	-.360663	8.04714	5426
CSAD	1.21469	1.0926	.672396	.452116	2.75092	21.7532	5426

Table 7.2.1.1 panel A summarises the descriptive statistics of equally weighted average market returns and CSAD calculation results for the different sectors in the UK market through the whole timeline of our data sample from 2000 to 2020. We have a total of 640 companies in our UK data sample and there are 44 companies in the Communication sector, 77 companies in the Consumer Discretionary sector, 65 companies in the Consumer Staples sector, 33

companies in the Energy sector, 116 companies in the Financial sector, 31 companies in the Health Care sector, 125 companies in the Industrials sector, 49 companies in the Materials sector, 32 companies in the Real Estate sector, 54 companies in the Technology sectors, and 14 companies in the Utilities sectors. Overall, from the results, the mean return of Sectors in Consumer Discretionary, Consumer Staples, Industrials, Real Estate, and Utilities are positive, suggesting that on average, these sectors performed positively during the sample period. The Communications, Energy, Financials, Health care, Materials, and Technology show a negative mean return during our data sample period, which means these sectors performed negatively over our data sample period. The consumer Staple sector has the highest mean return, while the energy sector has the lowest mean return during the selected time period. Turning to the value of CSAD calculation results, the Energy sector has the highest CSAD result, and the lowest CSAD result is shown in the Utilities sector.

Table 7.2.1.1 panel B reports the descriptive statistics of the equally weighted mean return and CSAD results for the different sectors in the German and French markets. We combine the Germany market sectors and the France market sectors, as some sectors only have a small number of companies in them. In this combined market, we have a total of 799 companies. There are 56 companies in the Communication sector, 144 companies in the Consumer Discretionary sector, 67 companies in the Consumer Staple sector, 19 companies in the Energy sector, 100 companies in the Financial sector, 56 companies in the Health Care sector, 128 companies in the Industrials sector, 57 companies in the Materials sector, 52 companies in the Real Estate sector, 102 companies in the Technology sector, and 18 companies in the Utilities sector. According to the results, sectors including Consumer staples, Health care, Industrials, Materials, and Utilities show positive mean returns over the sample period. Simultaneously, the Communications, Consumer Discretionary, Energy, Financials, Real Estate, and Technology sectors have performed negatively through the sample period. When we compared the results to those in the UK market, some of the UK market sectors have better performed than in the German and French market, including Communications, Consumer Discretionary, Consumer Staples, Financials, Industrials, and Real Estate. Regarding the CSAD results, the Real Estate sector has the highest average CSAD results and similarly to the UK market, the Utilities sector has the lowest mean CSAD value.

7.2.1.2 Normal regression model

Full range data from UK sectors using CCK model regression results

Table 7.2.1.2 panel A UK regression results under the CCK model

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0498***	0.0504***	0.0439***	0.0022	0.0783***	0.0271***
	(4.3947)	(3.9950)	(3.3385)	(0.1938)	(2.1147)	(2.4457)
$\|R_{m,t}\|$	0.7646***	0.8196***	0.7436***	0.6220***	0.9433***	0.6869***
	(30.6961)	(19.7321)	(30.3013)	(21.9866)	(7.3172)	(21.9371)
$R_{m,t}^2$	0.0030	0.0216	0.0148***	0.0022	0.0296	0.0141
	(0.3032)	(1.2405)	(3.1273)	(0.1646)	(1.4684)	(1.2390)
_cons	1.0753***	1.0422***	1.0266***	0.8011***	1.2040***	0.7134***
	(115.8018)	(67.8943)	(95.7502)	(87.7261)	(14.6872)	(63.1202)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.5238	0.4681	0.5580	0.3736	0.6832	0.6210

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0601***	0.0361***	0.0834***	0.0099	0.0719***	0.0076
	(3.1385)	(3.4808)	(3.8189)	(0.8347)	(3.5773)	(0.2091)
$\|R_{m,t}\|$	0.8109***	0.7024***	0.7699***	0.6841***	0.9303***	0.2264***
	(13.5100)	(35.2208)	(11.0624)	(31.5771)	(12.4564)	(2.5648)
$R_{m,t}^2$	0.0889***	0.0005	0.0314	-0.0156***	0.0327	0.0792***
	(3.6585)	(0.0773)	(1.2108)	(-2.4381)	(1.1713)	(2.3603)
_cons	1.1447***	1.0082***	1.3473***	0.7276***	1.1458***	0.6835***
	(51.3819)	(111.5489)	(50.5179)	(74.3060)	(45.0622)	(22.5453)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.5654	0.5180	0.4791	0.5176	0.6003	0.4170

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.2 Panel B Full range data from European countries Germany and France sectors using CCK model regression results

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0265***	0.0297	0.0424***	-0.0058	0.0653***	0.0474***
	(2.4724)	(1.3271)	(2.5096)	(-0.3964)	(2.6101)	(2.8715)
$\|R_{m,t}\|$	0.6487***	0.4807***	0.9519***	0.4525***	0.5995***	0.6212***
	(22.2302)	(8.6384)	(13.3669)	(9.5317)	(5.6834)	(25.3759)
$R_{m,t}^2$	0.0230***	0.0988***	0.0403	0.0824***	0.0665***	0.0891***
	(2.1547)	(5.6041)	(1.6154)	(2.8228)	(2.5302)	(14.8806)
_cons	1.5085***	1.4844***	1.2744***	0.9516***	1.3371***	1.3820***
	(110.4368)	(57.7134)	(47.3859)	(71.0360)	(23.2368)	(88.4910)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.3617	0.5249	0.5152	0.3079	0.5080	0.5711

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0601***	0.0271	0.0415*	0.0166	0.0719***	-0.0035
	(2.5169)	(1.6384)	(1.6730)	(0.7786)	(4.7802)	(-0.2402)
$\|R_{m,t}\|$	0.6769***	0.7056***	0.4739***	1.3477***	0.7679***	0.6160***
	(8.0008)	(13.6155)	(9.1829)	(30.3996)	(22.4536)	(9.5173)
$R_{m,t}^2$	0.0601*	0.0449***	0.1571***	0.0361***	0.0022	0.0544*
	(1.9258)	(2.1008)	(14.2343)	(6.0487)	(0.2055)	(1.7444)
_cons	1.4149***	1.4789***	1.1372***	1.2288***	1.6276***	0.8003***
	(42.8377)	(70.4569)	(46.4157)	(44.6371)	(88.1440)	(39.4115)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.4387	0.3895	0.7870	0.8153	0.4192	0.4404

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.2 panel A reports the herding estimates results under the standard CCK model in the UK market. The coefficient of $R_{m,t}$ is positive and significant for 8 different sectors and the UK market giving some evidence that herding is less likely when the market return is increasing in these sectors. This finding is broadly in accord with the literature with tends to associate more herding with severe market falls. The coefficients of $|R_{m,t}|$are highly significant and positive for all the 11 sectors and the whole market. In order to confirm the existence of herding behaviour, we need to observe a significantly negative coefficient of the squared market return. According to the panel, we see that the Consumer Discretionary, Health care, and Utilities sectors have a significantly positive coefficient of squared market return, indicates the existence of anti-herding behaviour. This means investors in these sectors most likely rely on their private information related to the market. The UK whole market and sectors including Communication, Consumer Staples, Energy, Financials, Industrials, Materials, and Technology sectors show the presence of neither herding nor anti-herding presence. Only the Real Estate sector has a significantly negative coefficient of squared market return which indicates the existence of herding behaviour in this sector over our sample period. This means that investors making investment decisions related to real estate are more likely to follow other market participants decisions and ignore their own information.

Similarly, in table 7.2.1.2 panel B, we present the regression results for the different sectors in Germany and France market under the CCK model. According to the regression results, the coefficient of $R_{m,t}$ is positive and significant for 5 different sectors and the Germany and France markets giving some evidence that herding is less likely when the market return is increasing in these sectors. The coefficients of $|R_{m,t}|$are highly significant and positive for all the 11 sectors and the whole market. Most sectors exhibit anti-herding behaviour, including the Communications, Consumer Staples, Energy, Financials, Industrials, Materials, and Real Estates sectors. These sectors as well as the whole combined markets have a significantly positive coefficient of squared market return, indicating the existence of anti-herding behaviour in these sectors. The Consumer Discretionary, Health Care, Technology, as well as the Utilities sectors have an insignificant coefficient of squared market return, showing no herding or anti-herding behaviour in these sectors. In summary, in our whole data sample, when we estimate herding behaviour using the CCK model, in both the UK market and the European markets consisting of Germany and France, we only detect herding behaviour presence in the UK Real Estate sector. Three sectors show anti-herding behaviour in the UK market and seven other sectors show anti-herding behaviour in the German and French markets.

7.2.1.3 Solution 1 Regression results without constant

Table 7.2.1.3 Panel A regression results without constant in the UK market

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0866***	0.0461***	0.0706***	-0.0016	0.0881***	0.0358***
	(4.5495)	(3.0901)	(3.0343)	(-0.0878)	(2.8030)	(2.5123)
$\|R_{m,t}\|$	2.4711***	2.4614***	1.8875***	2.0895***	1.6907***	1.6754***
	(27.1328)	(52.5960)	(25.0728)	(33.7685)	(36.3906)	(62.1956)
$R_{m,t}^2$	-0.3286***	-0.3934***	-0.0962***	-0.3606***	-0.0184*	-0.1679***
	(-5.7168)	(-13.9421)	(-2.8310)	(-7.2303)	(-1.8041)	(-12.2208)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.7335	0.7755	0.7206	0.7283	0.7924	0.7890

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0920***	0.0780***	0.0869***	0.0050	0.0928***	0.0279
	(3.1221)	(3.9077)	(2.7841)	(0.3469)	(2.3888)	(0.7080)
$\|R_{m,t}\|$	2.2897***	2.0228***	2.3594***	1.4805***	2.3438***	1.0006***
	(27.9894)	(22.6176)	(40.2188)	(32.9095)	(30.3225)	(17.7172)
$R_{m,t}^2$	-0.1823***	-0.1876***	-0.2411***	-0.1192***	-0.1971***	-0.0206
	(-4.0936)	(-3.7605)	(-7.8893)	(-6.4963)	(-4.8992)	(-0.6731)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.7817	0.7324	0.7640	0.7379	0.7791	0.6466

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.3 Panel B regression results without constant in Germany and France market

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0418*	0.0904***	0.0420***	-0.0236	0.0838***	0.0879***
	(1.7520)	(2.3299)	(2.3135)	(-1.2626)	(3.0179)	(2.4558)
$\lvert R_{m,t}\rvert$	2.9341***	1.8865***	2.5690***	2.2974***	1.6500***	2.0186***
	(25.0510)	(20.2348)	(47.4414)	(42.3587)	(27.1475)	(28.2135)
$R_{m,t}^2$	-0.4712***	-0.0676*	-0.2595***	-0.4915***	-0.0570***	-0.0593*
	(-5.9285)	(-1.6966)	(-9.7370)	(-10.3267)	(-2.6509)	(-1.7441)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.7314	0.7206	0.7702	0.7317	0.7489	0.7397

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0884***	0.0292	0.0553***	0.0308*	0.0901***	-0.0236
	(3.3809)	(1.2206)	(2.3333)	(1.8091)	(4.3587)	(-1.4391)
$\lvert R_{m,t}\rvert$	2.2363***	2.6991***	1.6952***	2.3491***	2.5999***	1.7650***
	(48.6439)	(38.4967)	(59.5852)	(94.8644)	(51.1007)	(40.4871)
$R_{m,t}^2$	-0.1787***	-0.3723***	0.0075	-0.0315***	-0.3096***	-0.1886***
	(-7.3930)	(-8.9499)	(0.9599)	(-8.3723)	(-13.4267)	(-6.3798)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.7388	0.7515	0.8130	0.8515	0.7570	0.7560

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Using our solution 1 to avoid the influence of the error term in the CAPM model, we can find out how the different results compare with the results calculated under the CCK model. Using this solution, most of the sectors, as well as the whole market, show the existence of herding behaviour. This is shown by the significantly negative coefficient of the squared market return. In the UK market, the results shown in table 7.2.1.3 panel A, show a significantly negative coefficient of squared market return in the Communications, Consumer Discretionary, Consumer Staples, Financials, Health Care, Industrials, Materials, Real Estate, and Technology sectors. Also, the Energy sector is significant at the 10% level. The Utilities sector does not have herding behaviour. Turning to the German and French market in Panel B, we have captured significant evidence of herding behaviour in sectors including Consumer Discretionary, Consumer Staples, Energy, Health Care, Industrials, Real Estate, Technology, and Utilities. Both Communication and Financial sectors are significant at the 10% level, and the Materials sector does not have herding behaviour present in the market. Overall, by using solution 1 using the regression without constant value, we can detect and capture the existence of herding behaviour in most sectors over our sample period.

7.2.1.4 Solution 2 Regression results in SCSAD

Table 7.2.1.4 Panel A Regression results under SCSAD model in the UK market

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R^2_{m,t} + \gamma_3 R^3_{m,t} + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	1.9955***	1.9805***	1.6614***	1.6953***	1.6208***	1.4133***
	(51.4428)	(62.9447)	(59.0579)	(74.1816)	(58.9508)	(77.4244)
$R^2_{m,t}$	0.0230	-0.0041	0.0313*	-0.0214	0.0088	0.0034
	(1.2035)	(-0.4162)	(1.7169)	(-1.3201)	(1.4941)	(0.4705)
$R^3_{m,t}$	-0.0286***	-0.0573***	-0.0021	-0.0458***	-0.0006	-0.0169***
	(-3.3123)	(-8.2392)	(-1.0366)	(-6.9981)	(-1.5604)	(-7.9814)
_cons	0.0864***	0.0676***	0.0578***	0.0379***	0.0482***	0.0456***
	(6.6461)	(4.8885)	(3.9979)	(3.6860)	(2.2813)	(4.9322)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.6954	0.7517	0.6985	0.6951	0.7913	0.7685

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.9956***	1.6912***	1.9547***	1.2294***	1.9845***	0.9349***
	(63.5806)	(58.1576)	(82.7094)	(52.2093)	(68.7310)	(38.6499)
$R^2_{m,t}$	0.0452***	0.0276	0.0420***	-0.0129*	0.0346*	0.0108
	(2.6185)	(1.3821)	(2.7618)	(-1.8306)	(1.7252)	(0.5215)
$R^3_{m,t}$	-0.0157***	-0.0097***	-0.0206***	-0.0086***	-0.0136***	0.0003
	(-2.9785)	(-2.0936)	(-6.0564)	(-5.0236)	(-3.2088)	(0.1059)
_cons	-0.0000	0.0813***	0.0135	0.0481***	0.0354*	-0.0083
	(-0.0001)	(5.8526)	(0.6718)	(4.7773)	(1.8211)	(-0.4639)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.7685	0.6999	0.7414	0.7093	0.7572	0.6450

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.4 Panel B Regression results under SCSAD model in Germany and France market

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	2.3113***	1.6949***	2.1516***	1.8264***	1.4828***	1.8601***
	(52.3154)	(54.5977)	(71.8741)	(80.2258)	(63.0927)	(74.1975)
$R_{m,t}^2$	-0.0012	0.0178	0.0018	-0.0379*	0.0237***	0.0176
	(-0.0619)	(0.9018)	(0.2161)	(-1.8649)	(2.1002)	(1.5921)
$R_{m,t}^3$	-0.0469***	-0.0014	-0.0243***	-0.0812***	-0.0022	-0.0010
	(-4.3055)	(-0.6213)	(-6.4393)	(-8.5048)	(-1.2472)	(-0.7305)
_cons	0.0724***	0.0430	0.0535***	0.0312***	0.0106	0.0466***
	(3.8822)	(1.5072)	(3.2255)	(2.4624)	(0.3643)	(2.6407)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.6913	0.7119	0.7520	0.7033	0.7444	0.7326

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.9260***	2.1636***	1.6654***	2.2367***	2.0708***	1.5170***
	(104.5210)	(72.7065)	(64.7012)	(108.9923)	(64.2167)	(92.4128)
$R_{m,t}^2$	0.0373***	0.0020	0.0102*	0.0007	0.0235***	-0.0284***
	(3.3519)	(0.1108)	(1.9025)	(0.2653)	(2.1993)	(-2.2063)
$R_{m,t}^3$	-0.0136***	-0.0385***	0.0023***	-0.0013***	-0.0298***	-0.0205***
	(-8.8612)	(-6.4614)	(2.6382)	(-5.3574)	(-8.4091)	(-6.4302)
_cons	0.0200	0.0538***	0.0212	0.0273	0.0617***	0.0170
	(1.0595)	(2.5750)	(1.5579)	(1.5932)	(2.8372)	(1.4251)
N	5426	5426	5426	5426	5426	5426
adj. R^2	0.7236	0.7236	0.8140	0.8486	0.7257	0.7417

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.4 panel A and panel B reports the herding estimated results using our solution 2 that fits the regressions under the SCSAD method. This method avoids the error term's influence in the CAPM model and can detect herding even when herding behaviour is not obvious in the selected market. In this method, we need to capture a significantly negative coefficient of cubic market return to confirm the existence of herding behaviour. According to the results, most of the sectors, including Communications, Consumer Staples, Financials, Health Care, Industrials, Materials, Real Estate, and Technology as well as the whole market, show the existence of herding behaviour demonstrated by the significantly negative coefficient of the cubic market return. The Consumer Discretionary, Energy, and Utilities sectors have neither herding nor anti-herding behaviour. In the German and French markets. Communications, Energy, and Financials do not have clear evidence of herding behaviour. We have captured significant herding behaviour in Consumer Discretionary, Consumer Staples, Health Care, Industrials, Materials, Real Estate, Technology, and Utilities. In summary, the new SCSAD method can detect herding behaviour if it is not significant using the conventional methods. We have captured clear evidence of herding behaviour in most sectors over our sample period from the results in a different market.

7.2.1.5 Solution 3 Regression considering large market returns

As herding is more likely to happen during large market movements, we will check herding behaviour under different market conditions with different absolute market returns. The different market conditions include absolute market returns larger than |0.5%|, |1%|, |2%|, as well as |3%|. The following tables show the regression results of different sectors in the different stock markets under various market conditions.

In the UK market

Table 7.2.1.5 panel A Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0659***	0.0524***	0.0496***	0.0071	0.0817***	0.0302***
	(5.4467)	(3.9970)	(3.5649)	(0.5742)	(2.2555)	(2.6155)
$\|R_{m,t}\|$	0.8615***	0.9787***	0.7657***	0.7492***	1.0949***	0.7619***
	(16.9048)	(11.6933)	(17.9791)	(12.1006)	(6.4993)	(12.7189)
$R^2_{m,t}$	-0.0102	-0.0138	0.0134***	-0.0229	0.0204	0.0025
	(-0.8453)	(-0.5630)	(2.1807)	(-1.3064)	(0.9535)	(0.1694)
_cons	0.9798***	0.9140***	0.9976***	0.6996***	0.9173***	0.6367***
	(26.5666)	(16.5109)	(29.6577)	(17.8959)	(5.4084)	(15.2448)
N	1675	2464	2071	1751	3348	2187
adj. R^2	0.5779	0.4482	0.5897	0.3904	0.6986	0.6375

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0643***	0.0425***	0.0881***	0.0141	0.0774***	0.0082
	(3.2694)	(3.8488)	(3.9411)	(1.1442)	(3.8188)	(0.2202)
$\|R_{m,t}\|$	0.8767***	0.7450***	0.8027***	0.7134***	0.8741***	0.1473
	(7.6419)	(20.5986)	(6.3297)	(20.9624)	(6.1191)	(0.9235)
$R^2_{m,t}$	0.0786***	-0.0034	0.0273	-0.0182***	0.0416	0.0888***
	(2.3951)	(-0.4635)	(0.7965)	(-2.6217)	(1.1145)	(2.1281)
_cons	1.0771***	0.9527***	1.3048***	0.6826***	1.2014***	0.7645***
	(14.2646)	(33.6921)	(15.0498)	(25.0120)	(12.4449)	(7.1249)
N	2650	2024	2862	2276	2420	2648
adj. R^2	0.6009	0.5579	0.4721	0.5154	0.6036	0.4479

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.5 panel B Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0914***	0.0595***	0.0682***	0.0361***	0.0887***	0.0384***
	(6.0925)	(3.8697)	(4.0107)	(2.1746)	(2.4479)	(2.8406)
$\|R_{m,t}\|$	0.9441***	1.0535***	0.7178***	0.7610***	1.3078***	0.9307***
	(9.2422)	(6.3923)	(11.1788)	(5.3165)	(6.2602)	(8.8898)
$R_{m,t}^2$	-0.0185	-0.0272	0.0185***	-0.0226	0.0085	-0.0204
	(-1.0922)	(-0.7356)	(2.7738)	(-0.8192)	(0.3850)	(-1.1379)
_cons	0.8809***	0.8324***	1.0781***	0.6935***	0.4132	0.4115***
	(7.7545)	(5.2017)	(12.7547)	(4.5728)	(1.4167)	(3.5645)
N	581	1055	725	465	1953	832
adj. R^2	0.5749	0.4053	0.5898	0.3508	0.7093	0.6208

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0703***	0.0606***	0.0990***	0.0193	0.0945***	0.0107
	(3.0641)	(4.4345)	(3.8950)	(1.3464)	(4.3057)	(0.2434)
$\|R_{m,t}\|$	0.8928***	0.7781***	0.9231***	0.6817***	0.5969***	0.0101
	(4.3461)	(12.0428)	(4.3001)	(12.1812)	(2.3551)	(0.0363)
$R_{m,t}^2$	0.0762*	-0.0050	0.0117	-0.0148*	0.0771	0.1031*
	(1.7312)	(-0.5572)	(0.2602)	(-1.9333)	(1.5474)	(1.9256)
_cons	1.0591***	0.9036***	1.1434***	0.7376***	1.6001***	0.9674***
	(5.2240)	(11.3824)	(5.3512)	(9.7689)	(6.1753)	(3.4274)
N	1117	695	1355	919	1022	1109
adj. R^2	0.6005	0.5793	0.4533	0.4438	0.5944	0.4740

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.5 panel C Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1220***	0.0757***	0.0958***	0.0643***	0.0952***	0.0462***
	(4.6461)	(3.1133)	(3.9015)	(2.2714)	(2.3853)	(2.2796)
$\|R_{m,t}\|$	1.1656***	1.3763***	0.5119***	0.3776	1.8126***	1.6712***
	(3.1985)	(2.6166)	(4.0848)	(0.7215)	(6.3192)	(6.6392)
$R_{m,t}^2$	-0.0407	-0.0739	0.0340***	0.0261	-0.0166	-0.1033***
	(-0.9591)	(-0.9305)	(4.1600)	(0.3742)	(-0.7197)	(-3.8012)
_cons	0.5215	0.3433	1.5886***	1.4072	-1.1807*	-0.9921***
	(0.7924)	(0.4186)	(5.2677)	(1.5841)	(-1.8842)	(-2.1511)
N	113	229	160	67	688	202
adj. R^2	0.5062	0.3110	0.6908	0.4034	0.7164	0.5488

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0704*	0.0916***	0.1305***	0.0112	0.1199***	0.0238
	(1.9419)	(3.9188)	(3.2856)	(0.5337)	(3.7513)	(0.3217)
$\|R_{m,t}\|$	0.4447	0.7248***	0.9530*	0.7220***	0.0608	-0.5042
	(0.8604)	(4.1878)	(1.7302)	(4.0274)	(0.0888)	(-0.6775)
$R_{m,t}^2$	0.1267*	0.0028	0.0102	-0.0188	0.1354	0.1478
	(1.7845)	(0.1983)	(0.1291)	(-1.4001)	(1.4708)	(1.5779)
_cons	1.8824***	1.0266***	1.0915	0.6472	2.6239***	2.1023
	(2.1802)	(2.9075)	(1.2402)	(1.5734)	(2.3282)	(1.6423)
N	242	140	336	270	247	207
adj. R^2	0.5710	0.5820	0.3726	0.3314	0.5996	0.4856

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.5 panel D Market return larger than |3%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0786*	0.0462	0.0997***	0.0893***	0.1012***	0.0513
	(1.8631)	(0.8563)	(2.7451)	(2.4934)	(2.2060)	(1.6597)
$\|R_{m,t}\|$	1.6314	3.4716	0.1213	2.9049*	2.4546***	2.2754***
	(1.5761)	(1.5424)	(0.4686)	(1.9546)	(6.5667)	(2.7127)
$R_{m,t}^2$	-0.0920	-0.3312	0.0568***	-0.2498	-0.0443*	-0.1628***
	(-0.9140)	(-1.2979)	(4.1432)	(-1.4234)	(-1.8821)	(-2.1043)
_cons	-0.5373	-3.7656	2.8413***	-3.9257	-3.8800***	-2.3667
	(-0.2203)	(-0.7799)	(3.3970)	(-1.3074)	(-3.3864)	(-1.1317)
N	33	62	57	16	292	72
adj. R^2	0.3214	0.1491	0.7877	0.6437	0.6950	0.3024

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0773	0.0972***	0.1517***	0.0021	0.1186***	0.0081
	(1.1871)	(2.1875)	(2.1692)	(0.0765)	(2.2108)	(0.0692)
$\|R_{m,t}\|$	0.7613	0.8524*	1.0900	0.9771***	0.1619	-1.7060
	(0.5482)	(1.7909)	(0.7581)	(2.1001)	(0.1021)	(-0.8586)
$R_{m,t}^2$	0.1002	-0.0058	-0.0012	-0.0375	0.1252	0.2408
	(0.7158)	(-0.1767)	(-0.0084)	(-1.1941)	(0.7541)	(1.2908)
_cons	0.9963	0.6554	0.7572	-0.0988	2.4219	5.3836
	(0.3131)	(0.4876)	(0.2274)	(-0.0764)	(0.6828)	(1.1073)
N	70	41	103	111	75	65
adj. R^2	0.5549	0.5628	0.2745	0.3045	0.5643	0.4717

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Using the standard CCK model to detect herding under different market conditions, panel A to panel D reports the regression results of sectors in the UK market. We can find out that the coefficients of the $R_{m,t}$ is significant and positive for 8 sectors and the UK market with the market return larger than |0.5%|, increase to 9 sectors when market return larger than |1%| and reduce to 6 sectors with market return larger than |3%|, which giving some evidence that herding is less likely when the market return is increasing in these markets. The coefficients of $|R_{m,t}|$are highly significant and positive for the whole market and 10 sectors when the market return larger than |0.5%| and |1%|, it shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 3 sectors have significantly positive coefficient of $|R_{m,t}|$ with market return larger than |3%|. As we expected, herding behaviour is more likely to be present in the market when there is a significant market movement. In panel A, Consumer Discretionary, Health Care and Utilities show significantly positive coefficients of squared market return, which means there is anti-herding behaviour in their market, only the Real Estate sector has a significantly negative coefficient of squared market return, which is indicative of herding. In panel B, the significance of anti-herding behaviour is reduced. Only the Consumer Discretionary sector has significant anti-herding behaviour. Both Health Care and Utilities sectors are significant at the 10% level, herding behaviour in the Real Estate sector is also significant at the 10% level. In panel C, with the market return larger than |2%|, we have captured considerable evidence of herding behaviour in the Financial sector. We still have the Consumer Discretionary sector with significant anti-herding behaviour. Anti-herding behaviour in the Health Care sector is significant at the10% level. In panel D, the market returns larger than |3%|, only Consumer Discretionary presence significant anti-herding behaviour, both Energy and Financials sectors show herding behaviour and herding behaviour in the Energy sector is significant at the 10% level. Overall, with the increase of absolute market return, from panel A to panel D, anti-herding behaviour decreases from three sectors to one sector. We have more herding behaviour presence in different sectors compared with the herding presence in the whole market. According to these various panels, the entire market does not have either herding or anti-herding behaviour under different market conditions.

In the markets of Germany and France

Table 7.2.1.5 panel E Market return larger than |0.5%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0339***	0.0281	0.0480***	-0.0023	0.0660***	0.0496***
	(3.0054)	(1.2046)	(2.8393)	(-0.1477)	(2.6382)	(2.9198)
$\|R_{m,t}\|$	0.7495***	0.4110***	1.3701***	0.5799***	0.6356***	0.6560***
	(14.5950)	(4.5084)	(14.8167)	(5.0422)	(3.9751)	(15.5852)
$R_{m,t}^2$	0.0080	0.1068***	-0.0273	0.0526	0.0628***	0.0861***
	(0.6066)	(5.0713)	(-1.2637)	(1.2030)	(1.9651)	(14.1557)
_cons	1.4009***	1.5639***	0.8468***	0.8514***	1.2771***	1.3347***
	(38.5017)	(21.9955)	(12.8191)	(13.3271)	(9.3067)	(33.1573)
N	2306	2982	2642	2099	3659	2772
adj. R^2	0.4353	0.5709	0.5551	0.3210	0.5057	0.6340

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0649***	0.0298*	0.0455*	0.0211	0.0740***	-0.0013
	(2.7837)	(1.7381)	(1.8023)	(1.1425)	(4.8552)	(-0.0826)
$\|R_{m,t}\|$	0.8735***	0.8862***	0.5992***	1.5427***	0.8927***	0.7039***
	(6.6167)	(10.0866)	(5.9523)	(25.8281)	(16.4836)	(5.6137)
$R_{m,t}^2$	0.0335	0.0139	0.1429***	0.0235***	-0.0162	0.0396
	(0.9486)	(0.5418)	(9.1903)	(4.1124)	(-1.2867)	(0.9783)
_cons	1.1922***	1.2947***	0.9844***	0.9373***	1.4816***	0.7148***
	(12.8523)	(22.0371)	(12.0839)	(15.7014)	(34.6575)	(9.2639)
N	2914	2787	2768	2902	3071	2548
adj. R^2	0.4754	0.4134	0.8160	0.8642	0.4198	0.4398

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.5 panel F Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0496***	0.0342	0.0525***	-0.0056	0.0691***	0.0607***
	(3.5182)	(1.2883)	(2.7291)	(-0.2571)	(2.6473)	(3.1457)
$\|R_{m,t}\|$	0.8477***	0.3368***	1.8779***	1.1462***	0.7236***	0.6433***
	(8.9843)	(2.3279)	(16.2212)	(4.3367)	(3.1572)	(8.1724)
$R_{m,t}^2$	-0.0057	0.1139***	-0.0979***	-0.0636	0.0542	0.0873***
	(-0.3296)	(4.4362)	(-5.5250)	(-0.9593)	(1.4181)	(13.7042)
_cons	1.2898***	1.6865***	0.1729	0.2853	1.1220***	1.3606***
	(12.7535)	(10.4539)	(1.3230)	(1.2292)	(4.2077)	(12.5396)
N	821	1526	1155	648	2295	1244
adj. R^2	0.4488	0.6140	0.5289	0.3362	0.5019	0.6875

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0847***	0.0350*	0.0525*	0.0227	0.0856***	-0.0012
	(3.3197)	(1.7121)	(1.9181)	(1.3786)	(5.0636)	(-0.0613)
$\|R_{m,t}\|$	1.1218***	1.2214***	0.8813***	1.8249***	1.0136***	1.0316***
	(5.7206)	(8.8314)	(4.6674)	(25.4537)	(11.0794)	(5.2359)
$R_{m,t}^2$	0.0044	-0.0386	0.1130***	0.0063	-0.0324***	-0.0091
	(0.1109)	(-1.3274)	(4.7951)	(1.2670)	(-2.0259)	(-0.1998)
_cons	0.8363***	0.8951***	0.5619***	0.3870***	1.3189***	0.3135*
	(4.1598)	(6.3511)	(2.5474)	(3.8137)	(12.4035)	(1.6768)
N	1426	1244	1244	1408	1538	988
adj. R^2	0.4830	0.3859	0.8236	0.9100	0.3798	0.4516

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.5 panel G Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0485***	0.0266	0.0776***	-0.0399	0.0828***	0.0904***
	(2.0450)	(0.6588)	(2.7356)	(-0.7169)	(2.5199)	(2.9396)
$\|R_{m,t}\|$	0.7586***	-0.2137	2.0342***	3.2241	0.8819***	0.4131
	(2.6567)	(-0.5805)	(6.8113)	(1.5499)	(2.0880)	(1.6193)
$R_{m,t}^2$	0.0097	0.1574***	-0.1176***	-0.4050	0.0402	0.1040***
	(0.2652)	(3.6285)	(-3.7241)	(-1.2528)	(0.7627)	(6.6995)
_cons	1.3350***	2.9152***	-0.0280	-2.6311	0.7928	1.9166***
	(2.7079)	(4.3453)	(-0.0477)	(-0.8528)	(1.0637)	(3.4682)
N	131	391	274	65	856	256
adj. R^2	0.5574	0.6691	0.3498	0.1963	0.4626	0.7738

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1236***	0.0694*	0.0596*	0.0225	0.1174***	-0.0289
	(3.2139)	(1.9655)	(1.7488)	(1.2109)	(4.9871)	(-0.7000)
$\|R_{m,t}\|$	1.7147***	1.7073***	2.3342***	2.1922***	1.0814***	1.9201***
	(3.6616)	(3.9160)	(4.8492)	(19.0758)	(3.9064)	(3.7037)
$R_{m,t}^2$	-0.0534	-0.0981*	-0.0207	-0.0138***	-0.0389	-0.1171*
	(-0.9328)	(-1.9263)	(-0.4267)	(-2.1383)	(-1.1960)	(-1.8594)
_cons	-0.3204	0.1026	-2.6002***	-0.6788***	1.2020***	-1.2262
	(-0.3814)	(0.1301)	(-2.9106)	(-2.5322)	(2.3943)	(-1.3264)
N	330	251	295	342	442	139
adj. R^2	0.4517	0.2628	0.8091	0.9433	0.3273	0.4095

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.5 panel H Market return larger than |3%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0306	-0.0086	0.0835***	-0.0046	0.1031***	0.0980***
	(0.7006)	(-0.1352)	(2.1222)	(-0.0325)	(2.2758)	(2.0503)
$\|R_{m,t}\|$	0.8866	-0.1285	1.8284***	12.0427	0.8070	0.1530
	(0.9716)	(-0.1918)	(2.3664)	(0.9184)	(1.0065)	(0.2316)
$R_{m,t}^2$	-0.0083	0.1538***	-0.1021	-1.5551	0.0456	0.1193***
	(-0.0929)	(2.7247)	(-1.4845)	(-0.9142)	(0.5907)	(3.0495)
_cons	1.1492	2.5297	0.6053	-19.1356	1.0210	2.8066
	(0.5377)	(1.4315)	(0.3088)	(-0.7631)	(0.5255)	(1.4738)
N	28	120	88	14	352	66
adj. R^2	0.6161	0.7174	0.2794	0.0543	0.4162	0.8193

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.2203***	0.0793	0.0500	0.0189	0.1303***	-0.0894
	(4.3024)	(1.1785)	(1.2445)	(0.8632)	(3.6885)	(-1.1096)
$\|R_{m,t}\|$	4.7366***	2.1224	4.8668***	2.4315***	1.2625	5.4857***
	(5.0548)	(1.0026)	(4.8059)	(14.3437)	(1.5473)	(3.2999)
$R_{m,t}^2$	-0.3047***	-0.1377	-0.2239***	-0.0253***	-0.0564	-0.4638***
	(-3.9812)	(-0.6597)	(-2.5380)	(-2.8247)	(-0.7188)	(-3.0468)
_cons	-8.0335***	-0.8707	-9.7412***	-1.6428***	0.7958	-9.6416***
	(-3.3784)	(-0.1813)	(-3.7678)	(-2.8603)	(0.4167)	(-2.4285)
N	91	59	133	129	148	36
adj. R^2	0.5364	0.2271	0.7248	0.9488	0.2697	0.4329

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

According to the results, we can find out that the coefficients of the $R_{m,t}$ is significant and positive for 5 sectors and Germany and France markets with the market return larger than |0.5%|, |1%| and |2%| which giving some evidence that herding is less likely when the market return is increasing in these markets. The coefficients of $|R_{m,t}|$are highly significant and positive for the whole market and all 11 sectors when the market return larger than |0.5%| and |1%|, it shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 5 sectors have significantly positive coefficient of $|R_{m,t}|$ with market return larger than |3%|. The results for the market return increasing from |0.5%| to |3%| in the markets of Germany and France are shown in Table 7.2.1.5. In panel E with a market return larger than |0.5%|, five sectors which consist of Communications, Energy, Financials, Materials, and Real Estate, have a significantly positive coefficient of squared market return, indicative of anti-herding behaviour. Other sectors and the whole market show no evidence of the existence of herding behaviour. In panel F with market returns larger than |1%|, we have Communications, Financials, and Materials with significant anti-herding behaviour. We also have Consumer Discretionary and Technology sectors with clear evidence of herding behaviour, as both sectors have a significantly negative coefficient of the squared market return. In panel G, when market returns are larger than |2%|, the Communications and Financials sectors shows significant anti-herding behaviour. Sectors including Consumer Discretionary, Industrials, Real Estate, and Utilities have evidence of herding behaviour, and herding behaviour in the Industrials and Utilities sectors is significant at 10% level. With market return larger than |3%|, panel H reports that significant anti-herding behaviour exists in the Communications and Financials sector, and significant herding behaviour is present in the Health Care, Materials, Real Estate, and Utilities sectors.

In summary, under different market conditions with larger absolute market returns, anti-herding behaviour reduced from 5 sectors in panel E to 2 sectors in panel H. At the same time, significant herding behaviour increases from 0 sectors in panel E to 4 sectors in panel H. Thus, the results supports that herding behaviour is more likely to be present in periods of significant absolute market return.

7.2.1.6 Larger market movements based on a proportion of the data condition

In the UK market

In this section, we detect herding under market conditions where we use different proportions of the observations based on the size of absolute return. We investigate the largest 50% of returns by their absolute size, the largest 10% of returns by absolute size as well as the largest 5% of returns by absolute size. The regression results are reported in the various following tables.

Table 7.2.1.6 panel A Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0582***	0.0526***	0.0476***	0.0078	0.0846***	0.0299***
	(5.0404)	(4.0616)	(3.5334)	(0.6774)	(2.3469)	(2.6426)
$\|R_{m,t}\|$	0.8046***	0.9819***	0.7580***	0.6768***	1.1718***	0.7445***
	(20.9971)	(12.9454)	(20.4792)	(14.2233)	(6.3522)	(14.2723)
$R_{m,t}^2$	-0.0021	-0.0145	0.0139***	-0.0086	0.0160	0.0051
	(-0.1933)	(-0.6251)	(2.4398)	(-0.5391)	(0.7352)	(0.3722)
_cons	1.0363***	0.9111***	1.0077***	0.7593***	0.7486***	0.6555***
	(48.3012)	(19.3480)	(39.9709)	(31.3955)	(3.5014)	(20.4434)
N	2713	2713	2713	2713	2713	2713
adj. R^2	0.5659	0.4604	0.5872	0.3832	0.7041	0.6414

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0632***	0.0400***	0.0884***	0.0127	0.0747***	0.0079
	(3.2202)	(3.7380)	(3.9342)	(1.0510)	(3.6936)	(0.2120)
$\|R_{m,t}\|$	0.8676***	0.7072***	0.8087***	0.6962***	0.8967***	0.1486
	(7.7062)	(23.1175)	(6.1099)	(21.9638)	(6.8019)	(0.9473)
$R_{m,t}^2$	0.0799***	0.0008	0.0265	-0.0165***	0.0383	0.0887***
	(2.4620)	(0.1161)	(0.7559)	(-2.3701)	(1.0638)	(2.1392)
_cons	1.0871***	0.9963***	1.2976***	0.7063***	1.1749***	0.7629***
	(14.8356)	(48.3803)	(13.8550)	(30.9073)	(14.1708)	(7.3384)
N	2713	2713	2713	2713	2713	2713
adj. R^2	0.5970	0.5433	0.4700	0.5160	0.6096	0.4472

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.6 panel B Largest 10% (10% of absolute value (above 5% and 5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0905***	0.0667***	0.0805***	0.0354***	0.0954***	0.0428***
	(5.9344)	(3.6748)	(4.4085)	(2.2349)	(2.3150)	(2.8422)
$\|R_{m,t}\|$	0.9924***	1.2953***	0.6864***	0.7829***	1.9834***	0.9910***
	(9.2766)	(5.0009)	(9.5659)	(6.2870)	(6.5098)	(6.8504)
$R_{m,t}^2$	-0.0248	-0.0646	0.0217***	-0.0260	-0.0244	-0.0276
	(-1.4121)	(-1.3334)	(3.2444)	(-1.0304)	(-1.0597)	(-1.2821)
_cons	0.8091***	0.4919	1.1404***	0.6658***	-1.8343***	0.3150*
	(6.7050)	(1.5650)	(10.4471)	(5.3852)	(-2.5130)	(1.6647)
N	542	542	542	542	542	542
adj. R^2	0.5884	0.3969	0.5898	0.3674	0.7160	0.5909

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0668***	0.0615***	0.1202***	0.0209	0.1064***	0.0188
	(2.3740)	(4.1917)	(3.6115)	(1.2484)	(4.2581)	(0.3508)
$\|R_{m,t}\|$	0.6411***	0.7938***	0.9730***	0.6617***	0.3731	-0.1136
	(2.0377)	(10.3654)	(2.3935)	(7.8484)	(0.9498)	(-0.2713)
$R_{m,t}^2$	0.1061*	-0.0064	0.0072	-0.0130	0.1030	0.1149*
	(1.9601)	(-0.6635)	(0.1103)	(-1.5130)	(1.5994)	(1.7301)
_cons	1.4833***	0.8765***	1.0583*	0.7815***	1.9843***	1.1960***
	(3.6181)	(8.4241)	(1.8686)	(5.2708)	(3.9140)	(2.1992)
N	542	542	542	542	542	542
adj. R^2	0.5722	0.5747	0.4041	0.3946	0.6085	0.4875

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.6 panel C Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1018***	0.0707***	0.0914***	0.0391***	0.1022***	0.0484***
	(5.3998)	(3.1063)	(4.0656)	(2.0793)	(2.2013)	(2.6635)
$\|R_{m,t}\|$	1.1313***	1.3453***	0.5806***	0.9266***	2.5538***	1.5122***
	(6.5114)	(2.9504)	(5.2367)	(4.9548)	(6.7029)	(7.4396)
$R_{m,t}^2$	-0.0395	-0.0710	0.0295***	-0.0465	-0.0484***	-0.0863***
	(-1.6149)	(-0.9924)	(3.8510)	(-1.4163)	(-2.0667)	(-3.6825)
_cons	0.5756***	0.4066	1.3977***	0.4689***	-4.3440***	-0.6618*
	(2.3745)	(0.5962)	(5.8281)	(2.1106)	(-3.6067)	(-1.9508)
N	271	271	271	271	271	271
adj. R^2	0.5760	0.3219	0.5814	0.4005	0.6944	0.5871

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0704***	0.0743***	0.1399***	0.0113	0.1213***	0.0268
	(2.0135)	(4.0394)	(3.2269)	(0.5383)	(3.9236)	(0.3971)
$\|R_{m,t}\|$	0.4831	0.7272***	0.8796	0.7214***	0.1322	-0.2756
	(1.0050)	(6.1487)	(1.3836)	(4.0577)	(0.2078)	(-0.4415)
$R_{m,t}^2$	0.1227*	0.0010	0.0180	-0.0187	0.1287	0.1288
	(1.8030)	(0.0856)	(0.2066)	(-1.4073)	(1.4690)	(1.5368)
_cons	1.8015***	1.0093***	1.2580	0.6488	2.4671***	1.5616
	(2.3113)	(4.9331)	(1.1663)	(1.5930)	(2.4231)	(1.5728)
N	271	271	271	271	271	271
adj. R^2	0.5690	0.5640	0.3544	0.3321	0.6058	0.4944

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the UK market, we are using the standard CCK method to detect the existence of herding behaviour under the market condition with different proportions of the observations based on different sizes of absolute return. We can find out that the coefficients of the $R_{m,t}$ is significant and positive for 8 sectors as well as the UK market with the largest 50% of the absolute market return and increase to 9 sectors and the overall markets with largest 5% of the absolute market return, which giving some evidence that herding is less likely when the market return is increasing in these markets. The coefficients of $|R_{m,t}|$are highly significant and positive for 10 sectors and the whole markets when we select largest 50% of the absolute market return, it shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 7 sectors have significantly positive coefficient of $|R_{m,t}|$ with largest 5% of the absolute market return. In panel A, with the largest 50% of absolute market returns, we found out that the Real Estate sector has a significantly negative coefficient of squared market return, indicating herding. Also, Consumer Discretionary, Health Care, and Utilities have a significantly positive coefficient of squared market return, which indicates anti-herding behaviour exists in the market. The regression results in panel B are based on the largest 10% of absolute returns. According to the results, we found significant evidence of anti-herding behaviour exists in the Consumer Discretionary sector, and some evidence of anti-herding behaviour exists in both the Health Care and Utilities sectors, which is significant at 10% level. In panel C, under the market condition with the largest 5% of absolute returns, Consumer Discretionary and Health Care still show anti-herding behaviour in the market, and anti-herding in the Health Care sector is significant at the 10% level. At the same time, we have captured significant evidence of herding behaviour in the Energy and Financial sectors, as both sectors have a significantly negative coefficient of the squared market return. In summary, anti-herding behaviour is reduced along with the decrease in the percentage of absolute value returns. We have caught more clear evidence of herding behaviour in the market under the market condition with the largest absolute value proportion. Also, there are more possibilities to detect herding at the sector level than in the whole market. There is neither herding behaviour nor anti-herding behaviour at the whole market level.

In the markets of Germany and France

Table 7.2.1.6 panel D Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0312***	0.0273	0.0474***	-0.0050	0.0681***	0.0499***
	(2.8212)	(1.1551)	(2.8087)	(-0.3268)	(2.6640)	(2.9338)
$\|R_{m,t}\|$	0.6963***	0.3868***	1.3451***	0.5310***	0.6962***	0.6610***
	(14.5360)	(3.9438)	(14.4940)	(5.6910)	(3.4347)	(15.4304)
$R_{m,t}^2$	0.0168	0.1092***	-0.0235	0.0642	0.0567	0.0856***
	(1.2771)	(5.0343)	(-1.0677)	(1.6150)	(1.5814)	(14.0450)
_cons	1.4534***	1.5994***	0.8754***	0.8898***	1.1735***	1.3277***
	(46.1911)	(19.6214)	(13.4459)	(19.9653)	(5.4770)	(32.0401)
N	2713	2713	2713	2713	2713	2713
adj. R^2	0.4143	0.5716	0.5531	0.3286	0.5064	0.6362

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0661***	0.0308*	0.0458*	0.0204	0.0757***	-0.0020
	(2.8250)	(1.7898)	(1.8136)	(1.1156)	(4.9020)	(-0.1351)
$\|R_{m,t}\|$	0.8953***	0.8963***	0.6088***	1.5617***	0.9251***	0.6944***
	(6.4883)	(10.0434)	(5.9438)	(25.4066)	(15.5827)	(5.7807)
$R_{m,t}^2$	0.0307	0.0123	0.1418***	0.0223***	-0.0208	0.0411
	(0.8589)	(0.4766)	(9.0306)	(3.9114)	(-1.5902)	(1.0335)
_cons	1.1647***	1.2837***	0.9720***	0.9046***	1.4412***	0.7246***
	(11.4632)	(21.1283)	(11.5922)	(14.1297)	(28.4233)	(10.1697)
N	2713	2713	2713	2713	2713	2713
adj. R^2	0.4760	0.4126	0.8168	0.8674	0.4150	0.4382

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.6 panel E Largest 10% (10% of absolute value (above 5% and 5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0537***	0.0295	0.0584***	0.0001	0.0931***	0.0781***
	(3.3754)	(0.8213)	(2.4771)	(0.0038)	(2.4246)	(3.2626)
$\|R_{m,t}\|$	0.7304***	-0.1018	2.2242***	1.1365***	0.8431	0.5626***
	(5.8181)	(-0.3424)	(12.4666)	(3.6872)	(1.4495)	(3.7740)
$R_{m,t}^2$	0.0105	0.1493***	-0.1390***	-0.0611	0.0431	0.0936***
	(0.5036)	(3.8856)	(-6.3758)	(-0.8330)	(0.6793)	(10.1053)
_cons	1.4594***	2.6301***	-0.4069	0.2946	0.9062	1.5360***
	(9.4570)	(5.3982)	(-1.4652)	(1.0296)	(0.7427)	(5.7123)
N	542	542	542	542	542	542
adj. R^2	0.4267	0.6569	0.4548	0.3168	0.4256	0.7298

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1027***	0.0488*	0.0583*	0.0241	0.1087***	-0.0087
	(3.1051)	(1.8361)	(1.8862)	(1.3710)	(4.9347)	(-0.3687)
$\|R_{m,t}\|$	1.4653***	1.5396***	1.4809***	2.0287***	1.0626***	1.3200***
	(4.4228)	(6.9931)	(4.5665)	(20.5608)	(4.6700)	(5.3508)
$R_{m,t}^2$	-0.0304	-0.0803***	0.0552	-0.0052	-0.0372	-0.0476
	(-0.6268)	(-2.3247)	(1.5562)	(-0.8964)	(-1.3307)	(-1.0082)
_cons	0.2089	0.4135	-0.6055	-0.1513	1.2378***	-0.1111
	(0.4182)	(1.3487)	(-1.2139)	(-0.7699)	(3.1775)	(-0.3864)
N	542	542	542	542	542	542
adj. R^2	0.4599	0.3360	0.8202	0.9350	0.3325	0.4658

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.1.6 panel F Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0621***	0.0220	0.0791***	0.0021	0.1243***	0.0884***
	(3.1045)	(0.4724)	(2.7781)	(0.0670)	(2.4982)	(2.9159)
$\|R_{m,t}\|$	0.5599***	-0.2459	2.0449***	1.5556***	1.0018	0.4323*
	(2.7628)	(-0.5514)	(6.7377)	(2.7917)	(1.0761)	(1.7555)
$R_{m,t}^2$	0.0325	0.1596***	-0.1185***	-0.1352	0.0330	0.1027***
	(1.0990)	(3.3550)	(-3.7088)	(-1.2309)	(0.3949)	(6.8493)
_cons	1.7396***	3.0067***	-0.0518	-0.2199	0.3804	1.8641***
	(5.7879)	(3.2918)	(-0.0863)	(-0.3508)	(0.1557)	(3.5371)
N	271	271	271	271	271	271
adj. R^2	0.4423	0.6841	0.3482	0.2771	0.4199	0.7717

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1351***	0.0746***	0.0592*	0.0227	0.1182***	-0.0137
	(3.3619)	(2.1769)	(1.7088)	(1.1836)	(4.2256)	(-0.4396)
$\|R_{m,t}\|$	2.0683***	1.7513***	2.4533***	2.2784***	1.0275***	1.5388***
	(4.0252)	(4.3616)	(4.7678)	(18.1940)	(2.3313)	(4.4893)
$R_{m,t}^2$	-0.0847	-0.1026***	-0.0308	-0.0181***	-0.0339	-0.0740
	(-1.4528)	(-2.1309)	(-0.6036)	(-2.5903)	(-0.7311)	(-1.4000)
_cons	-1.1324	0.0149	-2.9011***	-0.9869***	1.3373	-0.4866
	(-1.1521)	(0.0210)	(-2.9412)	(-3.1402)	(1.4761)	(-0.9805)
N	271	271	271	271	271	271
adj. R^2	0.4792	0.2786	0.8019	0.9466	0.2937	0.4388

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France, with the largest 50% of absolute market returns, we can find out that the coefficients of the $R_{m,t}$ is significant and positive for 5 sectors as well as the markets of Germany and France with the largest 50% of the absolute market return and increase to 6 sectors and the overall markets with largest 5% of the absolute market return, which giving some evidence that herding is less likely when the market return is increasing in these markets. The coefficients of $|R_{m,t}|$are highly significant and positive for all 11 sectors and the whole markets when we select largest 50% of the absolute market return, it shows a positive relationship between the CSAD and the market return in the different markets. Then it reduces to only 8 sectors have significantly positive coefficient of $|R_{m,t}|$ with largest 5% of the absolute market return. We have found that the Communications, Financials, Materials, and Real Estate sectors have a significantly positive coefficient, which indicates the existence of anti-herding behaviour. In panel E with the largest 10% of absolute market returns, both Consumer Discretionary and Industrials sectors have clear evidence of herding behaviour. The squared market return variable has a significantly negative coefficient. Also, the Communications and Financials sectors have a significant anti-herding presence in the market. In panel F, under the market condition with the largest 5% of absolute market return, the Consumer Discretionary, Industrials, and Real Estate sectors have a significantly negative coefficient of squared market return, which indicates herding behaviour exists in the market. Also, only the Communications sector has clear evidence of anti-herding behaviour in the market over the sample period. Overall, herding is more likely to be present during times of more significant market movement. With an increase of absolute market return or reduction in the proportion of the largest absolute market return, we have captured more evidence of herding behaviour in different sectors over the sample period, and no clear evidence of herding behaviour in the whole market.

7.2.1.7 Performance of the proposed Solutions

The studies in this empirical chapter provide a good opportunity to evaluate how all the proposed solutions perform as all of the solutions have been used. We can test how the proposed solutions perform by looking at the goodness-of-fit of the regressions based on them. Adjusted R^2 is a goodness-of-fit or model accuracy measure corrected for degrees of freedom for linear models. A higher adjusted R^2 value indicates a higher amount of variability being explained by our model and vice-versa. By comparing the values of the adjusted R^2, we can compare the effectiveness of the different methods while detecting herding. When we detect herding among different sectors in different markets under the standard CCK model, the range of adjusted R^2 is from 30% to 82%, with most of them around or lower than 50%. While using solution 1, the range of adjusted R^2 is from 72% to 85%, mainly around 74%, and under solution 2, the range is from 64% to 85%. Solution 3 is to detect herding under larger price movements in the market, with the method using the CCK model, the value of adjusted R^2 is similar to the value of R^2 using the full range of data, but in some particular sectors such as Materials and Real Estate, we have captured the larger value of adjusted R^2 which could provide more explanatory power. Comparing the value of the adjusted R^2 value we can find out that our new solutions, particularly solutions 1 and 2, have much more explanatory power and that approximately half of the observed variation can be explained by the model's inputs.

7.2.2 The First Time period from 2001 to 2010

In order to further detect the existence of herding behaviour in our data sample, we divide our whole sample period into two parts. The first part is from 03/Jan/2000 to 31/Dec/2010, and the second part is from 01/Jan/2011 to 20/Oct/2020 so we can have a clear view of these two decades over our sample period. The following table shows the descriptive statistics of equally weighted average market return and CSAD results in the UK market as well as markets of Germany and France in the first time period from 2000 to 2010.

7.2.2.1 Descriptive Statistics

Table 7.2.2.1 Panel A Descriptive statistics data of UK sectors in first time period

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.001433	.06357	.736437	.542339	-1.00802	9.30761	2869
CSAD	1.52232	1.39932	.601157	.36139	1.39042	7.11007	2869
Communications							
$R_{m,t}$	-.041097	.017385	1.02648	1.05366	-.32278	5.44503	2869
CSAD	1.77105	1.57529	.902433	.814385	1.55578	7.67795	2869
Consumer Discretionary							
$R_{m,t}$	.000205	.046242	.864192	.746827	-.672007	9.52461	2869
CSAD	1.49859	1.34824	.705962	.498382	1.6808	8.4355	2869
Consumer Staples							
$R_{m,t}$	.034659	.061053	.655343	.429474	-.443158	9.98212	2869
CSAD	1.17266	1.06644	.512391	.262545	1.52869	7.44676	2869
Energy							
$R_{m,t}$	.021005	.066886	1.33949	1.79422	-.554044	10.8318	2869
CSAD	2.07678	1.8507	1.18353	1.40074	4.15665	38.0791	2869
Financials							
$R_{m,t}$	-.003934	.055776	.96692	.934934	-.614406	11.0685	2869
CSAD	1.22704	1.06211	.707606	.500706	2.84993	18.0111	2869
Health Care							
$R_{m,t}$	-.031408	-.009188	1.0513	1.10522	.080095	9.30207	2869
CSAD	1.94607	1.71476	1.10181	1.21398	3.43053	32.0124	2869
Industrials							
$R_{m,t}$	.006262	.060981	.777465	.604451	-.899381	7.91318	2869
CSAD	1.46172	1.35625	.584905	.342113	1.04299	5.6732	2869
Materials							
$R_{m,t}$	.009547	.055844	1.13036	1.27772	-.544116	9.60607	2869
CSAD	1.97061	1.7742	1.05714	1.11754	3.65165	35.4231	2869
Real Estate							
$R_{m,t}$	.00878	.053184	1.03206	1.06516	-.472617	10.5576	2869
CSAD	1.1734	1	.700582	.490815	1.80148	7.7991	2869
Technology							
$R_{m,t}$	-.044387	.018263	1.09376	1.19631	-.532931	9.76244	2869
CSAD	1.99102	1.77624	1.08179	1.17028	3.41657	34.461	2869
Utilities							
$R_{m,t}$	.016053	.034527	1.00523	1.01048	-.105743	21.3196	2869
CSAD	1.00113	.855155	.830869	.690343	10.3351	185.575	2869

Table 7.2.2.1 Panel B Descriptive statistics data of Germany and France sectors in first time period

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.007532	.044239	.826512	.683121	-.550532	7.21462	2869
CSAD	1.95538	1.86204	.680086	.462516	.84461	6.4663	2869
Communications							
$R_{m,t}$	-.045389	.005889	1.29213	1.6696	-.191775	7.63995	2869
CSAD	2.23264	2.02245	1.15735	1.33946	3.34511	31.2721	2869
Consumer Discretionary							
$R_{m,t}$	.002287	.031098	.886019	.78503	-.582921	6.83878	2869
CSAD	1.86583	1.67244	.910649	.829282	2.42438	13.6919	2869
Consumer Staples							
$R_{m,t}$	.018804	.027438	.701682	.492357	-.380608	6.26616	2869
CSAD	1.30039	1.22092	.526021	.276698	1.26525	7.66171	2869
Energy							
$R_{m,t}$	.011098	.05684	1.4679	2.15474	-.313755	8.75743	2869
CSAD	1.86986	1.64721	1.13397	1.28588	3.58673	31.3397	2869
Financials							
$R_{m,t}$	-.022708	.016179	.979039	.958517	-.429475	6.97916	2869
CSAD	1.94717	1.78329	.861776	.742658	1.94852	12.6521	2869
Health Care							
$R_{m,t}$	-.000503	.022756	1.07972	1.1658	-.167789	9.61537	2869
CSAD	2.15359	1.98172	.969431	.939796	2.26792	19.0032	2869
Industrials							
$R_{m,t}$	.001724	.036323	.952804	.907835	-.397337	7.20402	2869
CSAD	1.99388	1.87089	.815233	.664605	1.89195	12.8008	2869
Materials							
$R_{m,t}$	.021295	.067937	1.3461	1.81198	-.362805	19.7128	2869
CSAD	1.81552	1.47609	1.84787	3.41464	6.11459	44.9496	2869
Real Estate							
$R_{m,t}$	-.013551	0	1.05141	1.10547	.243264	10.0666	2869
CSAD	2.465	2.20196	1.33067	1.77069	2.89392	26.3121	2869
Technology							
$R_{m,t}$	-.041261	.02594	1.28878	1.66094	-.36944	7.30916	2869
CSAD	2.38247	2.20463	.974911	.950451	1.12484	6.52079	2869
Utilities							
$R_{m,t}$	.027847	.017708	.868459	.754222	-.232694	7.51105	2869
CSAD	1.29356	1.16155	.727595	.529395	2.81583	21.7832	2869

In table 7.2.2.1 panel A, we can see that the whole UK market performed negatively during the first time period. The Consumer Discretionary, Consumer Staples, Energy, Industrials, Materials, Real Estate, and Utilities show a positive market performance during the first time period, on the contrary, sectors including Communications, Financials, Health Care, and Technology performed negatively during the first time period. Turning to the CSAD results, the Energy sector has the highest mean value, while Utilities has the lowest mean value. The descriptive results for Germany and France's market are shown in panel B, similarly to the UK market, the whole market performed negatively during the time period from 2000 to 2010. The Communications, Financials, Health Care, and Technology and the Real Estate sectors also performed negatively. The Consumer Discretionary, Consumer Staples, Energy, Industrials, Materials, and Utilities sectors performed positively. Regarding the CSAD results of the markets of Germany and France, Real Estate has the highest mean value and similarly to the UK market the Utilities sector has the lowest mean value of the CSAD result.

7.2.2.2 Normal regression model

Regression results of the first time period under CCK model

Table 7.2.2.2 panel A and panel B reports the regression results under the CCK model (Equation 3.3) for the first time period. In this period, we captured significant evidence of herding behaviour in the whole market, and both the Industrials sector and the Real Estate sectors in the UK market. In contrast, Health Care, Technology, and Utilities have significant anti-herding behaviour. Other sectors, Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, and Materials, have neither herding nor anti-herding behaviour. During the first time period in the markets of Germany and France, we only captured herding behaviour in the Technology sector and that was only significant at the 10% level. Also, Communications, Consumer Discretionary, Financials, Materials, and Real Estate have a significantly positive coefficient of squared market return, which means that these sectors have clear evidence of anti-herding. The whole market and other sectors such as Consumer Staples, Energy, Health Care, Industrials, and Utilities have neither herding behaviour nor anti-herding behaviour over the first sample period. In summary, within the UK market, two sectors, Industrials and Real Estate, have herding behaviour detected during the first sample period. Turning to the markets of Germany and France, only the Technology sector has evidence of herding behaviour, which is only significant at the 10% level.

7.2.2.3 Solution 1 Regression without constant value over the first time period

Using our solution 1 to avoid the influence of the error term in the CAPM model. In table 7.2.2.3 in the Appendix, we can find out how the different results compare with the results calculated under the CCK model. Using solution 1 that fits the regressions without a constant value, most of the sectors and the whole market show the existence of herding behaviour. This is shown by the significantly negative coefficient of the squared market return. In the UK market, the results shown in panel A, where only the Utilities sector does not have a significantly negative coefficient of squared market return, which means no herding behaviour exists in this sector. All the other sectors and the whole market have significantly negative coefficients of squared market return, which implies herding behaviour exists in these sectors over the first sample period. Turning to the German and French market in Panel B, during the first time period, we can see that the coefficient of squared market return in the market and all sectors is significantly negative, which means all sectors in Germany and France market have herding behaviour. Overall, by using solution 1 using the regression without constant value, we can detect and capture the existence of herding behaviour in most sectors over our sample period.

7.2.2.4 Solution 2 Regression results in SCSAD over the first time period

Solution 2 shows in table 7.2.2.4 in the Appendix, which detects herding behaviour under the SCSAD method, avoids the error term's influence in the CAPM model and can detect herding even when herding behaviour is not obvious in the selected market. In this method, we need to observe a significantly negative coefficient of cubic market return to confirm the existence of herding behaviour. Similar to the results shown for solution 1, according to the results, under the SCSAD method, we can find out that the Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Materials, Real Estate, and Technology sectors, as well as the whole market have a significantly negative coefficient of cubic market return, which is indicative of the existence of herding behaviour. Only the Utilities sector has neither herding behaviour nor anti-herding behaviour in the UK market over the first sample period. In the markets of Germany and France, we see that all sectors have a significantly negative coefficient of cubic market return which confirms herding behaviour exists in all sectors over the first sample period.

Overall, during the first sample period, we only detected partial evidence of herding behaviour using the standard CCK method. Under the CCK model, only the Industrials and Real Estate sectors have herding behaviour in the UK market, and the Technology sector in the markets of Germany and France. Under solution 1 regression without constant value and solution 2 which fits the SCSAD method, most of the sectors have herding behaviour detected. Only the UK market's utility sector does not have herding or anti-herding behaviour over the first sample period.

7.2.2.5 Solution 3 Regression considering large market returns

In the UK market

During the first sample period from 2000 to 2010. Using the standard CCK model to detect herding under different market conditions, panel A to panel D reports the regression results of sectors in the UK market. As we expected, herding behaviour tends to be more likely to be present in the market when there is a significant market movement. As the market return increases from |0.5%| in table 7.2.2.5 panel A to |3%| in panel D in the Appendix, we have several sectors that have a significantly negative coefficient of squared market return, which indicates the existence of herding behaviour over the sample period. In panel A with a market return larger than |0.5%|, we have the Real Estate sector with significant herding behaviour and the Industrials sector, which is significant at the 10% level. The Health Care, technology and Utilities sectors have a significantly positive coefficient of squared market return, which indicates that anti-herding behaviour exists in these stock market sectors. We do not capture clear evidence of herding when market return larger than |1%| are investigated in panel B. Both the Health Care and Utilities sectors show clear evidence of anti-herding behaviour. When market return larger than |2%| are considered, the Financials sector shows clear evidence of herding behaviour, shown by the significantly negative coefficient of the squared market return. Under the market condition of market returns larger than |3%|, both the Consumer Staples and Financials sectors have herding behaviour, while herding in the Financial sector is significant at the 10% level. In the whole market, we have captured evidence of herding behaviour under the market condition with absolute market return larger than |0.5%| and |3%|, with both results significant at the 10% level. Under the different market conditions, with the increase of absolute market return, anti-herding behaviour in various sectors decreases from 3 sectors in panel A to 1 sector in panel D. In summary, in the UK market over the first sample period, with the increase of absolute market return, we do have more herding behaviour in different sectors. Also, anti-herding behaviour reduces in different sectors.

7.2.2.5 In the markets of Germany and France

In the market of Germany and France over the first sample period, with absolute market return larger than |0.5%|, none of the sectors has evidence of herding behaviour. Four sectors have significant anti-herding behaviour, including Communications, Consumer Discretionary, Materials, and Real Estate. When the absolute market returns are larger than |1%|, the Communications, Materials, and Real Estate sectors have significant anti-herding behaviour. Other sectors have neither herding nor anti-herding behaviour. In panel G with absolute market return larger than |2%|, only the Communication sector has significant anti-herding behaviour, and the Health Care sector has a significantly negative coefficient of squared market return, which indicates herding. In panel H, under the condition with market return larger than |3%|, the Communication sector still has significant anti-herding behaviour. The Consumer Staples and Health Care sectors have significant evidence of herding behaviour over the first sample period. Overall, as the absolute market return increase from |0.5%| into |3%|, the sectors with anti-herding behaviour decreases from 4 in table 7.2.2.5 panel A to 2 in panel H in the Appendix. Also, the sectors with herding behaviour increase from 0 in panel E to 2 in panel H. There is more herding at sector level than the whole market, as there is no clear evidence of herding behaviour across the entire market under different market conditions.

7.2.2.6 Larger market movements based on a proportion of the data condition

In the UK market

In the UK market over the first sample period, we used the standard CCK model to detect herding behaviour under the market condition with different proportions of observations. In table 7.2.2.6 panel A, we can find out that with the largest 50% of observations of absolute market return, the Health Care, Technology, and Utilities sectors have a significantly positive coefficient of squared market return indicative of anti-herding. Also, the coefficient of squared market return in the Real Estate sector is significantly negative, which means herding behaviour exists in this sector. Herding in the Industrials sector and the whole market are significant at the 10% level. According to panel B, the market condition reported with the largest 10% of absolute returns, we found out that both the Health Care and Technology sector have clear evidence of anti-herding behaviour. The Utilities sector has some evidence of anti-herding behaviour, which is significant at the 10% level. Also, we have found out that the squared market return coefficient in the Financial sector is significantly negative, which means the existence of herding behaviour in this sector over the sample period. With the largest 5% of absolute market returns in panel C, we only have the Technology sector with a significantly positive coefficient of the squared market return coefficient, indicating anti-herding behaviour. We also captured clear evidence of herding behaviour in the Financial sector. Overall, with a smaller proportion of the largest absolute value of market return, anti-herding in the market is significantly reduced**.** We have captured clear evidence of herding behaviour in different sectors.

In the markets of Germany and France

In the markets of Germany and France, with the top 50% observations based on the largest absolute market returns we have four sectors with a significantly positive coefficient of the squared market return, Communications, Consumer Discretionary, Materials and Real Estate, which indicates that these sectors have anti-herding behaviour in the market. Other sectors have neither herding behaviour nor anti-herding behaviour. In panel E, with the largest 10% of absolute market return, both Communications and Materials sectors have significant evidence of anti-herding. The Real Estate sector has some evidence of anti-herding behaviour, which is significant at the 10% level. In panel F, under the market condition with the top 5% of the largest absolute market return, we only captured significant evidence of anti-herding behaviour in the Communications sector. We also find the Health Care sector has a significantly negative coefficient of squared market return, which indicates herding. We do not capture any clear evidence of herding behaviour for the whole market, which shows that there is more herding behaviour at the sector level. In summary, Germany and France's results are similar to the UK market under different market conditions. The presence of anti-herding in various sectors is reduced along with the decrease in the proportion of the largest absolute market return observations.

7.2.3 The second Time period from 2011 to 2020

Our second time period is from 01/Jan/2011 to 20/Oct/2020. This period covers the stock market after the global financial crisis until recent times. We can find out whether herding behaviour exists over this period.

7.2.3.1 Descriptive statistics

Table 7.2.3.1 Panel A Descriptive statistics data of UK sectors in the second time period

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.004014	.035934	.676277	.457351	-2.02772	23.6514	2557
CSAD	1.33173	1.26503	.48748	.237637	3.98842	38.5344	2557
Communications							
$R_{m,t}$	-.00061	.029781	.719114	.517125	-.692015	8.38134	2557
CSAD	1.35349	1.24371	.617742	.381606	2.32728	13.7935	2557
Consumer Discretionary							
$R_{m,t}$	.000581	.031001	.839328	.704472	-4.01704	65.0892	2557
CSAD	1.37653	1.27597	.699321	.48905	7.52319	114.636	2557
Consumer Staples							
$R_{m,t}$	.0065	.023523	.609477	.371462	-.98625	12.0822	2557
CSAD	.9705	.916461	.380564	.144829	2.73463	21.6614	2557
Energy							
$R_{m,t}$	-.105821	-.041897	2.05508	4.22337	-.550039	24.161	2557
CSAD	2.52945	1.94058	2.56335	6.57074	5.67028	48.593	2557
Financials							
$R_{m,t}$	.004017	.030834	.786789	.619038	-1.10048	14.2882	2557
CSAD	1.00667	.921053	.479156	.229591	3.18968	23.5427	2557
Health Care							
$R_{m,t}$	.005532	.010238	.842419	.70967	-.505592	8.18448	2557
CSAD	1.57237	1.40212	.872875	.76191	2.80085	17.569	2557
Industrials							
$R_{m,t}$	.002507	.051073	.800836	.641339	-2.27431	29.6074	2557
CSAD	1.28005	1.19792	.531338	.28232	4.06903	39.6549	2557
Materials							
$R_{m,t}$	-.030782	-.006845	1.01273	1.02563	-.518604	7.5791	2557
CSAD	1.94881	1.79494	.881472	.776994	1.94517	11.1107	2557
Real Estate							
$R_{m,t}$	-.007902	.011896	.95971	.921042	-2.30833	29.893	2557
CSAD	1.10135	.991249	.623532	.388792	5.12912	61.1123	2557
Technology							
$R_{m,t}$	.02385	.042255	.777332	.604245	-1.33217	17.919	2557
CSAD	1.51499	1.38483	.722306	.521726	2.50834	16.8784	2557
Utilities							
$R_{m,t}$	.000376	.011602	.938628	.881022	-.569785	10.8859	2557
CSAD	.803445	.719531	.453947	.206068	3.25801	23.7979	2557

Table 7.2.3.1 Panel B Descriptive statistics data of Germany and France sectors in second time period

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	.001067	.018327	.743392	.552632	-.951935	11.5146	2557
CSAD	1.81065	1.71795	.599263	.359116	1.64122	13.4325	2557
Communications							
$R_{m,t}$	-.003287	.024732	1.00837	1.01681	.012345	26.1926	2557
CSAD	1.74796	1.58346	1.06741	1.13937	10.9013	232.905	2557
Consumer Discretionary							
$R_{m,t}$	-.007814	.012096	1.09144	1.19125	-.489413	9.52678	2557
CSAD	2.07293	1.75042	1.22721	1.50605	2.39391	10.4483	2557
Consumer Staples							
$R_{m,t}$	.00538	.012269	.660974	.436886	-.186105	6.46578	2557
CSAD	1.12274	1.03149	.505796	.255829	3.22272	26.4617	2557
Energy							
$R_{m,t}$	-.083849	-.05125	1.77423	3.14788	-.026271	7.41309	2557
CSAD	2.55575	2.08115	1.86756	3.48778	4.15604	44.8276	2557
Financials							
$R_{m,t}$	-.00082	.024974	1.0414	1.08452	-.493701	28.2534	2557
CSAD	1.86068	1.68008	1.17851	1.38888	8.25682	141.18	2557
Health Care							
$R_{m,t}$	.020815	.044768	1.05519	1.11344	-.310655	9.72742	2557
CSAD	1.81876	1.5725	1.07723	1.16042	4.08516	34.7752	2557
Industrials							
$R_{m,t}$	-.001485	.02736	.964163	.92961	-.467542	7.00891	2557
CSAD	2.02362	1.83154	.966735	.934576	2.34457	14.3747	2557
Materials							
$R_{m,t}$	-.005268	.004487	1.08591	1.1792	.004239	12.2982	2557
CSAD	1.64423	1.40369	1.24316	1.54544	5.69834	46.6012	2557
Real Estate							
$R_{m,t}$	.007857	.014915	1.66933	2.78667	-.03044	43.4138	2557
CSAD	2.28451	1.69563	2.73816	7.49751	6.66562	60.1496	2557
Technology							
$R_{m,t}$	.022772	.028215	1.0493	1.10102	-.436979	8.56122	2557
CSAD	2.12793	1.93176	1.02475	1.05011	3.02886	20.4225	2557
Utilities							
$R_{m,t}$	.00389	.007573	.810498	.656907	-.543012	8.73568	2557
CSAD	1.12619	1.03058	.592253	.350764	2.45895	19.0771	2557

In the above tables, panel A and panel B show the different UK and Germany and France market sectors' descriptive statistics over the second sample period. In the UK market, we can find out that Consumer Discretionary, Consumer Staples, Financials, Health Care, Industrials, Technology and Utilities have a positive mean market return. Other sectors such as Communications, Energy, Materials, and Real Estate and the whole market have performed negatively over the second sample period. Turning to the Germany and France market, the entire market has performed positively. There are fewer sectors that have performed positively than in the UK market. Consumer Staples, Health Care, Real Estate and Technology have performed positively. Besides these sectors, other sectors have performed negatively over the second sample period. Then we focus on the CSAD results in the different markets. In the UK market, the Energy sector has the highest CSAD result while the Utilities sector has the lowest result. In the market of Germany and France, similarly to the UK market, the Energy sector has the highest CSAD.

7.2.3.2 Normal regression model

Regression results of the second time period under CCK model

Table 7.2.3.2 in the Appendix shows the regression results under the CCK model (Equation 3.3) in different markets, panel A shows the UK market results, and Germany and France's results are reported in panel B. In the second period from 2011 to 2020, we can find out that in the UK market, Consumer Discretionary, Financials and Health Care have significantly positive coefficients of squared market return, which shows these sectors have anti-herding behaviour. The entire market has anti-herding behaviour significant at the 10% level. Also, we have captured significant evidence of herding behaviour in the Technology sector as it has a significantly negative coefficient of the squared market return. Other sectors do not have either herding or anti-herding behaviour. In the markets of Germany and France, we do not detect any significant herding behaviour in the second period. Only the whole market and several sectors have clear evidence of anti-herding behaviour, such as Communications, Consumer Staples, Energy Financials, Health Care, Materials, and Real Estate sectors. Overall, during the second sample period, we only capture clear evidence of herding behaviour in the Technology sector in the UK market. Other sectors in the UK and the markets of Germany and France do not have significant evidence of herding behaviour in the market.

7.2.3.3 Solution 1 Regression without constant value over the second time period

The tables 7.2.3.3 in the Appendix report the results of solution 1 based on regression without constant value. According to the results, we can find out that in the UK market, the whole market and most of the sectors have a significantly negative coefficient of squared market return, and we can confirm herding behaviour appears in the market over the second sample period. During the second sample period, only the Energy sector does not have clear evidence to show the existence of herding behaviour. Then we focus on the markets of

Germany and France. Using the method that regresses without a constant value, we have captured clear evidence of herding behaviour in the entire market and several sectors, Consumer Discretionary, Consumer Staples, Health Care, Industrials, Real Estate, Technology, and Utilities. Other sectors such as Communications, Energy, Financials, and Materials do not have either herding or anti-herding behaviour over the second sample period.

7.2.3.4 Solution 2 Regression results in SCSAD over the second time period

Solution 2 is the SCSAD method shown in table 7.2.3.4 in the Appendix, which is another way to avoid the error term's influence in the CAPM model and can detect herding even if it is not extremely obvious. Under this method, we have captured clear evidence of herding behaviour in the whole UK market and most of the UK market sectors. The Communications, Consumer Staples, Financials, Health Care, Industrials, Materials, Real Estate, Technology, and Utilities sector have shown herding behaviour. According to the results in Germany and France market, the entire market as well as the Consumer Discretionary, Consumer Staple, Health Care, Industrials, Real Estate, Technology, and Utilities sectors have a significantly negative coefficient of cubic market return and confirm the existence of herding behaviour in these sectors over the second sample period. We do not capture any evidence of herding or anti-herding behaviour in other sectors.

7.2.3.5 Solution 3 Regression considering large market returns

In the UK market

In the UK market over the second sample period from 2011 to 2020, panels A to D of the table 7.2.3.5 in the Appendix reports the regression under different market conditions using the standard CCK model. In panel A with absolute market returns larger than |0.5%|, we find that both the Real Estate and Technology sectors have a significantly negative coefficient of squared market return, which indicates herding. The Materials sectors has evidence of herding as well, and it is significant at the 10% level. The Financial sector has anti-herding behaviour, and it is significant at the 10% level. In panel B with absolute market return larger than |1%|, four sectors have clear evidence of herding behaviour, Materials, Real Estate, Technology, and Utilities, as shown by a significantly negative coefficient of squared market return. Other sectors do not have either herding or anti-herding behaviour under this market condition. When the absolute market returns are larger than |2%|, the Consumer Discretionary sector has significant anti-herding behaviour, and the Materials sector has clear evidence to show the existence of herding behaviour. In panel D, we see that the Energy sector has a significantly negative coefficient of squared market return, which indicates herding behaviour, and similar to panel C, the Consumer Discretionary sector still presents significant anti-herding behaviour. Under these market conditions, the entire market does not have significant herding behaviour. In summary, over the second sample period in the UK market and with the increase of absolute market return, we can observe more herding behaviour in different sectors than the whole market, especially under the market condition with absolute market return larger than |0.5%|, and |1%|. When the absolute market returns are larger than |2%|, and |3%|, we may not see significant results in the regression due to the reduction in the number of observations.

In the markets of Germany and France

Over the second time period from 2011 to 2020 in the markets of Germany and France, in panel E, with absolute market return larger than |0.5%|, we have captured significant evidence of herding behaviour in the Consumer Discretionary sector, and the presence of anti-herding behaviour in the Communications, Financials, and Real Estate sectors, while anti-herding behaviour is significant at the 10% level in the Real Estate sector. In panel F, we find that both Communications and Financials sectors have a significantly positive coefficient of squared market return, which indicates anti-herding behaviour, and the Consumer Discretionary sector has a significantly negative coefficient of squared market return, which means the existence of herding behaviour. In panel G, under the market condition with absolute market return larger than |2%|, both Communications and Financials sectors show clear evidence of anti-herding behaviour. The Consumer Discretionary, Consumer Staples, Materials, and Technology sectors have a significantly negative coefficient of squared market return, which indicates herding, and herding in Consumer Staples and Materials sectors is significant at the 10% level. In panel H, with market return larger than |3%|, we do not capture any evidence of anti-herding behaviour in the market. We found that Materials, Real Estate, Technology, and Utilities have clear evidence of herding behaviour. Herding in the Technology sector is significant at the 10% level. In summary, along with the absolute market return increase from |0.5%| to |3%| we have captured significant evidence of herding behaviour in different sectors. Herding behaviour increased from one sector in panel E to four sectors in panel H. Simultaneously, anti-herding behaviour reduced from two sectors in panel E to zero in panel H. We have fewer observations available in our data sample with the increase of the absolute market return, making it more difficult to find significant results.

7.2.3.6 Larger market movements based on a proportion of the data condition

In the UK market

Over the second sample period, according to the results reported in table 7.2.3.6 in the Appendix from panel A to C, we will determine the existence of herding in different sectors under different market conditions. In panel A, with the largest 50% of absolute market returns, we found the Consumer Discretionary sector has a significantly positive coefficient of squared market return, indicating anti-herding. Also, Real Estate and Technology have a significantly negative coefficient of squared market return, which means both sectors exhibit herding behaviour. Some evidence of herding behaviour was found in the Materials sector, although it is only significant at the 10% level. In panel B, under the market condition with the largest 10% of absolute market return, we find that Energy, Materials, Real Estate, Technology, and Utilities have a significantly negative coefficient of squared market return indicative of herding. The largest 5% of the absolute market returns to detect herding behaviour are shown in panel C. According to the results, we have captured clear evidence of herding behaviour in six sectors that have a coefficient of squared market return that is significantly negative, and these sectors are Communications, Energy, Materials, Real Estate, Technology, and Utilities. The whole market also has herding behaviour that is significant at the 10% level. Overall, under different regressions with a smaller proportion of absolute market return selected, more herding behaviour in various sectors proves that herding is more likely to be present during periods of more significant market movements. Also, there is more herding at the sector level than in the entire market.

In the markets of Germany and France

In the markets of Germany and France, with the largest 50% absolute market return selected, in panel D, we have found out that the coefficient of squared market return in both Communications and Financials is significantly positive, indicating anti-herding. Some evidence of anti-herding was found in the Consumer Staples sector with significance at the 10% level. At the same time, we have captured significant evidence of herding behaviour in the Consumer Discretionary sector as it has a significantly negative coefficient of the squared market return. In panel E, we have found that the Consumer Discretionary, Real Estate, and Technology sectors have a significantly negative coefficient of squared market return, which means herding behaviour is present in these sectors. Herding behaviour is present in the Industrials sector, which is significant at the 10% level. Also, both Communication and Financials sectors show significant evidence of anti-herding. According to the results reported in panel F, under the market condition with the largest 5% of the largest absolute market return, we see that both Communications and Financials sectors have clear evidence of anti-herding. We also see that Consumer Discretionary, Materials, Real Estate, and Technology have significant evidence of herding behaviour. As a result, herding is more likely to appear in the market during a larger market movement period, and there is more herding at the sector level than the whole market level.

7.2.4 Further investigation time period 2006 to 2010

The sample period from 2006 to 2010 incorporates the global financial crisis. We select this period of time from our whole sample to further detect herding behaviour in the chosen market during the crisis period. This is to determine how the crisis impacts different sectors over this sample period. The following tables show the descriptive statistics of equally weighted average market returns and CSAD results of different sectors in the different markets.

7.2.4.1 Descriptive statistics

UK Descriptive statistics data

Table 7.2.4.1 Panel A Descriptive statistics data of UK sectors

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.010588	.063141	.894486	.800105	-.839327	7.66123	1305
CSAD	1.60097	1.42711	.699785	.489699	1.42726	6.18366	1305
Communications							
$R_{m,t}$	-.026231	.037248	.955634	.913236	-.456643	5.64855	1305
CSAD	1.69544	1.4843	.898437	.807189	1.71977	7.43828	1305
Consumer Discretionary							
$R_{m,t}$	-.02707	.016782	1.09078	1.18979	-.497512	7.33787	1305
CSAD	1.69286	1.48284	.840091	.705753	1.4366	6.45636	1305
Consumer Staples							
$R_{m,t}$	.02662	.064779	.771525	.595251	-.473609	9.18318	1305
CSAD	1.18462	1.06145	.53006	.280963	1.47103	6.7275	1305
Energy							
$R_{m,t}$	.011508	.054896	1.56548	2.45071	-.454989	8.93408	1305
CSAD	2.06303	1.8309	1.15899	1.34327	3.37088	24.4768	1305
Financials							
$R_{m,t}$	-.019727	.049916	1.1923	1.42158	-.462247	9.13933	1305
CSAD	1.35645	1.12575	.844247	.712753	2.37992	11.7845	1305
Health Care							
$R_{m,t}$	-.039712	-.025134	1.01482	1.02987	.42251	10.8317	1305
CSAD	1.92463	1.67777	1.09141	1.19118	3.67587	41.4317	1305
Industrials							
$R_{m,t}$	-.003112	.048213	.933656	.871714	-.743979	6.43442	1305
CSAD	1.53869	1.39762	.655181	.429262	1.02551	4.80211	1305
Materials							
$R_{m,t}$	.003908	.081491	1.34591	1.81147	-.634147	7.73086	1305
CSAD	2.11454	1.89941	1.04949	1.10143	1.71826	8.0037	1305
Real Estate							
$R_{m,t}$	-.047483	0	1.4296	2.04376	-.236344	6.13121	1305
CSAD	1.54859	1.34802	.798212	.637143	1.33033	5.53994	1305
Technology							
$R_{m,t}$	-.00953	.031991	.822897	.67716	-.715647	7.82882	1305
CSAD	1.70145	1.53448	.820478	.673184	2.06506	12.9931	1305
Utilities							
$R_{m,t}$	.00735	.035488	1.17751	1.38652	-.138218	17.7266	1305
CSAD	.909144	.789212	.784606	.615607	11.9099	220.493	1305

EU Descriptive statistics data

Table 7.2.4.1 Panel B Descriptive statistics data of Germany and France sectors

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	.001903	.057767	.897138	.804856	-.645947	8.25648	1305
CSAD	1.93778	1.8317	.707252	.500205	1.15563	7.51612	1305
Communications							
$R_{m,t}$	-.00762	.034987	1.0542	1.11134	-.363605	8.17922	1305
CSAD	1.90812	1.72245	.938545	.880867	2.76623	17.559	1305
Consumer Discretionary							
$R_{m,t}$	.00896	.050476	1.03412	1.0694	-.601247	5.93964	1305
CSAD	2.03698	1.76516	1.08711	1.18181	2.03998	9.58555	1305
Consumer Staples							
$R_{m,t}$	.022639	.053227	.771959	.59592	-.530817	6.42164	1305
CSAD	1.26406	1.18442	.523789	.274355	1.70739	9.65106	1305
Energy							
$R_{m,t}$	-.019682	.075373	1.72062	2.96052	-.373008	7.81874	1305
CSAD	1.83332	1.60953	1.12658	1.26918	3.73022	33.6697	1305
Financials							
$R_{m,t}$	-.02502	.030072	1.10413	1.21911	-.493426	6.44101	1305
CSAD	1.99137	1.75388	.936118	.876316	1.31862	5.99872	1305
Health Care							
$R_{m,t}$	.000689	.032378	1.11694	1.24756	-.046684	13.5267	1305
CSAD	1.99182	1.79032	.974948	.950524	3.13926	26.4046	1305
Industrials							
$R_{m,t}$	.011459	.049458	1.11471	1.24259	-.418985	6.97885	1305
CSAD	2.13398	1.97515	.959911	.921429	1.97338	11.3885	1305
Materials							
$R_{m,t}$	.026118	.095162	1.08782	1.18335	-.514314	6.888	1305
CSAD	1.56682	1.40283	.730087	.533027	1.55092	7.30687	1305
Real Estate							
$R_{m,t}$	-.005454	0	1.28861	1.66051	.295795	9.07688	1305
CSAD	2.94283	2.64606	1.60091	2.5629	2.7722	23.0139	1305
Technology							
$R_{m,t}$	-.009412	.059126	1.08802	1.18378	-.458182	9.57377	1305
CSAD	2.0697	1.94592	.754274	.56893	1.22425	8.15567	1305
Utilities							
$R_{m,t}$	.014766	.016664	.895747	.802363	-.273625	8.30857	1305
CSAD	1.24393	1.13675	.617015	.380707	1.65501	8.60357	1305

According to the descriptive statistics data shown in table 8.6.4.1, we see that in the UK market, the whole market and most of the sectors performed negatively over this sample period as Communications, Consumer Discretionary, Financials, Health Care, Industrials, Real Estate, and the Technology sector have a negative mean market return. Turning to the markets of Germany and France, only the Communications, Energy, Financials, Real Estate, and Technology sectors performed negatively during this period. For the CSAD results, in the UK market, the Materials sector has the highest value of CASD, while the utility sector has the lowest. Similarly, in the markets of Germany and France, the Utilities sector has the lowest CSAD value, and the Industrials sector has the highest value of CSAD.

7.2.4.2 Normal regression model

The tables 7.2.4.2 in the Appendix show the regression results for the different sectors in the markets under the standard CCK method (Equation 3.3). According to the results, in the UK market, we only captured a significantly negative coefficient of squared market return in the Industrials sector, which means we can confirm the existence of herding behaviour in this sector over this sample period. Apart from this, the entire market and other sectors do not have clear evidence to show they have either herding or anti-herding behaviour. In the markets of Germany and France, we do not detect any significant herding behaviour in the market over this sample period. We only see that Consumer Discretionary, and Real Estate show anti-herding behaviour. Other sectors have neither herding nor anti-herding behaviour. Overall, under the standard CCK method, we only have the Industrials sector in the UK market with significant herding behaviour. Both Consumer Discretionary and Real Estate in the markets of Germany and France have anti-herding behaviour over this sample period.

7.2.4.3 Solution 1 Regression without constant value

Our solution 1 in table 7.2.4.3 in the Appendix is fit the regressions without a constant term to avoid the influence of the error term in the CAPM model to detect herding behaviour in the market. Using this method, we find out that almost all UK market sectors have a significantly negative coefficient of squared market return over these years. Which means that apart from the Utility sector, all other sectors have clear evidence of herding behaviour over this sample period. In the markets of Germany and France we capture significantly negative coefficients of squared market return in all sectors and the whole market, which means that the entire market and all sectors in these markets have clear evidence of herding behaviour over this sample period. In summary, by using solution 1, we have captured clear evidence of herding behaviour in most of the sectors in the different markets. Only the Utilities sector in the UK market does not have either herding or anti-herding behaviour.

7.2.4.4 Solution 2 Regression results in SCSAD

Our solution 2 in table 7.2.4.4 in the Appendix uses the SCSAD method to avoid the disadvantages of the standard CCK method. To confirm the existence of herding behaviour, we need to observe a significantly negative coefficient of the cubic market return. According to the results shown in the above tables, in the UK market, we have similar results to solution 1. Most sectors and the market have clear evidence of herding behaviour as they have a significantly negative coefficient of the cubic market return. In addition, the Utilities sector does not have either herding or anti herding behaviour over this sample period. Turning to the markets of Germany and France, we see that all sectors and the entire market have significantly negative coefficients of the cubic market return, which indicates that all sectors have herding behaviour over this sample period. As a result, both solutions 1 and 2 which avoid the disadvantages of the standard CCK model capture more clear evidence of herding behaviour in the selected market.

7.2.4.5 Solution 3 Regression considering large market returns

In the UK market

Table 7.2.4.5 in the Appendix from panel A to panel D reports the regression results of different UK market sectors under various market conditions. In panel A, we observe clear evidence of herding in the whole market. A significantly negative coefficient of squared market return is only captured in the Industrials sector, which indicates herding, and it only significant at the 10% level. In panel B, we capture significant evidence of herding behaviour in the Financial sector and the entire market. Anti-herding behaviour is present in the Technology sector, which is significant at 10% level. In panel C, both Energy and Financials sectors have a significantly negative coefficient of squared market return, which means the existence of herding behaviour. Also, Health Care and Technology sectors have significant evidence of anti-herding behaviour. In panel D, the Health Care sector has a significantly positive coefficient of squared market return, which means anti-herding behaviour and anti-herding behaviour is also significant at the 10% level in the Technology sector. Also, we capture clear evidence of herding behaviour in several sectors such as Consumer Staples, Energy, and Financials, as these sectors have a significantly negative coefficient of the squared market return. Overall, with the increase of absolute market return, herding is more likely to be present in different sectors. According to our results, significant evidence of herding increase from 0 sectors to three sectors as the absolute market returns increase from |0.5%| to |3%|.

In the markets of Germany and France

According to the results shown in the above table 7.2.4.5 in the Appendix from panel E to panel H. We can find out that when the absolute market returns larger than |0.5%|, both Consumer Discretionary and Real Estate sectors show the existence of anti-herding behaviour. This is demonstrated by the significantly positive coefficient of the squared market return. In panel F with an absolute market return larger than |1%|, only the Real Estate sector has significant evidence of anti-herding behaviour. In panel G, the coefficient of the squared market return in the Health Care sector is significantly negative, which indicates the existence of herding behaviour. Other sectors do not have evidence of either herding or anti-herding behaviour. With absolute market returns larger than |3%|, both Consumer Staples and Health Care sectors have significant evidence of herding behaviour. In contrast, other sectors have neither herding nor anti-herding behaviour presence in the market over this sample period. In the markets of Germany and France over this sample period, we have found out that herding behaviour increases from zero sectors in panel E to two sectors in panel H. The existence of anti-herding behaviour reduced from two sectors in panel E to zero sectors in panel H.

7.2.4.6 Larger market movements based on a proportion of the data condition

In the UK market

Using different proportions of the largest absolute market return, we have found out that in table 7.2.4.6 in the Appendix panel A, only the Industrials sector have a significantly negative coefficient of squared market return, which indicates herding. In panel B, under the market condition with the largest 10% of absolute market return, the entire market, Energy and Financials sectors have significant evidence of herding behaviour. There is some evidence of anti-herding behaviour in the Health Care sector as it has a significantly positive squared market coefficient significant at the 10% level. In panel C, with the largest 5% of absolute market return, the Financials sector has clear evidence of herding behaviour, and significant anti-herding behaviour exists in the Health Care sector. Overall, herding behaviour has been detected under various market conditions over this sample period, and there is more herding behaviour at the sector level then in the whole market.

In the markets of Germany and France

In the markets of Germany and France, both Consumer Discretionary and Real Estate sectors have significant anti-herding behaviour in panel D. Both sectors have a significantly positive coefficient of squared market return over this sample period under the market condition with the largest 50% of absolute market returns selected. In panel E, with the largest 10% of absolute market returns chosen, we do not have anti-herding in the market, and only the Health

Care sector has clear evidence of herding behaviour. In panel F, with the selection of the top 5% of absolute market returns, we have found that both the Health Care and Utilities sectors have a significantly negative coefficient of squared market return, which indicates herding. In summary, with a smaller proportion of the largest absolute return selected, the existence of anti-herding is reduced, and more herding can be detected in different sectors over the sample period under larger market movement conditions.

7.2.5 Investigate herding behaviour in 2020

In this sub-sample period, we are using the market return from 01/Jan/2020 to 20/Oct 2020, as the stock market could be affected by many things during this year, such as the coronavirus (Covid-19) pandemic starting from the beginning of the year. The new coronavirus pandemic initially crushed the US stock market at the beginning of the year, and this situation had an impact on different industries. We try to detect herding behaviour over this sample period and determine whether there was herding behaviour in the market in this particular time period.

7.2.5.1 Descriptive statistics

Table 7.2.5.1 panel A Descriptive statistics data in the UK market

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.128064	-.015995	1.46285	2.13994	-1.59583	10.4304	210
CSAD	2.01404	1.71835	1.07185	1.14886	2.27549	9.96203	210
Communications							
$R_{m,t}$	-.078805	.074176	1.21271	1.47066	-.930895	7.23885	210
CSAD	1.79206	1.54625	1.05109	1.1048	1.87815	7.29191	210
Consumer Discretionary							
$R_{m,t}$	-.17153	-.009529	1.99263	3.97059	-2.8022	21.3903	210
CSAD	2.37009	1.87285	1.7255	2.97734	4.03259	25.7541	210
Consumer Staples							
$R_{m,t}$	-.075034	-.02432	1.03065	1.06224	-1.8503	12.5323	210
CSAD	1.32882	1.17168	.720124	.518578	2.31769	10.2692	210
Energy							
$R_{m,t}$	-.419355	-.256553	3.63163	13.1887	-.488494	15.4717	210
CSAD	4.14521	3.34782	2.94363	8.66495	3.14096	19.5532	210
Financials							
$R_{m,t}$	-.10916	-.015316	1.49001	2.22014	-.908628	8.5874	210
CSAD	1.42178	1.07458	.948128	.898946	2.10569	8.00028	210
Health Care							
$R_{m,t}$	.006012	.043703	1.30853	1.71226	-.355254	6.49211	210
CSAD	1.98366	1.6193	1.20572	1.45376	1.96214	8.19219	210
Industrials							
$R_{m,t}$	-.169908	-.068309	1.80959	3.27461	-1.68665	11.5904	210
CSAD	2.10923	1.8085	1.15304	1.3295	2.28342	10.7169	210
Materials							
$R_{m,t}$	-.037934	.035997	1.57588	2.4834	-1.05966	7.57846	210
CSAD	2.57756	2.24058	1.25814	1.58292	1.6626	7.21295	210
Real Estate							
$R_{m,t}$	-.312203	-.171576	2.01567	4.06291	-.998163	8.20459	210
CSAD	2.0313	1.71728	1.34768	1.81625	3.07833	19.9687	210
Technology							
$R_{m,t}$	-.000465	.078042	1.50656	2.26972	-1.80474	12.5188	210
CSAD	1.89943	1.66506	.984764	.96976	2.00859	9.30408	210
Utilities							
$R_{m,t}$	-.068844	-.000933	1.77855	3.16325	-.939355	6.90832	210
CSAD	1.27779	.961402	.928037	.861254	2.15243	8.38654	210

Table 7.2.5.1 panel B Descriptive statistics data in In Germany and France market

variable	mean	p50	sd	variance	skewness	kurtosis	N
All							
$R_{m,t}$	-.038026	-.021877	1.19389	1.42538	-2.0533	14.4247	210
CSAD	2.50865	2.23978	1.01455	1.02931	1.63971	7.52537	210
Communications							
$R_{m,t}$	-.035686	.059301	1.32311	1.75061	-2.00501	12.4557	210
CSAD	2.23095	2.0027	1.03874	1.07899	1.22282	5.18928	210
Consumer Discretionary							
$R_{m,t}$	-.066401	.000122	1.76381	3.11104	-1.09099	8.60853	210
CSAD	3.19586	2.86597	1.53208	2.34726	1.44863	5.94093	210
Consumer Staples							
$R_{m,t}$	-.009172	.007151	.92621	.857866	-.558442	7.10914	210
CSAD	1.55549	1.30611	.838452	.703001	2.32571	10.6355	210
Energy							
$R_{m,t}$	-.124943	-.00743	2.49296	6.21484	-.542901	7.90531	210
CSAD	3.39972	2.68706	2.59425	6.73014	2.39895	10.502	210
Financials							
$R_{m,t}$	-.030588	0	1.57093	2.46782	-1.04997	7.90014	210
CSAD	2.59564	2.15148	1.40196	1.96549	1.24592	4.41669	210
Health Care							
$R_{m,t}$	.05033	.122323	1.38453	1.91691	-1.38301	11.5419	210
CSAD	2.14258	1.86697	1.1025	1.21551	1.67548	6.4382	210
Industrials							
$R_{m,t}$	-.057471	.064759	1.40986	1.98772	-1.06481	8.50666	210
CSAD	2.78232	2.56807	1.31386	1.72624	1.18844	5.29394	210
Materials							
$R_{m,t}$	-.101632	-.152394	2.19124	4.80153	.101845	5.88336	210
CSAD	3.13455	1.99175	2.9062	8.44598	2.18379	7.29978	210
Real Estate							
$R_{m,t}$	-.086618	-.052519	.946557	.895971	-1.33017	8.18762	210
CSAD	1.79471	1.62257	.904169	.817521	1.28556	5.68535	210
Technology							
$R_{m,t}$	.004707	.020942	1.64407	2.70295	-.937695	9.53816	210
CSAD	3.0104	2.52101	1.77531	3.15171	2.21628	9.2208	210
Utilities							
$R_{m,t}$	.087752	.053194	1.16122	1.34844	-1.73365	13.9994	210
CSAD	1.44119	1.24822	.854672	.730463	2.29594	10.5423	210

According to the descriptive statistic results report in table 7.2.5.1. In the UK market, the entire market and most sectors have a negative value of average market return over this sample period. Negatively performing sectors were Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Industrials, Materials, Real Estate, Technology, and Utilities. Only the Health Care sector performed positively during this year. In the markets of Germany and France, the Health Care, Technology, and Utilities sectors performed positively. The whole market and other sectors performed negatively over the 2020 period.

7.2.5.2 Normal regression model

Regression results

Table 7.2.5.2 in the Appendix show the results by using the standard CCK model (Equation 3.3) to detect the existence of herding behaviour over this sample period. We find that in the UK market, both the Communication and Materials sectors have a significantly negative coefficient of squared market return, which is indicative of herding. Other sectors have neither herding nor anti-herding behaviour present. The results for the markets of Germany and France are shown in panel B. The Financials and Health Care sectors show a significantly negative coefficient of squared market return, which indicates that herding behaviour exists in the market. Also, some evidence of herding in Communications and Technology sectors is shown with a significance level of 10%. Thus, under the standard CCK method, we have captured evidence of herding in several sectors in the different market over the 2020 period.

7.2.5.3 Solution 1 Regression without constant value

By using solution 1 of fitting the regressions without constant value in table 7.2.5.3 in the Appendix, in both the UK market and the markets of Germany and France, we find all the coefficient of the squared market in different sectors are significantly negative, which indicates that there is herding behaviour in all sectors of the different markets.

7.2.5.4 Solution 2 Regression results in SCSAD

Using solution 2 to detect herding under the SCSAD method, we have captured clear evidence of herding in various sectors shown in table 7.2.5.4 in the Appendix. In the UK market, the entire market and the Communications, Consumer Staples, Energy, Financials, Health Care, Industrials, Materials, Real Estate, and Technology sectors have a significantly negative coefficient of squared market return, indicating the existence of herding in the market. There is also some evidence of herding in the Utilities sectors, with significance at the

10% level. Neither herding nor anti-herding was found in the Consumer Discretionary sector. According to the results shown in panel B, in the markets of Germany and France, we have captured clear evidence of herding behaviour in the market and all sectors, as all sectors have a significantly negative coefficient of the squared market return. Overall, without the error term's influence in the CAPM model, we find clear evidence of herding behaviour present in the market over our sample period.

7.2.5.5 Solution 3 Regression considering large market returns

In the UK market

In solution 3, we investigate herding under various market condition by considering larger market movements. In table 7.2.5.5 in the Appendix, from panel A to panel B, the absolute market return increases from |0.5%| to |1%|. In panel A, we found out that the Materials sector has a significantly negative coefficient of squared market return, which means the existence of herding behaviour. Also, herding behaviour exists in the Communication sector with significance at the 10% level. Other sectors do not have either herding or anti-herding behaviour. In panel B, with absolute market return larger than |1%|, both Materials and Utilities sectors have clear evidence of herding behaviour. Other sectors and the whole market do not have either herding or anti-herding behaviour. In summary, with the increase of the absolute market return, we can detect herding in more sectors over the sample period.

In the markets of Germany and France

In panel C, in the Germany and France market, with absolute market returns larger than |0.5%|, we have found that Financials, Health Care, and Technology have a significantly negative coefficient of squared market return which indicates that herding behaviour exists in the market. Herding presence in the entire market and the Real Estate sector is also significant at the 10% level. Other sectors do not have either herding or anti-herding behaviour over the sample period. In panel D, with absolute market return larger than |1%|. We have captured clear evidence of herding behaviour in the Financials, Health Care, Materials, Real Estate, and Technology sectors. The coefficient of the squared market return in all these sectors is significantly negative. Also, there is some evidence of herding in the whole market and the Consumer Discretionary sector, with significance at the 10% level. As a result, herding behaviour is more likely to exist when the market has larger movements.

7.2.5.6 Larger market movements based on a proportion of the data condition

By detecting herding behaviour under the different market conditions with different proportions of observations, we also find some clear evidence of herding in different sectors in table 7.2.5.6 in the Appendix. With the largest 50% of absolute market returns in the UK market, we have found out that both Communications and Materials sectors have a significantly negative coefficient of squared market return, which indicates the existence of herding behaviour. Also, in the markets of Germany and France, the Financials, Health Care, Materials, Real Estate and Technology sectors have clear evidence of herding behaviour. Other sectors do not have either herding or anti-herding behaviour. And the whole market has some evidence of herding behaviour with significance at the 10% level. In summary, under the market condition of larger market movements, we can capture clear evidence of herding behaviour in the market.

In this section, we have detected the existence of herding behaviour in different sectors among the UK, Germany and France markets. We have applied the standard CCK model, and several new approaches to estimates the herding behaviour in different sectors. According to the results, there is evidence of herding present in the UK, German and French markets in the different periods through our data sample. Under the standard CCK model, during the full range of time, we only the Real Estate sector in the UK market has herding behaviour with anti-herding behaviour present in some other sectors. During the first time period from 2000 to 2010, we have more herding behaviour detected than in the second time period from 2011 to 2020. When we narrow down the time period to broadly correspond with the global financial crisis period from 2006 to 2010 we only capture moderate evidence of herding behaviour in the UK market. And in the year 2020, we see that Communications and Materials sectors have herding behaviour in the UK market. Also, the Financials and Materials sectors have herding behaviour in the markets of Germany and France. Overall, using the standard CCK model to estimates the herding behaviour in the market, we can only detect whether extreme herding behaviour exists in the market, when market return movements are small, the CCK method can barely capture the evidence of herding behaviour. Using our solution 1 to estimates the herding behaviour by fitting the standard regression model without a constant value and avoiding the influence of error term in the CAPM model, we can improve the accuracy of the herding estimation. By using solution 1, we have captured clear evidence of herding behaviour in most of the sectors in the different markets during different time periods. Also, when estimating herding behaviour by fitting regression models using solution 2, the SCSAD method, we have similar results. Within different time periods in our data sample, we have observed significant herding behaviour in most sectors among the different markets. Our third solution to estimate herding behaviour is to detect herding behaviour under different market conditions with larger market movements. We determine the larger market movements in two ways, one is to have the market return larger than a specific value and the other way is to restrict the observations of our data sample. As a result, we have found out that, with the increase of market movements, we have more herding behaviour and less anti-herding behaviour detected in the market. Using data at the sector level, we can observe different sectors' performance in different periods and compare them with the whole market performance. Although the CCK model does not provide much evidence of herding, it detects the greatest herding only during the first period, including the global financial crisis. Compare with prior literature, our results mainly constant with prior research that in the financial, services, and technology sectors herding is detected only in the highly volatile markets. But the modified SCSAD model and other methods observed strong evidence of herding across our data sample period. In reality, each sector has its own herding triggers, depending on market conditions. We can observe there is more herding behaviour in different sectors than in the entire market. We also find there is more herding behaviour when the market is in turmoil or has larger movements. With selected data samples having a larger absolute market return or a smaller proportion of absolute market return, we can see increased herding behaviour in different sectors and a decrease in anti-herding behaviour.

8.0 Comparing strength of herding between Banks and Financial sector

Additionally, we investigate the banking industry and the Financial sector. The banking industry performs several different roles in the economic system. First, it improves information issues between investors and borrowers by monitoring the parties and ensuring that depositors' money is being used correctly. Banking services also provide an intertemporal calming of risk that cannot be dispersed at a given time and provide savers with insurance against unexpected consumption shocks. Additionally, they play an important role in corporate governance. Overall, banks make a significant contribution to economic growth around the world. The relative importance of the different roles of banks has varied widely from country to country and over time, but banks have always been vital to the financial system (Berger, Molyneux and Wilson, 2020). Given the importance of banking services, it is interesting to assess how sensitive the banking and Financial sectors are to the information related to the market as well as market movements. In this context we note that banking companies are highly connected via loans and other financial exposure and are often thought to be at particular risk of financial contagion. Non-banking financial sector companies undertake a more diverse range of activities which perhaps may make them less susceptible to herding although some institutions, such as, fund managers may have particularly strong exposure to financial markets. Some institutions, such as, large banks, are subject to considerable analysis so decisions about them may be more based on considered opinion rather than irrational herding. Overall, it is interesting to consider and compare the levels of herding in the banking and Financial sectors.

In this section, we combine the UK, German and French markets and select a total of 50 banks out of 216 companies in the Financial sector. We detect herding behaviour among the banks and compare the results with the Financial sector excluding the banking industry. By comparing the significance of the coefficient of squared and cubic market return, we can find out whether there is herding behaviour in the market. By comparing the absolute value of the squared and cubic market return coefficient, we can then examine the strength of herding.

8.1 Full range of data

Table 8.1 Strength of herding of Banks and Financial sector

	Normal regression model (CCK)		Regression results without constant	
	Banks	Financials	Banks	Financials
$R_{m,t}$	0.0165	0.0331	0.0202	0.0454*
	(1.5101)	(1.6413)	(1.4221)	(1.8046)
$\lvert R_{m,t}\rvert$	0.5464***	0.4943***	1.3454***	1.7294***
	(17.9459)	(8.4546)	(45.8302)	(35.0431)
$R^2_{m,t}$	0.0209***	0.0353	-0.0765***	-0.2025***
	(2.6234)	(1.2852)	(-7.2034)	(-6.4352)
_cons	0.8450***	0.8620***		
	(54.9157)	(50.5412)		
N	5426	5426	5426	5426
adj. R^2	0.5850	0.4504	0.7752	0.7315
	Market return larger than |0.5%|		Market return larger than |1%|	
	Banks	Financials	Banks	Financials
$R_{m,t}$	0.0185*	0.0385*	0.0196	0.0490*
	(1.6576)	(1.8021)	(1.6036)	(1.8282)
$\lvert R_{m,t}\rvert$	0.5906***	0.5295***	0.6238***	0.4648***
	(11.7614)	(4.6095)	(7.6849)	(2.2555)
$R^2_{m,t}$	0.0161	0.0305	0.0126	.0408
	(1.5979)	(0.8345)	(0.9729)	(0.8352)
_cons	0.7853***	0.8226***	0.7355***	0.9026***
	(19.2978)	(12.0019)	(7.7803)	(4.7563)
N	3036	2256	1523	823
adj. R^2	0.6106	0.4700	0.6182	0.4261
	Market return larger than |2%|		Market return larger than |3%|	
	Banks	Financials	Banks	Financials
$R_{m,t}$	0.0206	0.0755	0.0033	0 .0977
	(1.2684)	(1.6096)	(0.1560)	(1.1305)
$\lvert R_{m,t}\rvert$	0.4448***	0.5681	0.5221	1.2951
	(2.4394)	(1.1658)	(1.3555)	(1.0110)
$R^2_{m,t}$	0.0280	0.0303	0.0220	-0.0342
	(1.3470)	(0.3993)	(0.6269)	(-0.2622)
_cons	1.1472***	0.7337	0.9019	-1.1369
	(3.3326)	(0.9672)	(0.9509)	(-0.3872)
N	454	174	178	49
adj. R^2	0.5956	0.3514	0.6447	0.3081
	Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))		Largest 10% of returns (10% of absolute value (above 5% and 5% below 0))	

	Banks	Financials		Banks	Financials
$R_{m,t}$	0.0180	0.0366*		0.0210	0.0586*
	(1.5952)	(1.7562)		(1.3577)	(1.9287)
$\|R_{m,t}\|$	0.5944***	0.5114***		0.5167***	0.4472*
	(10.8825)	(4.9834)		(3.2011)	(1.7273)
$R_{m,t}^2$	0.0157	0.0333		0.0221	0.0439
	(1.4929)	(0.9567)		(1.1421)	(0.7994)
_cons	0.7798***	0.8412***		0.9709***	0.9295***
	(16.3528)	(15.2201)		(3.4105)	(3.3603)
N	2713	2713		542	542
adj. R^2	0.6069	0.4700		0.6034	0.4103
	Largest 5% of returns (5% of absolute value (above 2.5% and 2.5% below 0))			Regression results in SCSAD	
	Banks	Financials		Banks	Financials
$R_{m,t}$	0.0027	0.0694*	$R_{m,t}$	1.1707***	1.4281***
	(0.1451)	(1.7836)		(67.1517)	(71.4508)
$\|R_{m,t}\|$	0.4118	0.6355*	$R_{m,t}^2$	-0.0003	0.0062
	(1.5248)	(1.7222)		(-0.0605)	(0.3056)
$R_{m,t}^2$	0.0300	0.0227	$R_{m,t}^3$	-0.0051***	-0.0195***
	(1.1148)	(0.3440)		(-4.8704)	(-4.1239)
_cons	1.2317***	0.5960	_cons	0.0297***	0.0484***
	(2.0638)	(1.2200)		(2.4059)	(3.3729)
N	271	271	*N*	5426	5426
adj. R^2	0.6285	0.4008	adj. R^2	0.7598	0.7042

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8.1 reports the herding estimates results under the standard CCK model in our whole data sample which contains firms from the UK, German and French markets. We compare the strength of herding behaviour between the Banking industry and the Financial sector. The banking industry is not included in the Financial sector in our data sample. According to the results, we find that, under the normal CCK regression model, the banking industry has a significantly positive coefficient of squared market return, indicating the existence of anti-herding behaviour in the industry. At the same time, the Financial sector has an insignificant coefficient of squared market return, showing neither herding nor anti-herding behaviour. We use our solution 1 to avoid the influence of the error term in the CAPM model by fitting the regression without a constant value. The results show that both the banking industry and Financial sector have a significantly negative coefficient of squared market return, which indicates the existence of herding behaviour. Also, by comparing the absolute value of the coefficient of the independent variables such as squared market return, we can compare the strength of herding under different market condition and the different models we fit. The regression coefficient represents the parameter of the influence of the independent variable on the dependent variable. The larger the regression coefficient is, the greater the influence of the independent variable on the dependent variable is. According to the results, we find that the Financial sector has a bigger absolute value of the coefficient which means there is a larger degree of herding during our sample period. Then we investigate herding under market conditions with larger market movements. By selecting market returns larger than a particular value and different proportions of the observations, we do not capture significant evidence of herding behaviour in the market, perhaps because we are not investigating sufficiently large returns or because the data sets are not sufficiently large. We also estimated results using our second solution, which fits the regression under the SCSAD method. This method avoids the influence of error terms in the CAPM model and can detect herding behaviour even when herding behaviour is not obvious in the market. From the results, we can find out that both the banking industry and Financial sector have clear evidence of herding behaviour, shown by the significantly negative coefficient of the cubic market return. However, by comparing the absolute value of the coefficient, the banking industry is less affected by herding behaviour than the Financial sector.

8.2 The First Time period from 2001 to 2010

Table 8.2 Strength of herding of Banks and Financial sector from 2001 to 2010

	Normal regression model (CCK)		Regression results without constant	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0133	0.0206***	0.0265	0.0359***
	(0.8159)	(1.9808)	(1.2715)	(2.0634)
$\|R_{m,t}\|$	0.6036***	0.5972***	1.4148***	1.8509***

	(15.8580)	(24.7835)	(36.0569)	(29.2034)
$R^2_{m,t}$	0.0200***	-0.0170***	-0.0739***	-0.2751***
	(2.1892)	(-2.6414)	(-5.7276)	(-7.6612)
_cons	0.8902***	0.8793***		
	(43.5423)	(74.5875)		
N	2869	2869	2869	2869
adj. R^2	0.6032	0.4668	0.7727	0.7574
	Market return larger than |0.5%|		Market return larger than |1%|	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0154	0.0280***	0.0194	0.0364***
	(0.9212)	(2.6005)	(1.0710)	(2.8638)
$\|R_{m,t}\|$	0.6226***	0.6888***	0.6205***	0.6849***
	(10.0673)	(16.9198)	(6.3634)	(8.6227)
$R^2_{m,t}$	0.0181	-0.0324***	0.0182	-0.0308***
	(1.5794)	(-4.5115)	(1.2504)	(-2.7546)
_cons	0.8624***	0 .7896***	0.8723***	0.7895***
	(16.1124)	(25.0858)	(7.2666)	(8.2927)
N	1542	1233	790	490
adj. R^2	0.6284	0.4828	0.6435	0.4080
	Market return larger than |2%|		Market return larger than |3%|	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0134	0.0376*	-0.0131	0.0008
	(0.5874)	(1.9848)	(-0.4547)	(0.0335)
$\|R_{m,t}\|$	0.3575*	0.9357***	0.2887	0.9198
	(1.7131)	(3.3038)	(0.7714)	(1.2547)
$R^2_{m,t}$	0.0401*	-0.0621*	0.0445	-0.0650
	(1.8033)	(-1.9364)	(1.3758)	(-0.8997)
_cons	1.4908***	0.3709	1.7022*	0.4440
	(3.5738)	(0.6996)	(1.7694)	(0.2584)
N	259	113	102	32
adj. R^2	0.6296	0.3321	0.6846	0.2242
	Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))		Largest 10% of returns (10% of absolute value (above 5% and 5% below 0))	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0151	0.0259***	0.0159	0.0462***
	(0.8976)	(2.4369)	(0.7106)	(3.1831)
$\|R_{m,t}\|$	0.6241***	0.6707***	0.4118***	0.6516***
	(9.5773)	(17.9806)	(2.1148)	(4.8581)
$R^2_{m,t}$	0.0180	-0.0295***	0.0357*	-0.0255
	(1.5272)	(-4.2114)	(1.6694)	(-1.4748)
_cons	0.8601***	0.8085***	1.3543***	0.8407***
	(14.5372)	(30.3609)	(3.6282)	(4.2759)
N	1435	1435	286	286
adj. R^2	0.6277	0.4863	0.6315	0.3594
	Largest 5% of returns (5% of absolute value (above 2.5% and 2.5% below 0))		Regression results in SCSAD	
	Banks	Financial	Banks	Financial

$R_{m,t}$	-0.0093	0.0346***	$R_{m,t}$	1.2328***	1.4574***
	(-0.3581)	(2.0377)		(51.9066)	(46.0772)
$\lvert R_{m,t}\rvert$	0.3914	1.0452***	$R^2_{m,t}$	-0.0022	-0.0008
	(1.2988)	(5.3998)		(-0.3287)	(-0.0739)
$R^2_{m,t}$	0.0373	-0.0747***	$R^3_{m,t}$	-0.0048***	-0.0304***
	(1.3251)	(-3.2591)		(-4.1163)	(-5.7061)
_cons	1.3820*	0.1571	_cons	0.0417***	0.0456***
	(1.9707)	(0.4776)		(2.3235)	(3.0063)
N	143	143	N	2869	2869
adj. R^2	0.6930	0.4075	adj. R^2	0.7580	0.7200

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We now consider our first time subset time period from 2001 to the end of 2010. Using the standard CCK model, the regression results show that the banking industry has evidence of anti-herding behaviour, shown by a significantly positive coefficient of the squared market return. In contrast, the Financial sector has clear evidence of herding behaviour in the market. Under the regression model without a constant value, we capture clear evidence of herding behaviour in both the banking industry and the Financial sector, shown by the significantly negative coefficient of the squared market return. By comparing the absolute value of the coefficient of squared market returns, we can find out that the Financial sector has more herding behaviour than the banking industry. When we select the market returns larger than a particular value and then fit the standard CCK model to estimate herding behaviour, we find out that when the market return is larger than 0.5% and 1% in absolute terms, there is clear evidence of herding behaviour in the Financial sector, and the herding behaviour is significant at 10% level when the market returns are larger than |2%|. This also shows that herding behaviour is stronger in the Financial sector than in the banking industry. Using data samples under market conditions with different proportions of observations, we find that herding behaviour in the Financial sector exists under market conditions with the largest 50% and 5% of the observations, shown by the significantly negative coefficient of the squared market return and the banking industry has anti-herding behaviour when the market condition selects the largest 10% of returns in absolute terms. By using solution 2 to estimate the herding behaviour, we fit the regression model using the SCSAD method. According to the results, both the banking industry and the Financial sector have a significantly negative coefficient of cubic market return, which indicates herding behaviour. After comparing the absolute value of the coefficient of cubic market return, we also find that we have captured evidence of greater herding behaviour in the Financial sector.

8.3 The second Time period from 2011 to 2020

Table 8.3 strength of herding of Banks and Financial sector from 2011 to 2020

	Normal regression model (CCK)		Regression results without constant	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0127	0.0490	-0.0025	0.0547
	(1.3018)	(1.2295)	(-0.1905)	(1.1582)
$\lvert R_{m,t}\rvert$	0.5159***	0.4149***	1.3059***	1.6355***
	(17.2937)	(4.4007)	(51.7786)	(27.1129)
$R^2_{m,t}$	0.0089	0.0809*	-0.0987***	-0.1368***
	(1.1115)	(1.7256)	(-9.7349)	(-3.1847)
_cons	0.7840***	0.8333***		
	(48.4589)	(31.1695)		
N	2557	2557	2557	2557
adj. R^2	0.5887	0.4633	0.7979	0.7140
	Market return larger than |0.5%|		Market return larger than |1%|	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0136	0.0524	0.0090	0.0663
	(1.3708)	(1.2244)	(0.8087)	(1.1844)
$\lvert R_{m,t}\rvert$	0.5867***	0.4401***	0.6791***	0.4522
	(13.5139)	(2.3295)	(10.6787)	(1.2859)
$R^2_{m,t}$	0.0003	0.0779	-0.0104	0.0774
	(0.0327)	(1.2888)	(-1.0343)	0.9725)
_cons	0.6963***	0.8020***	0.5600***	0.7860***
	(20.0512)	(7.1489)	(7.4516)	(2.3837)
N	1494	1023	733	333
adj. R^2	0.6123	0.5021	0.6033	0.4937
	Market return larger than |2%|		Market return larger than |3%|	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0071	0.1277	0.0012	0.2258
	(0.4405)	(1.2936)	(0.0591)	(1.2938)
$\lvert R_{m,t}\rvert$	0.7496***	0.9954	1.3202***	3.623
	(5.0752)	(1.0393)	(3.5892)	(0.8668)
$R^2_{m,t}$	-0.0172	0 .0214	-0.0621***	-0.2053
	(-1.1099)	(0.1634)	(-2.0963)	(-0.4978)

_cons	0.4165	-0.2072		-1.1830	-7.1412
	(1.4102)	(-0.1318)		(-1.2422)	(-0.7536)
N	195	61		76	17
adj. R^2	0.5795	0.4408		0.6679	0.4676
	Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))			Largest 10% of returns (10% of absolute value (above 5% and 5% below 0))	
	Banks	Financial		Banks	Financial
$R_{m,t}$	0.0127	0.0514		0.0071	0.0740
	(1.2607)	(1.2439)		(0.4967)	(1.2181)
$\|R_{m,t}\|$	0.6110***	0.4245***		0.7587***	0.4950
	(12.8632)	(2.5730)		(6.5201)	(1.2284)
$R^2_{m,t}$	-0.0026	0.0802		-0.0180	0.0728
	(-0.2830)	(1.3981)		(-1.3519)	(0.8578)
_cons	0.6628***	0.8178***		0.3972*	0.7197*
	(15.6952)	(9.4289)		(1.8992)	(1.7432)
N	1279	1279		255	255
adj. R^2	0.6080	0.4997		0.5960	0.4957
	Largest 5% of returns (5% of absolute value (above 2.5% and 2.5% below 0))			Regression results in SCSAD	
	Banks	Financial		Banks	Financial
$R_{m,t}$	0.0017	0.0931	$R_{m,t}$	1.1184***	1.4249***
	(0.0911)	(1.2283)		(73.4502)	(50.8385)
$\|R_{m,t}\|$	0.8232***	0.7295	$R^2_{m,t}$	-0.0101*	0.0178
	(3.5768)	(1.2044)		(-1.6600)	(0.5155)
$R^2_{m,t}$	-0.0237	0.0468	$R^3_{m,t}$	-0.0084***	-0.0109*
	(-1.1427)	(0.4537)		(-8.8484)	(-1.6640)
_cons	0.2349	0.3258	_cons	0.0305***	0.0489***
	(0.4347)	(0.4125)		(2.1158)	(2.3928)
N	127	127	N	2557	2557
adj. R^2	0.5524	0.4752	adj. R^2	0.7797	0.6984

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8.3 reports the regression results for the second sample period from 2011 to 2020. According to the results, under the standard CCK model, we do not capture clear evidence of herding behaviour in the market. The Financial sector shows some evidence of the presence of anti-herding behaviour which is significant at the10% level. Using solution 1 to estimate the herding behaviour by fitting the regression model without a constant value we have captured clear evidence that herding behaviour exists in both sectors, shown by the significantly negative coefficient of the squared market returns. Comparing the absolute value of the coefficients, the Financial sector has a bigger squared market return coefficient, which means it is more affected by herding behaviour in the market. When we estimate the herding behaviour under different market conditions with larger market movements neither the banking industry nor the Financial sector have clear evidence of herding behaviour when absolute market returns are larger than 0.5%, 1%, and 2%. Only the banking industry has herding behaviour under market conditions with absolute market return larger than 3%, shown by a significantly negative coefficient of the squared market return. Under market conditions with different proportions of observations, we do not capture clear evidence of herding behaviour in the market. When we use solution 2 to estimate the herding behaviour by fitting the regression model using the SCSAD method we find that both the banking industry and the Financial sector have a significantly negative coefficient of cubic market return, which indicates the existence of herding behaviour. Also, by comparing the absolute value of the cubic market return's coefficient, the Financial sector was more influenced by the herding effect. Comparing the results with those during first time period, there is less herding behaviour present in the post crisis market. When markets have larger price movements, only the banking industry has herding behaviour when market returns are larger than |3%|, while herding behaviour exists in the Financial sector during the second time period under different market conditions.

8.4 Further investigation time period 2006 to 2010

Table 8.4 strength of herding between Banks and Financial sector from 2006 to 2010

	Normal regression model (CCK)		Regression results without constant	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0129	0.0276***	0.0208	0.0343*
	(0.6053)	(2.3495)	(0.8392)	(1.7810)
$\|R_{m,t}\|$	0.6120***	0.5532***	1.3296***	1.6403***
	(11.7839)	(18.6882)	(28.6768)	(28.1716)
$R_{m,t}^2$	0.0190*	-0.0125**	-0.0582***	-0.2146***
	(1.8212)	(-1.9624)	(-4.6945)	(-7.6158)
_cons	0.9174***	0.8760***		

	(26.3558)	(46.9272)			
N	1305	1305		1305	1305
adj. R^2	0.6286	0.4826		0.7910	0.7691
	Market return larger than |0.5%|			Market return larger than |1%|	
	Banks	Financial		Banks	Financial
$R_{m,t}$	0.0144	0.0322***		0.0176	0.0402***
	(0.6650)	(2.6896)		(0.7758)	(3.0651)
$\|R_{m,t}\|$	0.6277***	0.5964***		0.6001***	0.5748***
	(7.9930)	(13.2996)		(5.1647)	(6.9985)
$R^2_{m,t}$	0.0176	-0.0192***		0.0202	-0.0151
	(1.3670)	(-2.6011)		(1.2628)	(-1.3524)
_cons	0.8880***	0.8297***		0.9407***	0.8503***
	(11.5308)	(20.7895)		(6.0598)	(7.9450)
N	792	667		472	301
adj. R^2	0.6504	0.5055		0.6551	0.4867
	Market return larger than |2%|			Market return larger than |3%|	
	Banks	Financial		Banks	Financial
$R_{m,t}$	0.0122	0.0420***		-0.0137	0.0208
	(0.4609)	(2.5059)		(-0.4282)	(0.8807)
$\|R_{m,t}\|$	0.4157*	0.8621***		0.3800	1.0362
	(1.7099)	(3.3955)		(0.9151)	(1.5976)
$R^2_{m,t}$	0.0349	-0.0493*		0.0369	-0.0691
	(1.4137)	(-1.7333)		(1.0429)	(-1.0585)
_cons	1.4003***	0.3403		1.5228	-0.0449
	(2.7634)	(0.7206)		(1.4034)	(-0.0304)
N	193	86		83	27
adj. R^2	0.6360	0.5236		0.6851	0.4547
	Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))			Largest 10% of returns (10% of absolute value (above 5% and 5% below 0))	
	Banks	Financial		Banks	Financial
$R_{m,t}$	0.0137	0.0322***		-0.0086	0.0474***
	(0.6231)	(2.6860)		(-0.3043)	(3.1129)
$\|R_{m,t}\|$	0.6219***	0.5917***		0.4220	0.7692***
	(6.8183)	(12.8992)		(1.3630)	(4.8075)
$R^2_{m,t}$	0.0181	-0.0185***		0.0342	-0.0377***
	(1.3057)	(-2.4557)		(1.1839)	(-1.9900)
_cons	0.8970***	0.8351***		1.3757*	0.5031*
	(8.7821)	(20.1419)		(1.9254)	(1.8899)
N	653	653		130	130
adj. R^2	0.6496	0.5013		0.6864	0.5553
	Largest 5% of returns (5% of absolute value (above 2.5% and 2.5% below 0))			Regression results in SCSAD	
	Banks	Financial		Banks	Financial
$R_{m,t}$	-0.0142	0.0392***	$R_{m,t}$	1.1679***	1.3033***
	(-0.4101)	(2.1550)		(39.6976)	(0.2254)
$\|R_{m,t}\|$	0.3574	1.0532***	$R^2_{m,t}$	-0.0028	-0.0034
	(0.6848)	(3.6889)		(-0.4425)	(4.7877)

$R_{m,t}^2$	0.0381	-0.0702***	$R_{m,t}^3$	-0.0037***	-0.0234***
	(0.9145)	(-2.2108)		(-3.4077)	(-1.5958)
_cons	1.6177	-0.0535	_cons	0.0459	0.0549***
	(1.0871)	(-0.0981)		(1.5762)	(4.5530)
N	65	65	N	1305	1305
adj. R^2	0.6646	0.5671	adj. R^2	0.7804	0.7368

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The time period from 2006 to 2010 broadly corresponds to the financial crisis in 2008. According to the results, under the standard CCK model, we find the banking industry has anti-herding behaviour in the market which is significant at the 10% level, and the Financial sector has clear evidence of herding behaviour, shown by significantly negative coefficient of squared market return. Using solution 1, which fits the regression model without a constant value, we find out that both the banking industry and the Financial sector show the existence of herding behaviour. There has more herding in the Financial sector, as it has a larger absolute value of the coefficient of the squared market return. Under market conditions of the increase of absolute value of market return, we have captured evidence of herding behaviour under market conditions with absolute market return larger than |0.5%| in the financial sector. Also, along with the change of proportions of observations, we also find herding behaviour under the market conditions associated with the largest 50%, 10% and 5% of observations, shown as the significantly negative coefficient of the squared market return. Under the regression model using the SCSAD method, both the banking industry and the financial sector have a significantly negative coefficient of cubic market return, which indicates herding, and the financial sector is more affected by the herding behaviour. Compared to the first time period, we find that the banking industry has less anti-herding behaviour under the CCK model during the period of turmoil, although only significant at the 10% level, while it has significant anti-herding behaviour in the first time period. Considering the subsample with market returns larger than particular values, we can see that financial sector has clear evidence of herding behaviour under different market conditions, and by comparing the absolute value of the coefficients of squared market return, we can compare the strength of herding in the Financial sector and the banking industry. When market returns are larger than |0.5%| and |1%|, the absolute value of the coefficient of squared market return for the Financial sector in the first time period is larger than in the time period from 2006 to 2010, which indicates that more herding behaviour exists in the sector. When we consider market returns larger than |2%|, we see somewhat more herding behaviour in the financial sector during the financial crisis time period than in the first time period, shown by a larger absolute value of the coefficient of squared market return. Under market conditions determined by different proportion of total observations, along with the increase of market price movement, there is more herding behaviour detected in the Financial sector. Also, during the first time period, under market conditions based on the largest 10% and 5% of observations, more herding were detected in the Financial sector than in the market turmoil period. When solution 2, the SCSAD method, is used to estimate herding behaviour, herding in the Financial sector is stronger than in the Banking industry. Also, during the first time period, a higher level of herding behaviour was detected in both the Financial sector and the banking industry than in the market turmoil period. Compared with the second time period which covers the post financial period we find out that, under the standard CCK model, there is some evidence of anti-herding presence in the Financial sector which is significant at the 10% level during the second time period. Using solution 1 to estimate herding behaviour, both the banking industry and the Financial sector have herding behaviour during both time periods. By comparing the absolute value of the coefficient of squared market return, we find that there was a higher level of herding in the banking industry during the second period, and more herding behaviour present in the Financial sector during the market turmoil period. When the market has larger movements, herding behaviour is mainly present in the Financial sector during the turmoil period, but in the second period which is the post crisis period, only the banking industry has clear evidence of herding presence when market returns are larger than |3%|. Under the SCSAD method, we have similar results to those using solution 1, finding that both the banking industry and the Financial sector have significant herding behaviour in the market. Also, the banking industry has more herding behaviour during the second period, and there is more herding behaviour in the Financial sector during the market turmoil period.

8.5 Investigate herding behaviour in 2020

Table 8.5 Strength of herding between Banks and Financial sector in 2020

	Normal regression model (CCK)		Regression results without constant	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0288	0.0195	-0.0304	-0.0421
	(1.0793)	(0.5145)	(-1.0022)	(-1.0145)
$\|R_{m,t}\|$	0.5307***	0.7042***	1.2431***	1.6643***
	(6.9065)	(6.8022)	(21.9655)	(21.2752)
$R_{m,t}^2$	-0.0040	-0.0247	-0.0834***	-0.1689***
	(-0.3858)	(-1.3392)	(-8.6005)	(-8.1673)
_cons	0.9991***	0.9091***		
	(14.8590)	(13.6997)		
N	209	209	209	209
adj. R^2	0.6630	0.5318	0.8523	0.7997
	Market return larger than |0.5%|		Market return larger than |1%|	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0316	0.0131	0.0342	0.0138
	(1.1404)	(0.3310)	(1.1597)	(0.3070)
$\|R_{m,t}\|$	0.4872***	0.8379***	0.4673***	0.6989***
	(4.8254)	(5.6457)	(3.4743)	(2.7601)
$R_{m,t}^2$	0.0005	-0.0436*	0.0024	-0.0277
	(0.0384)	(-1.8229)	(0.1552)	(-0.8051)
_cons	1.0714***	0.7625***	1.1148***	0.9970***
	(9.3702)	(5.8543)	(5.7084)	(2.9351)
N	157	122	106	61
adj. R^2	0.6278	0.5521	0.6060	0.4640
	Market return larger than |2%|		Market return larger than |3%|	
	Banks	Financial	Banks	Financial
$R_{m,t}$	0.0418	0 .0829*	0.0485	0.1341***
	(1.2085)	(1.9285)	(1.5889)	(3.4948)
$\|R_{m,t}\|$	0.1353	0.6815	0.9740***	-0.7579
	(0.4835)	(1.6158)	(2.5840)	(-0.9289)
$R_{m,t}^2$	0.0305	-0.0124	-0.0308	0.1325

	(1.1616)	(-0.2784)		(-1.0252)	(1.5808)
_cons	1.9247***	0.8379		-0.5688	4.2209*
	(2.9219)	(0.9530)		(-0.5702)	(2.3780)
N	49	22		27	8
adj. R^2	0.5218	0.6323		0.7944	0.8744
	Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))			Regression results in SCSAD	
	Banks	Financial		Banks	Financial
$R_{m,t}$	0.0337	0.0092	$R_{m,t}$	1.0322***	1.3796***
	(1.1355)	(0.2254)		(20.0781)	(20.2622)
$\|R_{m,t}\|$	0.4724***	0.8222***	$R^2_{m,t}$	-0.0070	-0.0135
	(3.4603)	(4.7877)		(-0.7348)	(-0.8166)
$R^2_{m,t}$	0.0019	-0.0422	$R^3_{m,t}$	-0.0066***	-0.0187***
	(0.1211)	(-1.5958)		(-4.5971)	(-5.7511)
_cons	1.1046***	0.7866***	_cons	-0.0538	-0.0350
	(5.5163)	(4.5530)		(-0.8098)	(-0.5720)
N	105	105	N	209	209
adj. R^2	0.6055	0.5217	adj. R^2	0.8324	0.7766

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the year 2020, the Covid virus spread around the world and caused varying degrees of impact on stock markets in different countries. We analysed the stock market separately in this year of unusual crisis. Under the standard CCK model, we do not find herding or anti-herding in either the banking industry or the Financial sector. By fitting the regression model without a constant value, we have captured clear evidence of herding behaviour, and there is more herding in the Financial sector as it has a larger absolute value of the coefficient of the squared market return. With the absolute market return increases from 0.5% to 3%, we can see partial evidence of herding in the financial sector under the market condition with absolute market return larger than 0.5% which is significant at 10% level. Also, with the largest 50% of observations, we do not observe either herding or anti-herding in the market. When we estimate herding behaviour using the SCSAD method, both the banking industry and the financial sector have a significantly negative coefficient of cubic market return, which indicates herding.

In this section, we test for herding behaviour in the banking sector and the Financial industry in UK, Germany and France market, and compare the strength of the herding effect in the banking industry and the Financial sector. Overall, herding behaviour is present throughout our data sample period, especially in the time periods with larger market movement or during periods of market turmoil, such as the first time period from 2000 to 2010 and from 2006 to 2010. Also, by comparing the absolute value of the coefficient of squared market return and cubic market return, we find that herding behaviour is greater in the Financial sector than the banking industry. In a more general sense, financial services include investment, insurance, risk redistribution, and other financial activities, whereas, banks take deposits and make loans and provide other financial services. Banks are also typically divided into retail banks, which provide deposits and loans, and investment banks, which do large-scale businesses such as securities underwriting and initial public offerings.

9.0 Herding effect on market conditional volatility

This chapter will investigate the connections between herding behaviour and market volatility. Various prior work and general reasoning indicates there may be a link between herding and volatility. By definition, herding behaviour reflects investors being guided by the collective behaviour of other market participants. Herding can occur for a number of reasons. Management pay often depends on reputation, but the person in charge may not be sure about the quality of management. As a result, bad managers have an incentive to copy other managers' decisions to hide their low quality. Agents can also be compensated based on performance relative to their counterparts. In this case, risk-averse managers are less likely to deviate from their peers and tend to concentrate on their portfolio decisions. One view is that individuals are more likely to follow the behaviour of others when assets are difficult to value under extreme market conditions or when the market has great fluctuations, as the market fluctuations and information flow during these periods could block the reliability and accuracy of investment forecasts (Mobarek, Mollah and Keasey, 2014). This view would imply that volatility tends to cause herding. Another view is that if people adopt similar trading behaviour and heavily trade on particular stocks it could increase the price movement of these stocks within a short period of time, and thus their corresponding volatility. This is related to the idea that herding may contribute to the formation of asset bubbles (Gleason, Mathur, and Peterson 2004). From this viewpoint herding may cause volatility. Thus, although links between herding and volatility are likely the direction of causality may not be entirely clear.

9.1 Volatility in financial markets

Volatility is one of the most critical variables in pricing financial instruments. For instance, volatility is a vital variable used to put a fair price on options and other derivatives. It also has a significant impact on investment decision making, risk management and the creation of portfolios (Poon and Granger, 2002).

Shiller (1981) provides empirical evidence that suggests that stock prices and long-term interest rates are more volatile than standard asset pricing models can attest. In addition, the difference between equity prices, long-term bond holding yields and long-term interest rates exceeds the upper limit implied by the difference between dividends and short-term interest rates. Moreover, in many cases, stock prices and long-term interest rates diverged significantly beyond the upper limits of their estimates. Excessive volatility in financial markets can also have a large and widespread negative influence on the world economy as in the financial crisis in 2008, which caused great economic turmoil. The fluctuation in volatility can be decomposed into fluctuations due to past market shocks and fluctuations due to persistence in volatility (Akgiray, 1989). In addition, non-financial incidents can influence market volatility, for example, the terrorist attack on 11 of September 2001 which brought market uncertainty, loss of public investment confidence and caused the US market to suffer great turmoil as well as negatively influencing the financial markets on different continents and the world economy (Poon and Granger, 2002).

Given the foregoing, it is important to have accurate volatility forecasts in the financial markets and this subject has drawn the attention of many academic researchers over recent years. There has also been much work analysing the relationship between volatility and other factors which may influence the financial markets. Dimson and Marsh (1990) focus on investigating and predicting volatility in UK equity market using daily stock returns. Akgiray (1989) uses the GARCH model to forecast stock market volatility and found that the model is effective in forecasts of monthly returns and shows high relative usefulness amongst practical models of stock returns an increase (decrease) in the volatility of some stock markets may lead to a corresponding increase (decrease) in the volatility of other national stock markets. Degiannakis and Filis (2017) state that cross-market volatility transmission effects are equivalent to cross-market information flows or “information channels”. They show persuasively that four asset classes (stocks, forex, commodities, and macro), representing different "information channels," can help forecast oil price volatility. Liu et al. (2019) extract data on the realized volatility of 27 stock markets around the world and forecast the realized volatility of China's stock market and show that global stock information does forecast the future volatility of Chinese stock market.

Intentional or unintentional herding impact differently on market volatility (Bikhchandani & Sharma, 2001). Intentional herding usually involves the blind imitation of others (Banerjee, 1992, Bikhchandani et al., 1992) or is due to manager reputation (Scharfstein & Stein, 1990). The link between investor behaviour and market volatility was first pointed out by Friedman (1953), who found that irrational investors can make the price unstable by buying when prices are high and selling when prices are low, while rational investors tend to push prices to fundamentals and sell high by buying at low prices. Following Friedman and the theory of Noisy Rational Expectations, Hellwig (1980) and Wang (1993) claim that volatility is driven by uninformed or liquid trading. The latter author observes that information asymmetry can lead to volatility, and that uninformed investors tend mostly to follow market trends, buying when prices rise and selling when they fall, a behaviour that we might equate with herding. Wang (1993) reports that such behaviour may be rational among uninformed investors if it occurs in the context of information asymmetry. Froot, Scharfstein and Stein (1992) also concluded that investors tend to imitate each other, which could lead to excess volatility and destabilize the market. This is often contrary to unintentional herding when rational investors rely on the same factors and arrive at the same investment decision (Hirshleifer et al., 1994) or are attracted by stocks with similar characteristics (Falkenstein, 1996). More recently, this relationship has been documented by Avramov, Chordia and Goyal (2006), who claim that both herding, and contrarian trading have a significant impact on daily volatility. The trading activity of contrarian and herding investors has a strong impact on the relationship between daily volatility and lagging returns. Consistent with the predictions of the rational expectations model, non-information based, liquidity-driven trading classified as herding behaviour increases volatility as share prices fall, while informed transaction trading which is classified as contrarian trading decreases volatility as share prices rise. In addition, in terms of information quality, the theoretical framework of Wang and Wang (2018) provide evidence about the relationship between market volatility and herding as well as social information which could have an impact on investor behaviour and influence investors' behaviour and market volatility. They argue that the information surrounding investors could have a strong impact on the decisions and expectations of those investors particularly for those who believe gurus. Thus, they run a numerical simulation and their empirical results show that market leaders, like gurus, play an important role in the market. They indicate that an increase in the information quality received by gurus could make investors herd more intensively and have an impact on market volatility. In addition, increasing the group size of investors following gurus with high quality and precise private information would lead to more intensive herding but reduce market volatility at the same time. Due to the changes in the investment environment, investors are more likely to have herding behaviour and follow the gurus during boom periods or when the market is suffering depression. So, market volatility could be affected by investors’ herding behaviour and primarily influenced by the information that is received by investors following gurus, which depends on the type of gurus, the number of gurus, herding intensity, and fundamental value level. With more gurus in the market, and if there is a good ratio of honest gurus to opportunistic gurus, the level of market volatility will be decreased. When gurus have poor information or increased sensitivity to price, the strength of the herd effect caused by gurus and investors who follow the gurus will leads to higher market volatility. The direction of the influence depends on the precision of the gurus' private information. Improving the quality of private information will lead to a herding among gurus and more trading based on this information, which will bring prices closer to fundamental value. However, this could also attract more investors to follow the gurus and make the price deviate from fundamental value.

9.2 Literature review

9.2.1 Investigations of the US market

Several authors assert explicitly that herd behaviour fuels investors’ irrational exuberance and amplifies volatility (Topol, 1991; Christie and Huang, 1995; Shiller, 2000). They add that investors will trade specific stocks due to a random lucky hit of positive news, and then other investors will mimic their behaviour and trade the same stocks, leading to abnormal trading volumes in specific stocks and generating high price volatility. There is a significant positive correlation between the herding effect and asymmetric fluctuation (Chiang and Zheng, 2010).

In an empirical study focused on the US stock market, Jlassi and Naoui (2015) provide a direct empirical link between market return dispersion and market conditional volatility and find significant evidence that herding behaviour exists in the S&P100 and DJIA using daily return data. Also, the level of herding is influenced by market liquidity changes and tends to be stronger during rising market periods. They have produced evidence to show that there is a significantly positive relationship between the herding effect and the conditional volatility of the US market, in that the presence of herding behaviour in the market increases market volatility. Additionally, they have found asymmetric herding to be present in the market which is only significant during lower volatility periods.

A study by Litimi, BenSaïda and Bouraoui (2016) investigates whether market excess volatility is driven by herding behaviour in the market. Applying the data at the sectoral level from listed companies in key indices including NYSE, AMEX, and NASDAQ, they capture clear evidence of herding behaviour in the US market, and it has an impact in different financial crises over different time periods, including Black Monday in 1987 and the latest global financial crisis in 2008. Regarding the factors influencing market volatility, among all sectors, herding behaviour only affects the volatility of a few specific stocks due to the reduced volatility of the inactive remaining stocks that are not influenced by herding behaviour, thus the volatility of the whole market is reduced. Consequently, they suggest that among all market sectors, herding could have an inhibiting impact on the volatility of average returns.

9.2.2 In the European market

In the Spanish stock market, by analysing the most traded stocks included in the Ibex-35, Blasco, Corredor and Ferreruela (2012) confirm that there would be a higher level of volatility expected in the stock market if there is a greater intensity of herding. The intensity level is not always constant and the herding effect has a direct linear influence on the volatility of the market. Volatility could be influenced by uninformed investors and liquidity trading, as asymmetry of information could increase volatility, these investors would more likely make their decisions based on market trends, and this kind of behaviour could be regarded as a herd effect. Hence, in the volatility forecasting process, a variable representing the herd effect can be seen as a key influence factor.

In another empirical study, Gavriilidis, Kallinterakis and Ferreira (2013) use quarterly portfolio data of Spanish mutual funds to investigate whether fund managers at the sectoral level are motivated by the intention to herd. Their results show evidence for most of the sectors in the Spanish market of the existence of intentional institutional herding. Also, fund managers have significant herding behaviour at the overall market level, influenced by market performance during periods when the market is suffering turmoil or the whole market is underperforming. The fund managers are more likely to herd under market condition of an increase of volatility and rising trading volume especially in a number of sectors including Consumer Services and industrial sectors, and their herding behaviour is mainly motivated by their career concern and is informational based.

Balcilar and Demirer (2013) examine the relationship between the volatility of the stock market and herding behaviour in the Borsa Istanbul an emerging market which is mainly dominated by foreign investors. During periods with high and extreme-volatility volatility in the market, they capture significant evidence of herding behaviour in the Turkish stock market. Also, for most market sectors, global factors, as well as volatility in the domestic market, are found to be important determinants of transactions. The Standard and Poor's (S&P) 500 index return, and the Chicago Board of Trade (CBOT) volatility index (VIX) are found to dominate the market, investors in the stock market chose to rely on these indexes and this can cause herding behaviour.

Messis and Zapranis (2014) examine the existence of herding behaviour in the Athens stock market and the influence of herding behaviour on the volatility of the stock market. They capture evidence to show the presence of herding behaviour. They also confirm that herding influences market volatility positively. Therefore, when the stock market has herding or anti-herding behaviour at a high level, both types of herding lead the market to have higher volatility. Thus, the herding effect can be treated as a risk factor that could affect market stability and could help investors to have a better understanding of asset allocation and market risk.

Among investors and traders in UK-listed Real Estate Investment Trusts (REITs), Akinsomi, Coskun, Gupta and Lau (2018) investigate the impact of different volatility periods on herding behaviour. According to their empirical results, the hypothesis of the existence of herding behaviour was not rejected within the low volatility period, and they also observed the presence of anti-herding behaviour when the market has high volatility. The low volatility regime of UK real estate investment trusts was the most persistent herding market regime and coincides with the bull market conditions of the LSE. The evidence suggests that when the overall stock market is performing well, this, in turn, means low volatility and therefore low risk, and agents in the REIT industry are more likely to herd. The results contradict the findings of (Balcilar and Demirer, 2013), which analyses the markets in the Gulf states, and find the evidence of herding behaviour in the market during periods of high and extreme volatility in the market.

9.2.3 In the global market

In the emerging markets, Venezia, Nashikkar and Shapira (2011) investigate trading behaviour among professional and amateur investors in the Israel market. They recorded that in their selected data sample, both amateurs and professional investors exhibit herding behaviour when they make investment decisions. Herding depends on several variables such as individual stocks' systematic risk and the size of the related firm. There are less connections between these variables and the behaviour of professional investors. However, amateurs tend to present more herding behaviour during transactions, and their herding is more likely driven by irrational behaviour. The availability of more information can also explain why larger firms tend to present less herding in their firm stock given information-based herding. They also detect that there is a significant positive correlation between herding and stock market volatility, especially in a group of amateur investors. The higher herding tendency of amateurs, along with the higher correlation between their herding and market volatility, could be a larger threat to the stability of the market than the actions of professional investors.

Using data on futures positions for nine different financial commodities, McAleer and Radalj (2013) provide an empirical test of the existence of herding behaviour and the relevant impact on the volatility of the market. Using futures data for currencies including AUD, CAD, GBP, JPY, and SFR against USD as well as oil, gold, S&P500 and Nikkei 225, their empirical results show that there is significant herding behaviour among the Canadian dollar, British pound, gold, S&P 500 and Nikkei 225 futures within the group of small traders. As herding is more likely to be present amongst small traders, especially for those traders or agents with less confidence in the information they have, this could have an impact on market volatility. Avery and Zemsky (1998) showed that herding occurs if there are two types of investors, well informed and poorly informed, and the proportion of these traders in the market is not well known. Since agents are unsure of the quality of the information they have, the actions of others are used to update their beliefs. Using Bayes' rule, given a series of decisions, the absolute weight of numbers may cause agents to discard their private information and herd if the suggested course of action implied by the agent's private signal conflicts with the decision of others. A cascade of information occurs as each agent makes decisions sequentially, but agents begin to ignore their private information’s in favour of the observing behaviour of previous agents. When the variance causality test is used to analyse whether the volatility among small traders spills over into the spot market, it is found that the spill over only occurs for Nikkei 225 futures.

In an analysis of cryptocurrencies, Baur and Dimpfl (2018) have found that volatility could be influenced by shocks in the market. Positive shocks have more impact on increasing market volatility than negative shocks, which implies an asymmetric effect different from that commonly observed in stock markets and which is often hypothesised to be due to company leverage. Increased volatility from positive shocks can be explained by an uninformed investor herd effect, buying out of fear of missing out on rising cryptocurrency valuations, and "push and sell" schemes. This would imply a causal relationship from volatility to herding. The smaller and therefore, asymmetric volatility response to negative shocks can be explained by the adverse behaviour of informed investors.

In the Chinese equity market, Fei and Liu (2021) explore the influence of herding behaviour on stock market volatility. They show that herding behaviour among investors has a significant impact on the dynamics of stock volatility and is highly correlated with the prediction of future volatility. They incorporate the herding measure in the HARQ model of Bollerslev et al. (2016), which exhibits more persistence in "normal times" and quicker mean reversion in "erratic times" compared to the standard HAR model with constant autoregressive parameters. The volatility forecasts constructed from the HAR (Heterogeneous Autoregressive) model of Corsi (2009) have arguably emerged as the preferred specification for realized volatility based forecasting, and other related reduced-form time series models that treat the realized volatility as directly observable, generally perform much better than the forecasts from traditional parametric GARCH and stochastic volatility models. When the herding measure is added to the HARQ model, it generates significantly more accurate volatility forecasts. Using data from all A-share listed companies in China, their findings support the existence of herding and anti-herding in China. Their results show that herding behaviour among investors has an asymmetric effect on volatility dynamics, which is, herding tends to increase volatility, while anti-herding tends to reduce market volatility.

9.2.4 Using simulation models

By applying simulation analysis and simulate the dynamics of expectations in systems of many agents as well as examining the return volatility with a borrowing constraint, Yamamoto (2010) conclude that herding is one of the influencing factors for volatility clustering. During periods with price decreases, the volatility tends to be higher than in periods when price increases. When agents have underperformed in the past, borrowing constraints are binding, so they lack funds. As they cannot buy any other shares until they sell some shares they currently hold, they are more likely sell them at once during a similar period, which could cause the market to have more selling pressure. Hence, with the influence of borrowing constraints, the herding effect exacerbates the asymmetry of volatility.

Di Guilmi, He and Li (2013) examine some behaviours such as trend chasing, switching between different trading strategies and herding which could influence market volatility in price and return and volatility clustering. These behaviours normally can be seen as the rational investment behaviour of participants in the financial markets. Based on long term observations, they found that switching among different strategies could decrease market volatility, but volatility could increase with higher switching intensity. On the contrary, both herding and trend-chasing increase market volatility and at the same time lead the market price to diverge from fundamental value. Strong herding behaviour will lead to high volatility of market share and market price, resulting in high volatility of price and return, while stronger switching will reduce return volatility, and have a non-monotonic effect on market share and price volatility.

To summarise the literature concerning the connections between herding and volatility, much theoretical work has indicated that there may be connections between herding and market volatility although the direction of causality is more contested. The prior empirical research in this area have produced mixed results with on strong consensus about the nature of the connections between herding and volatility with different studies producing quite different conclusions and some evidence that the relationship may be quite dependent on market conditions. Thus it is very appropriate to carry out further empirical work in this area using to new measured of herding we have developed earlier.

9.3 Measure of volatility

In finance, the volatility of a variable is often defined as the standard deviation of a sample shown as σ or the square root of the variance σ^2. It is calculated as:

$$\sigma^2 = \frac{1}{N-1}\sum_{t=1}^{N}(R_t - \bar{R})^2$$

Where R_t is the security return at time t and $\bar{R}$ is the mean return of the sample. In fact, σ can be calculated for any irregularly shaped distribution; in this kind of situation, the probability density must be derived empirically. Figlewski (1997) indicates that due to the sample mean statistical properties, estimates of the true mean of the sample could be extremely inaccurate, especially for small samples. As the volatility is calculated based on the deviation of the sample data from the mean, but when the range of the selected sample is in a short time period, it could be very inaccurate to estimate the true mean based on the sample mean. Volatility in the real world is constantly changing, so we need to estimate the volatility over time. In recent years, there have been a number of financial models developed and widely used in empirical studies to forecast time-varying volatility. The ARCH series model plays an important role in empirical studies related to volatility estimates. First, the most frequently used model Autoregressive Conditional Heteroskedasticity (ARCH) model was introduced by Engle (1982) and initially applied to describe UK inflationary uncertainty, it can be calculated as:

$$\sigma_n^2 = \omega + \sum_{i=1}^{m} \alpha_i u_{i-1}^2$$

Where: $\omega = \gamma V_L$, which is long-run variance weighted by the parameter γ, u_i is the continuously compounded return, α_i is the weight on the return i days ago. By collecting continuously compounded return u_i during a period of time, the volatility forecast is a function of the long-run variance level and a group of squared return observations. But the model assumes that positive and negative shocks have the same impact fluctuations. In practice, it is known that asset prices react differently to positive and negative shocks. At the same time, the main disadvantage with the ARCH model is that it requires a large amount of lags to capture volatility.

Another model to estimate volatility is known as the exponentially weighted moving average (EWMA) model, it can be seen as a specific case of a general weighting model, and the difference is that they assume that the weights decline exponentially back over time.

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2$$

Where λ is the weight on the estimation of previous volatility which has a value between 0 and 1, using the volatility calculated on day n-1 and latest squared return, we can estimate the volatility on day n. The influence of volatility and squared return in previous periods depends on the size of λ , a higher value of λ would increase the impact of volatility in the previous period, and a lower value of λ could maximise the effect of daily return on the estimation of current period volatility. This model requires less information, it only needs a current estimate of variance and the latest return, the estimation of variance in the current period will then feed into an estimation in the next period.

One of the most popular and widely applied methods to estimate volatility is known as generalised autoregressive conditional heteroskedastic GARCH (1,1) model developed by Bollerslev (1986), which explain the volatility of current period by using past volatility and past conditional volatility (Hwang and Satchell, 2005). This model not only incorporates the most recent estimates of variance and squared return, but also a variable that accounts for a long-run average level of variance.

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2$$

Where α stands for the weight on the return of the previous period, β represents the weight on an estimation of previous period volatility, and ω is the long term variance which equals γV_L. If we have ω equal to 0, α = $1-\lambda$, and $\beta = \lambda$, this model would be similar to the EWMA model, so EWMA is a special case of the GARCH model. By adding a weight to a variable of long-term variance estimate and that the variance tends to return to the long-term average, the GARCH model has a better theoretical justification than the EWMA model. The

GARCH model tends to be simplified, and a GARCH (1,1) model is usually sufficient.

In order to detect the relationship between market fluctuations and trading volume, Majand and Yung (1991) add the volume of transactions to the GARCH variance equation and use this model in the Treasury bond market to examine the relationship between the volatility of futures price and trading volume. According to their empirical results, they found that the current period volatility of futures prices of Treasury bonds can be explained by past volatility over time, and there is a positive correlation between trading volume and price volatility. Also, market volatility could be influenced by herding behaviour. As good news is exposed among investors, some of them are more likely to trade on a group of specific stocks and to be followed by other market participants making similar trading decisions, this could lead to abnormal returns and volatility on specific stocks in the market. Under this situation, Litimi, BenSaïda and Bouraoui (2016) introduce a method which adds CSAD results, as a proxy of herding behaviour, to the GARCH model in order to determine the influence of herding behaviour on the market volatility. Herding itself could increase the volatility of a particular stock, as investors mimic each other and trade a lot of that specific stock, which could have positive or negative influence on the stock price and corresponding volatility. However, since herding behaviour means a collective movement of investors toward a particular transaction, the overall market average volatility will decrease, and the consensus of investors will be reflected in the market average (Hwang and Salmon, 2004). Therefore, herding will have a positive impact on the volatility of a particular stock, while it will have a negative impact on the average market volatility. By investigating the US stock market and narrowing the focus down to a sectoral level, they have found that herding behaviour is present in the US market and in some sectors (but not all), herding is an important factor in increasing bubbles. Herding and trading volume have a restraining effect on the overall large-scale market and industry market fluctuations. Trading volume has an adverse effect on the fluctuations of the entire market and most industries, since the trading volume of informed traders is higher than that of ignorant traders, and the larger the observed trading, the higher the informed trading volume; therefore, market volatility is smaller. On the other hand, for those sectors that have less informed traders, trading volume could have a positive influence on conditional volatility. Since herding is the behaviour where investors mimic each other and towards a particular trade, then the overall market volatility will be decreased, and the market average should reflect this investor consensus. Hwang and Salmon (2004) have introduced the following regression model to estimates the current period volatility in the market:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma CSAD_t$$

With an average market return $R_{m,t} = \varepsilon_t \sim N(0, \sigma_t^2)$ which is normally distributed, coefficient γ will capture the evidence of the influence of herding effect, and conditional volatility.

9.4 Methodology

At first, in the analysis stage, we need to present a robust empirical result to show whether herding behaviour exists among each sector in the UK market. Given this, we apply the CCK method to detect the herding effect.

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}|$$

Where R_{mt} is the equally weighted average return in the market or different sector, and R_{it} stands for the return of single securities in each sector. As there would be a linear and increasingly positive relationship between CSAD result and market return R_{mt} if investors are rational, then if herding behaviour is present in the market, this relationship would become non- linear and negative, so that in order to capture the evidence of herding behaviour, we need to have a significantly negative coefficient of squared average market return in the following regression model:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

Due to the influence of the error term ε_t, it means the traditional model can only detect extreme herding behaviour in the market, so we introduce our solutions including solution 1 – the regression without a constant value, solution 2 – the SCSAD method, and solution 3 - considering larger market movements, these solutions avoid the disadvantages of the traditional model. By using the SCSAD model, we also need to have a significant negative coefficient of the cubic market return $R_{m,t}^3$ to confirm the existence of herding behaviour.

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$$

After this, we are going to investigate whether market volatility could be influenced by herding behaviour. It has long been widely accepted within the finance literature that returns volatility changes over time and that periods of high volatility tend to be found in clusters. The autoregressive conditional heteroskedastic (ARCH) model of Engle (1982) and the subsequent generalized autoregressive conditional heteroskedastic (GARCH) model proposed by Bollerslev (1986) have been developed as appealing techniques to address these well-known stylized facts. We apply a GARCH model here to estimate market volatility and examine the volatility influenced by those factors. This is similar to the research done by Litimi, BenSaïda and Bouraoui (2016) who examine the US market, and found herding has an impact on several sectors in the US market and can increase relative volatility. We are going to apply this method in the UK, as well as the German and France markets to detect the influence of herding in the selected markets.

We initially follow Litimi, BenSaïda and Bouraoui (2016) and directly use CSAD results as an influencing factor in the GARCH model. If CSAD is taken to be a measure of herding as in the Litimi, BenSaïda and Bouraoui (2016) paper, if there is more herding CSAD should be lower. So there should be a negative sign on CSAD if herding is positively related to volatility. In this case the regression model we will use is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma CSAD_t \qquad \text{(Equation 9.1)}$$

We also use the lagged CSAD results as the measure of herding:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma CSAD_{t-1} \qquad \text{(Equation 9.2)}$$

In this regression model, the CSAD results are factors that have an impact on volatility, and we will observe the significance of coefficient of these CSAD results to show the evidence of influence on market volatility.

Now there is an issue with this approach in that CSAD is a measure of dispersion of returns not of herding as such. There is herding if there is less dispersion than one would expect given some sort of underlying model of asset returns. In models broadly based on the assumption the asset prices follow the Capital asset pricing model (CAPM) the cross-sectional dispersion measurement would increase as market returns increase. Thus, one would expect CSAD to be positively related to herding regardless of whether there is herding present or not. It is more logical to use the level of dispersion compared to that expected as a measure of herding. In this respect we can consider the deviations from the expected amount of return dispersion. These deviations can be taken as the residuals when the underlying model of return dispersion is fitted. Negative residuals indicate there is less dispersion than expected and thus evidence of herding and conversely positive residuals are evidence of anti-herding. The size of the residuals can be taken as a measure of the magnitude of herding/anti-herding.

We initially modify the standard CCK regression model to capture the residual values in the equation in order to measure herding. By removing the independent variable of squared market return, we can use the residual from the CCK model to measure herding. In the modified CCK model if there is herding the actual residuals should be largely negative. Thus, we fit the modified CCK model to test herding.

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \nu_{1,t}$$

In this equation, $\nu_{1,t}$ stands for the residual from the regression model. We t use these residuals as an independent variable instead of CSAD in equation 9.1 With a negative residual value in the formula, if herding contributes to volatility, we should have a negative coefficient on the residuals in equation 9.3 and 9.4. Residual $\nu_{1,t}$ results as an influencing factor in the GARCH model the regression model we use is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{1,t} \qquad \text{(Equation 9.3)}$$

As we discussed earlier in the thesis, we have introduced the new methods which improve on the CCK approach to detect herding behaviour in the financial markets. In solution 1, we constrain the constant in the CCK regression to be zero, reducing the impact of error term in the CAPM when $|R_{m,t}|$ is small. Thus, we can also obtain residual values by using following equation.

$$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \nu_{2,t}$$

Then we fit the residual value $\nu_{2,t}$ into the modified GARCH model and can observe the impact of herding on market volatility using our improved approach to measuring herding.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{2,t} \qquad \text{(Equation 9.4)}$$

9.5 Empirical Results

In order to investigate the impact of herding on market volatility, we will apply various equations to estimate the market return volatility for each sector in different markets. First, we need to do unit root tests of the time series in our data sample, which will test whether the series are non-stationary and possess a unit root. Table below show the results of unit root test.

Table 9.5.1 Correlation test between CSAD results and Absolute average market return and variance

In the UK market (panel A)

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
	CSAD	CSAD	CSAD	CSAD	CSAD	CSAD
$\lvert R_{m,t} \rvert$	0.7213	0.6818	0.7440	0.6112	0.8143	0.7867
σ_t^2	0.6358	0.6109	0.6098	0.5464	0.3130	0.6346
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
	CSAD	CSAD	CSAD	CSAD	CSAD	CSAD
$\lvert R_{m,t} \rvert$	0.7397	0.7181	0.6851	0.7169	0.7702	0.5914
σ_t^2	0.3921	0.5788	0.4607	0.5947	0.4280	0.3112

In the markets of Germany and France (panel B)

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
	CSAD	CSAD	CSAD	CSAD	CSAD	CSAD
$\lvert R_{m,t} \rvert$	0.6000	0.6813	0.7149	0.5485	0.6931	0.7166
σ_t^2	0.5911	0.4031	0.5627	0.4611	0.3269	0.3159
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
	CSAD	CSAD	CSAD	CSAD	CSAD	CSAD
$\lvert R_{m,t} \rvert$	0.6508	0.6211	0.8393	0.8951	0.6420	0.6579
σ_t^2	0.3510	0.4605	0.4858	0.4575	0.5424	0.3522

According to the correlation test results between CSAD results and absolute average market return, we find that there is a highly positive relationship between the CSAD results and $\lvert R_{m,t} \rvert$, all sectors in the different markets have a correlation above 0.5. This is in according with our proposition above that there will inevitably be a strong correlation between CSAD and the absolute size of returns. Also, in the UK market, Communication, Consumer Discretionary, Consumer Staples, Financials, Industrials and Real Estate sector, as well as the whole market have a high correlation between the CSAD results and σ_t^2other sectors have less correlation between CSAD results and σ_t^2. In the markets of Germany and France, Consumer Discretionary, Technology sector and overall market have a high correlation between CSAD results and σ_t^2, other sectors have a lower correlation between CSAD results and σ_t^2.

Table 9.5.2 Augmented Dickey-Fuller Test Equation

In the UK market (panel A)

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
t-Statistic	-23.77806	-62.31826	-30.78465	-66.44631	-69.29120	-64.16810
Prob.*	0.0000***	0.0001***	0.0000***	0.0001***	0.0001***	0.0001***
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
t-Statistic	-68.21534	-23.98498	-65.35836	-45.33847	-35.14760	-72.48976
Prob.*	0.0001***	0.0000***	0.0001***	0.0001***	0.0000***	0.0001***

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)

Augmented Dickey-Fuller Test Equation

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
t-Statistic	-32.18287	-67.50634	-77.15844	-67.68993	-77.01821	-73.31639
Prob.*	0.0000***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
t-Statistic	-33.23922	-49.53855	-86.83003	-54.49832	-31.19154	-70.65521
Prob.*	0.0000***	0.0001***	0.0001***	0.0001***	0.0000***	0.0001***

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

According to the results shown in table 9.5.2, in both panel A and panel B the unit root tests are all highly significant, thus we can reject the hypothesis that the time series are non-stationary. Also, we confirm that the data series have the ARCH effect. Then we can fit the GARCH model to estimate the volatility. Throughout, this chapter we use Maximum Likelihood Estimation to fit the various GARCH models.

9.6 Estimation of average market conditional volatility using CSAD results

Table 9.6.1 Estimation of market volatility using CSAD results

In the UK market (panel A)

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma CSAD_t$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.128754*** (-29.11915)	-0.033797*** (-14.19051)	-0.195662*** (-26.14564)	-0.031275*** (-14.71429)	-0.068168*** (-9.619160)	-0.079344*** (-16.39245)
σ_{t-1}^2	0.925425*** (225.2877)	0.945744*** (284.9477)	0.887333*** (204.8421)	0.955683*** (292.0276)	0.969107*** (314.7251)	0.934830*** (226.5974)
$CSAD_t$	0.086209*** (12.18848)	0.048265*** (14.81863)	0.259492*** (24.13030)	0.042668*** (12.55700)	0.040330*** (6.239057)	0.107932*** (12.30909)
Constant	-0.086579*** (-9.081742)	-0.033781*** (-7.234381)	-0.294761*** (-19.14027)	-0.027891*** (-8.083393)	4.09E-05 (0.002121)	-0.070229*** (-7.576819)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.942927	0.960923	0.928558	0.958055	0.953261	0.942918
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.010497*** (-2.967658)	-0.152051*** (-27.80018)	-0.043764*** (-13.31834)	-0.159025*** (-21.75664)	-0.092547*** (-17.78979)	-0.038115*** (-6.028463)
σ_{t-1}^2	0.920502*** (194.2128)	0.923677*** (219.7047)	0.957891*** (277.4935)	0.924377*** (214.0446)	0.934564*** (219.6328)	0.920094*** (189.4454)
$CSAD_t$	0.044214*** (12.37482)	0.104154*** (11.44762)	0.031125*** (7.704386)	0.169580*** (12.69566)	0.057371*** (10.09922)	0.119146*** (12.78954)
Constant	-0.006521 (-0.918846)	-0.096519*** (-7.980704)	-0.013817*** (-1.745245)	-0.112628*** (-7.499632)	-0.042020*** (-4.027900)	-0.033982*** (-3.253938)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.893646	0.933669	0.948580	0.932252	0.917879	0.881454

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma CSAD_t$$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.049357*** (-18.37288)	-0.015420*** (-3.684002)	-0.038547*** (-14.04712)	-0.011413*** (-7.393796)	-0.024247*** (-4.771366)	-0.056480*** (-8.259074)
σ_{t-1}^2	0.944160*** (251.6528)	0.958217*** (273.7105)	0.966160*** (348.1925)	0.951797*** (269.9419)	0.953919*** (268.4961)	0.917736*** (175.7387)
$CSAD_t$	0.045217*** (11.33463)	0.040423*** (8.708272)	0.034214*** (11.36956)	0.027653*** (12.36874)	0.066852*** (12.12049)	0.051230*** (7.259884)
Constant	-0.051024*** (-7.489943)	-0.025021*** (-2.520602)	-0.033966*** (-6.005309)	-0.011212*** (-4.152641)	-0.021285*** (-1.379229)	-0.011305*** (-0.773760)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.948740	0.943467	0.970743	0.945458	0.937649	0.865508
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.021879*** (-5.114281)	-0.037781*** (-11.62172)	-0.008005 (-1.457691)	0.048059*** (3.718951)	-0.037911*** (-11.24345)	-0.018087*** (-9.461369)
σ_{t-1}^2	0.921460*** (199.2433)	0.935148*** (237.0963)	0.956437*** (376.9137)	0.946446*** (321.2832)	0.953933*** (312.7734)	0.959613*** (283.9696)
$CSAD_t$	0.073550*** (15.90541)	0.057454*** (14.87391)	0.116370*** (24.62873)	0.237147*** (25.81135)	0.067428*** (14.57009)	0.026568*** (10.48014)
Constant	-0.058116*** (-5.697269)	-0.055763*** (-7.252607)	-0.134777*** (-13.54156)	-0.458216*** (-17.19484)	-0.090191*** (-9.141762)	-0.003682 (-1.025121)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.894664	0.930938	0.971957	0.961164	0.962924	0.944791

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

Based on the results under the approach using equation 9.1, and use CSAD as an independent variable, we find out that the conditional volatility of the average market return in each sector was positively affected by CSAD among different markets. However, CSAD is a measure of how much returns are dispersed rather than of herding as such. Given most asset pricing models, such as the CAPM, we would expect dispersion to increase as market returns increase. Thus, as discussed above, we need to employ a measure of herding which allows for this effect.

9.7 Estimation of average market conditional volatility using residual results

Table 9.6.2 Estimation of market volatility using residual values

In the UK market (panel A)

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1} + \beta_1\sigma_{t-1}^2 + \gamma\nu_{1,t}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.133272*** (-30.53630)	-0.035466*** (-14.83417)	-0.216610*** (-28.77513)	-0.033052*** (-15.55016)	-0.069514*** (-9.798689)	-0.084174*** (-17.64718)
σ_{t-1}^2	0.937624*** (264.4207)	0.958357*** (318.7614)	0.914631*** (226.5632)	0.965741*** (320.8145)	0.973570*** (329.1769)	0.946349*** (267.7835)
$\nu_{1,t}$	0.113129*** (12.93175)	0.049781*** (12.35024)	0.275109*** (18.56721)	0.040740*** (10.34722)	0.046706*** (4.346800)	0.168106*** (13.90537)
Constant	0.030805*** (8.685353)	0.032035*** (9.944448)	0.060035*** (8.618807)	0.014138*** (7.868387)	0.046706*** (5.197951)	0.041932*** (8.303089)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.943118	0.960453	0.925615	0.957671	0.953089	0.943344
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.013648*** (-3.845716)	-0.157900*** (-29.09036)	-0.044915*** (-13.68808)	-0.166309*** (-22.57860)	-0.096692*** (-18.52808)	-0.040001*** (-6.238426)
σ_{t-1}^2	0.930886*** (203.0828)	0.937126*** (251.0321)	0.962879*** (300.9954)	0.947101*** (245.4434)	0.947545*** (236.8895)	0.934620*** (196.4988)
$\nu_{1,t}$	0.049457*** (9.612915)	0.120054*** (10.43733)	0.042142*** (8.162798)	0.102740*** (6.027566)	0.045690*** (5.445319)	0.056894*** (5.020192)
Constant	0.062193*** (11.52958)	0.038693*** (8.033983)	0.041552*** (8.230660)	0.056512*** (6.725595)	0.047231*** (7.586356)	0.060794*** (7.968069)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.892475	0.933404	0.948648	0.930702	0.916789	0.878442

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1} + \beta_1\sigma_{t-1}^2 + \gamma\nu_{1,t}$$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.051694*** (-19.25488)	-0.017258*** (-4.112732)	-0.040939*** (-14.90510)	-0.012356*** (-7.966378)	-0.026066*** (-5.099034)	-0.060216*** (-8.830359)
σ_{t-1}^2	0.954571*** (273.5776)	0.965859*** (289.3040)	0.974419*** (386.0973)	0.961267*** (283.9257)	0.962893*** (280.0841)	0.924542*** (182.4873)
$\nu_{1,t}$	0.039745*** (8.612007)	0.031597*** (5.223692)	0.036414*** (9.319959)	0.021909*** (8.548089)	0.067808*** (9.116102)	0.051757*** (5.298325)
Constant	0.027824*** (9.190887)	0.045454*** (6.777147)	0.025035*** (6.787085)	0.018056*** (9.547463)	0.100780*** (8.062662)	0.079134*** (9.083053)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.948233	0.942963	0.970517	0.944665	0.936926	0.864900
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.027474*** (-6.344756)	-0.040624*** (-12.38261)	-0.021395*** (-3.789634)	-0.013946 (-1.038306)	-0.041687*** (-12.27819)	-0.018625*** (-9.686166)
σ_{t-1}^2	0.935588*** (204.4645)	0.949502*** (251.5819)	0.976344*** (404.1413)	0.976195*** (339.3792)	0.967089*** (342.9876)	0.967022*** (295.1941)
$\nu_{1,t}$	0.052244*** (8.667071)	0.045401*** (9.652964)	0.118312*** (14.35369)	0.077432*** (3.891971)	0.055115*** (9.855257)	0.021291*** (6.523332)
Constant	0.072773*** (10.49633)	0.046402*** (9.913140)	0.036566*** (4.643797)	0.047076** (2.436359)	0.043951*** (7.823468)	0.023371*** (8.295944)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.891256	0.929334	0.969961	0.956513	0.962150	0.944111

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

We can use the residual values from the CCK model (Equation 3.3) as a measure of herding. These measure the difference in returns dispersion from that expected given the underlying asset pricing model. If the residuals are negative this will indicate less dispersion and thus more herding than expected under the asset pricing model. Based on the results under the approach using equation 9.3 and using residual values in the CCK model as the measure of herding, we find out that there is a direct linear relationship between herding and market volatility. The coefficient of residual value is significantly positive among each sector in the different markets, so this indicates that herding is negatively associated with contemporaneous volatility.

9.8 Estimation of average market conditional volatility using residual from solution 1 results

Table 9.6.3 Estimation of market volatility using residual value from solution 1

In the UK market (panel A)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{2,t}$$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.138203*** (-31.35712)	-0.036450*** (-15.07156)	-0.231040*** (-29.97010)	-0.034263*** (-15.98604)	-0.070074*** (-9.867092)	-0.089576*** (-18.60317)
σ_{t-1}^2	0.957955*** (288.3795)	0.973631*** (354.9620)	0.944005*** (246.8168)	0.977524*** (346.6076)	0.975043*** (330.9002)	0.966448*** (295.2375)
$\nu_{2,t}$	0.022081*** (4.632133)	0.013012*** (4.691130)	0.038756*** (4.040284)	0.005887** (2.355479)	0.022225** (2.263853)	0.063039*** (7.616413)
Constant	0.007634* (1.647125)	0.013075*** (3.934820)	0.016973* (1.887137)	0.007113*** (3.479802)	0.060332*** (3.676679)	0.001357 (0.227493)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.941594	0.959505	0.921122	0.956879	0.952970	0.941944
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.014109*** (-3.938649)	-0.161771*** (-29.59276)	-0.045391*** (-13.76468)	-0.166872*** (-22.57676)	-0.096690*** (-18.46206)	-0.037445*** (-5.816210)
σ_{t-1}^2	0.941160*** (210.0623)	0.951545*** (265.5558)	0.970576*** (312.8992)	0.955819*** (265.9022)	0.951555*** (241.1965)	0.936520*** (197.0763)
$\nu_{2,t}$	0.012946*** (3.216859)	0.019999*** (2.947618)	0.017180*** (4.651687)	-0.011059 (-0.890466)	-0.006165 (-1.001391)	-0.014886 (-1.456179)
Constant	0.046034*** (8.097825)	0.019094*** (3.063014)	0.021471*** (3.812797)	0.052258*** (5.246937)	0.047225*** (6.372371)	0.063311*** (7.650608)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.890850	0.932174	0.948223	0.930247	0.916349	0.877925

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)
$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{2,t}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.052932*** (-19.59723)	-0.018014*** (-4.284647)	-0.041525*** (-14.98975)	-0.013235*** (-8.494031)	-0.025987*** (-5.053941)	-0.062281*** (-9.120162)
σ_{t-1}^2	0.968490*** (311.0899)	0.970060*** (298.6419)	0.982978*** (418.1189)	0.970861*** (301.8335)	0.967124*** (281.7773)	0.929297*** (185.6429)
$\nu_{2,t}$	-0.000520 (-0.221562)	0.000965 (0.205600)	0.010092*** (3.569173)	-5.96E-05 (-0.035277)	0.032331*** (4.857472)	0.007582 (1.025551)
Constant	0.019532*** (5.848968)	0.039025*** (5.333283)	0.010144 (2.563844)	0.013641*** (6.995060)	0.071131*** (5.416412)	0.069359*** (7.010957)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.947525	0.942676	0.970115	0.943919	0.936236	0.864227
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.027322*** (-6.254185)	-0.041113*** (-12.41482)	-0.024695*** (-4.316252)	-0.012789 (-0.955301)	-0.042090*** (-12.26059)	-0.018611*** (-9.638915)
σ_{t-1}^2	0.943781*** (209.2942)	0.959944*** (263.2640)	0.982907*** (410.6838)	0.977740*** (345.9369)	0.976954*** (366.9634)	0.971288*** (301.4008)
$\nu_{2,t}$	-0.008130* (-1.783236)	-0.001548 (-0.487284)	0.054059*** (7.096606)	-0.119516*** (-6.869518)	0.001500 (0.412744)	0.001221 (0.472709)
Constant	0.068819*** (9.188433)	0.037832*** (7.383408)	0.003607 (0.425877)	0.124498*** (5.513446)	0.028942*** (4.576676)	0.019938*** (6.784750)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.889813	0.928123	0.969106	0.956768	0.961474	0.943674

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

We use the residual values from solution 1 (Equation 5.2) to investigate the impact of herding behaviour on market volatility. As discussed earlier in the thesis, solution 1 allows for the shortcomings of the CCK test of herding so should be more appropriate. In the UK market, we find out that there is a positive coefficient of residual value, indicating a negative effect of herding, from solution 1, and a positive and significant coefficient in the overall market, Communication, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials and Materials sectors. Herding behaviour does not have either a positive or negative impact on the Real Estate, Technology and Utilities sectors. In the markets of Germany and France, market volatility is significantly negatively influenced by the herding effect in the Consumer Discretionary, Energy and Materials sectors, and herding behaviour has a significant positive impact on the Real Estate sector. Volatility in the Health Care sector is also positively influenced by herding behaviour with significance at the 10% level. Other sectors do not have clear evidence of market volatility being influenced by herding behaviour.

9.9 Estimation of average market conditional volatility using lagged CSAD results

Table 9.6.4 Estimation of market volatility using lagged CSAD results

In the UK market (panel A)

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1} + \beta_1\sigma_{t-1}^2 + \gamma CSAD_{t-1}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.120476*** (-29.66009)	-0.033955*** (-16.52610)	-0.191573*** (-27.83424)	-0.029256*** (-14.62833)	-0.057245*** (-11.59485)	-0.065310*** (-16.46972)
σ_{t-1}^2	0.874581*** (225.0688)	0.892358*** (304.6292)	0.842375*** (198.1401)	0.927210*** (295.7328)	0.923573*** (428.6837)	0.850445*** (245.2986)
$CSAD_{t-1}$	0.220211*** (33.10759)	0.132115*** (46.08992)	0.411934*** (39.36711)	0.094817*** (29.17760)	0.344852*** (76.28341)	0.385158*** (52.56652)
Constant	-0.253078*** (-28.44058)	-0.122928*** (-30.43772)	-0.482926*** (-32.92478)	-0.072869*** (-22.32220)	-0.557865*** (-41.65408)	-0.315220*** (-41.09499)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.951225	0.970788	0.938474	0.962693	0.977297	0.961134
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.014943*** (-5.606844)	-0.142694*** (-28.05086)	-0.046857*** (-16.88283)	-0.144142*** (-21.69588)	-0.077179*** (-18.73668)	-0.025907*** (-4.959342)
σ_{t-1}^2	0.847803*** (233.7029)	0.879584*** (219.5675)	0.905519*** (308.0400)	0.869013*** (217.6371)	0.867222*** (254.4002)	0.870153*** (214.2316)
$CSAD_{t-1}$	0.180117*** (65.99941)	0.264814*** (30.68604)	0.162955*** (47.44511)	0.453194*** (36.67251)	0.264716*** (58.19927)	0.410821*** (52.68916)
Constant	-0.180751*** (-33.98334)	-0.290956*** (-25.55581)	-0.212998*** (-31.88883)	-0.377057*** (-27.42618)	-0.345677*** (-41.83476)	-0.252828*** (-29.48940)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.939364	0.942119	0.963269	0.944104	0.948507	0.919237

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1} + \beta_1\sigma_{t-1}^2 + \gamma CSAD_{t-1}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.047047*** (-18.96402)	-0.010853*** (-3.457108)	-0.033476*** (-14.49153)	-0.010666*** (-7.607571)	-0.030272*** (-7.685328)	-0.043097*** (-8.560425)
σ_{t-1}^2	0.901560*** (255.0985)	0.899878*** (339.6973)	0.918185*** (387.8987)	0.916892*** (281.5269)	0.910152*** (327.0508)	0.845833*** (217.7465)
$CSAD_{t-1}$	0.120137*** (32.10420)	0.230316*** (65.67810)	0.125613*** (48.98493)	0.073948*** (35.93433)	0.267966*** (62.04336)	0.353691*** (67.67567)
Constant	-0.165928*** (-26.17694)	-0.325448*** (-43.72815)	-0.165933*** (-34.79098)	-0.051383*** (-21.01422)	-0.343221*** (-28.91898)	-0.511769*** (-47.54502)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.955908	0.968077	0.979236	0.954708	0.962551	0.926390

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.028181*** (-7.772862)	-0.036820*** (-12.69632)	-0.018387*** (-5.992535)	-0.000869 (-0.100772)	-0.043485*** (-14.30863)	-0.014081*** (-8.743201)
σ_{t-1}^2	0.874591*** (218.3623)	0.893128*** (248.4942)	0.901215*** (615.5280)	0.895561*** (437.1737)	0.918535*** (326.8758)	0.921711*** (321.2583)
$CSAD_{t-1}$	0.196378*** (49.17595)	0.142393*** (40.53754)	0.316050*** (116.6487)	0.555127*** (88.00374)	0.162634*** (38.29792)	0.105364*** (48.92096)
Constant	-0.250278*** (-29.16098)	-0.187653*** (-27.38266)	-0.396124*** (-70.99613)	-1.114578*** (-61.64676)	-0.256311*** (-28.70774)	-0.072798*** (-24.22764)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.923759	0.944840	0.991117	0.982044	0.969677	0.960923

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

Using lagged CSAD results to forecast market volatility, we can find out that in the UK market as well as the markets of Germany and France, all sectors in the different markets have significantly positive coefficients of lagged CSAD results.

9.10 Estimation of average market conditional volatility using lagged residual results

Table 9.6.4 Estimation of market volatility using lagged residual values

In the UK market (panel A)

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{1,t-1}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.134439*** (-31.49639)	-0.035140*** (-14.77418)	-0.228486*** (-29.81335)	-0.034227*** (-16.25371)	-0.070331*** (-9.959234)	-0.087886*** (-18.57926)
σ_{t-1}^2	0.986698*** (278.2393)	0.995051*** (328.2156)	0.962193*** (225.7088)	0.993965*** (329.9306)	0.972156*** (329.7296)	0.991252*** (277.2205)
$\nu_{1,t-1}$	-0.171839*** (-19.77403)	-0.059125*** (-14.56840)	-0.146028*** (-9.411754)	-0.055294*** (-14.04650)	0.087305*** (8.154270)	-0.195332*** (-16.03063)
Constant	0.006216* (1.778631)	0.002572 (0.796910)	0.026606*** (3.713944)	0.003002* (1.677475)	0.083016*** (5.502584)	0.006561 (1.299741)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.945308	0.960872	0.922157	0.958350	0.953496	0.943979
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.013425*** (-3.752356)	-0.158647*** (-29.58669)	-0.044358*** (-13.47710)	-0.163926*** (-22.69180)	-0.096829*** (-18.51219)	-0.038117*** (-6.017421)
σ_{t-1}^2	0.939350*** (201.8410)	0.970992*** (259.3362)	0.975210*** (302.3621)	0.978864*** (257.6854)	0.953806*** (237.2305)	0.930585*** (197.3995)
$\nu_{1,t-1}$	0.009692* (1.855806)	-0.173764*** (-15.13262)	-0.030889*** (-5.930776)	-0.267830*** (-15.97464)	-0.018571*** (-2.206146)	0.133800*** (11.93071)
Constant	0.054475*** (9.974158)	0.018177*** (3.803041)	0.027599*** (5.436053)	0.022819*** (2.766933)	0.041397*** (6.627969)	0.064487*** (8.537952)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.890711	0.934819	0.948352	0.933374	0.916409	0.881002

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)
$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{1,t-1}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.052038*** (-19.60083)	-0.017965*** (-4.316971)	-0.040653*** (-14.81671)	-0.013194*** (-8.489965)	-0.025232*** (-4.911403)	-0.062129*** (-9.270654)
σ_{t-1}^2	0.991222*** (284.2440)	0.961278*** (289.4739)	0.993440*** (391.4796)	0.977188*** (285.4772)	0.964085*** (277.9938)	0.915760*** (183.1546)
$\nu_{1,t-1}$	-0.062606*** (-13.60985)	0.063597*** (10.57616)	-0.039111*** (-9.956991)	-0.013681*** (-5.295106)	0.038359*** (5.114037)	0.137968*** (14.33443)
Constant	0.005029* (1.669954)	0.051731*** (7.764667)	0.006166* (1.668515)	0.010685*** (5.599508)	0.097538*** (7.747541)	0.088381*** (10.29834)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.949259	0.943835	0.970583	0.944208	0.936266	0.869160
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.027827*** (-6.382681)	-0.040831*** (-12.38304)	-0.024577*** (-4.324881)	-0.015779 (-1.177210)	-0.041479*** (-12.28144)	-0.018589*** (-9.629945)
σ_{t-1}^2	0.942862*** (203.4092)	0.967339*** (252.9332)	0.977174*** (398.5345)	0.975504*** (339.1539)	0.990038*** (350.3600)	0.971219*** (294.3753)
$\nu_{1,t-1}$	0.004697 (0.769412)	-0.029301*** (-6.151050)	0.093429*** (11.17989)	0.102039*** (5.132676)	-0.070003*** (-12.49291)	0.000307 (0.093307)
Constant	0.064544*** (9.215004)	0.029969*** (6.341447)	0.035278*** (4.440476)	0.048409** (2.507716)	0.011947** (2.130241)	0.020420*** (7.204946)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.889761	0.928618	0.969522	0.956603	0.962550	0.943672

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

Using lagged residual values from the CCK model as the measure of herding to estimate the impact of herding on market volatility we found mixed results in the UK market, the signs of lagged residual values from the CCK model have mostly changed from the non-lagged regression. We see that the Consumer Discretionary, Consumer Staples, Financials, Industrials, Materials, Real Estate, Technology sectors and the overall market show a significantly negative coefficient of lagged residual values from the CCK model, which is indicative that market volatility is positively influenced by herding behaviour. Herding behaviour in the Communication and Energy and Utility sectors has an inhibiting effect on market volatility and there is also evidence of this in the Health Care sector with significance at the 10% level. In the markets of Germany and France, we have captured clear evidence that herding behaviour has a significant positive impact on the volatility of the entire market, and the Consumer Discretionary, Consumer Staples, Industrials and Technology sectors. Also, in Communication, Energy, Financials, Materials and Real Estate sectors, herding behaviour in the markets has an inhibiting effect on the market, shown by significantly positive coefficients of lagged residual value. Both Health Care and Utilities sectors were neither positively nor negatively influenced by herding behaviour.

9.11 Estimation of average market conditional volatility using lagged residual from solution 1 residual results

Table 9.6.4 Estimation of market volatility using lagged residual values from solution 1

In the UK market (panel A)

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2 + \gamma \nu_{2,t-1}$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.139400*** (-43.34468)	-0.033742*** (-18.47173)	-0.231037*** (-35.07821)	-0.036727*** (-22.63631)	-0.068980*** (-9.913093)	-0.089013*** (-23.60769)
σ_{t-1}^2	0.937007*** (387.3569)	0.986461*** (475.7794)	0.946456*** (289.5885)	0.974717*** (456.6261)	0.974172*** (337.4827)	0.968240*** (377.6924)
$\nu_{2,t-1}$	-0.240333*** (-69.27671)	-0.134650*** (-64.21303)	-0.369024*** (-45.02732)	-0.120376*** (-63.62991)	-0.146319*** (-15.21657)	-0.384102*** (-59.27208)
Constant	0.172195*** (51.16480)	0.078510*** (31.36809)	0.251027*** (32.76616)	0.059548*** (38.53584)	0.168184*** (10.47652)	0.175374*** (37.77067)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.968898	0.976906	0.942420	0.975290	0.954854	0.964397
	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.012268*** (-3.873830)	-0.165535*** (-38.31547)	-0.044363*** (-16.53392)	-0.166976*** (-27.91622)	-0.095631*** (-21.49898)	-0.038494*** (-6.085788)
σ_{t-1}^2	0.948650*** (238.9826)	0.930504*** (329.1155)	0.964144*** (381.8951)	0.957936*** (329.2489)	0.937637*** (279.4883)	0.933314*** (199.1653)
$\nu_{2,t-1}$	-0.137923*** (-38.77053)	-0.306178*** (-57.21111)	-0.158543*** (-52.78208)	-0.536745*** (-53.41184)	-0.238311*** (-45.62242)	-0.126565*** (-12.59830)
Constant	0.118179*** (23.53405)	0.209190*** (42.60116)	0.145016*** (31.74145)	0.287138*** (35.56080)	0.200985*** (31.88972)	0.098539*** (12.06893)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.914382	0.957641	0.965663	0.954292	0.939545	0.881351

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the markets of Germany and France (panel B)

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1} + \beta_1\sigma_{t-1}^2 + \gamma\nu_{2,t-1}$$

Sector	All	Communication	Consumer Discretionary	Consumer Staples	Energy	Financials
ε_{t-1}	-0.052515*** (-27.70059)	-0.016528*** (-4.179509)	-0.040575*** (-17.95026)	-0.014065*** (-11.64313)	-0.024119*** (-4.903064)	-0.060842*** (-9.378017)
σ_{t-1}^2	0.966935*** (442.1608)	0.970431*** (317.6533)	0.989009*** (514.5334)	0.974081*** (390.6343)	0.965948*** (294.0883)	0.926500*** (194.7970)
$\nu_{2,t-1}$	-0.122860*** (-74.60847)	-0.117359*** (-26.59878)	-0.120170*** (-52.06814)	-0.078594*** (-59.98998)	-0.145234*** (-22.82184)	-0.169504*** (-24.14675)
Constant	0.108609*** (46.25074)	0.117056*** (17.00862)	0.086698*** (26.84225)	0.044941*** (29.71762)	0.173973*** (13.88743)	0.182147*** (19.40770)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.974110	0.949293	0.980031	0.966295	0.941572	0.877388

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
ε_{t-1}	-0.028743*** (-7.594943)	-0.041380*** (-15.96882)	-0.024657*** (-4.337086)	-0.015564*** (-1.203505)	-0.041028*** (-16.24112)	-0.019378*** (-11.350640
σ_{t-1}^2	0.944265*** (241.1858)	0.955298*** (334.4277)	0.986535*** (414.2813)	0.976039*** (357.0566)	0.972172*** (495.0929)	0.971144*** (340.7685)
$\nu_{2,t-1}$	-0.166297*** (-42.11714)	-0.145250*** (-58.43692)	-0.083001*** (-10.95463)	-0.348835*** (-20.74613)	-0.180334*** (-67.42442)	-0.088761*** (-38.87082)
Constant	0.171820*** (26.36605)	0.139665*** (34.75281)	0.056055*** (6.674413)	0.282261*** (12.90165)	0.186234*** (39.92949)	0.052006*** (20.01549)
N	5425	5425	5425	5425	5425	5425
adj. R^2	0.916931	0.955900	0.969495	0.959599	0.979045	0.955950

t-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

We use lagged residual values from solution 1 which fits the CCK model and uses the regression without a constant value as the measure of herding to detect the impact of herding on market volatility. The results clearly show that in the UK market and in the markets of Germany and France, all sectors in the different markets have a significantly negative coefficient of lagged residual value from solution 1. Which is indicates that market volatility in different markets is significantly positively influenced by herding behaviour in the market, shown that herding behaviour in the market contributes to market volatility.

From the prior research, we have found out that the different types of relationship between herding and market volatility. Litimi, BenSaïda and Bouraoui (2016) find out that herding may inhibit market volatility, Blasco, Corredor and Ferreruela (2012), Messis and Zapranis (2014), Venezia, Nashikkar and Shapira (2011), Fei and Liu (2021), Baur and Dimpfl (2018), Yamamoto (2010) and Di Guilmi, He and Li (2013) find out that herding have significant impact on market volatility. Also, Gavriilidis, Kallinterakis and Ferreira (2013), Balcilar and Demirer (2013) and Akinsomi, Coskun, Gupta and Lau (2018) find out that investors tend to present herding behaviour during different level of market fluctuation. In this chapter, using CSAD result as an independent variable is not a proper way to test the influence of herding behaviour on market volatility as the CSAD is a measure of how much returns are dispersed rather than of herding as such. Using the residual value from the CCK model could avoid the disadvantages by using CSAD variable, as the residual value measure the difference in returns dispersion from that expected given the underlying asset pricing model, and we expected a negative coefficient of the residual value. According to our results, we have found directly linear relationship between herding and market volatility, indicates that herding is negatively associated with contemporaneous volatility among each sector in different markets. And partial evidence of market volatility is influenced by herding behaviour while using solution 1. Using lagged results, when we fit CSAD results as an independent variable, we do not have clear evidence to show the impact of herding behaviour on market volatility. While using lagged residual value from CCK model, we have captured the evidence of herding behaviour have positive impact on market volatility in different sectors. Also, in sectors such as Energy and Communication, herding behaviour have inhibited effect on the market volatility in different markets. Which is consistent with the results presented by Litimi, BenSaïda and Bouraoui (2016). The results using lagged residual value from solution 1, we have the market volatility in all the sectors in different markets is significantly positively influenced by herding behaviour in the market, shown that herding behaviour in the market contributes to market volatility. Which consistent with most of the prior literature that the herding could cause the market volatility.

9.12 Standard deviation of average sector returns

Figure 9.1 to 9.11 Standard deviation of average sector returns in the UK market

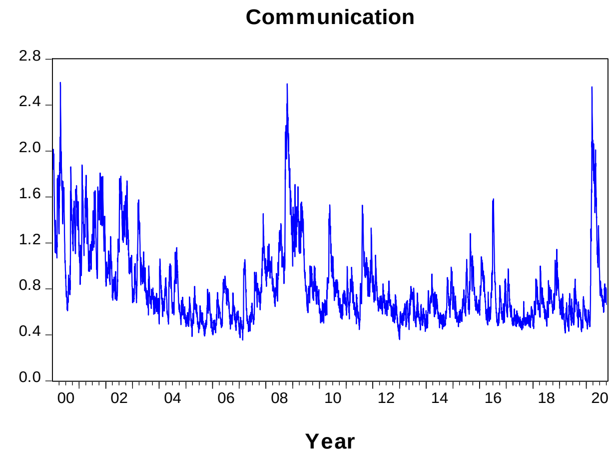

Figure 9.1

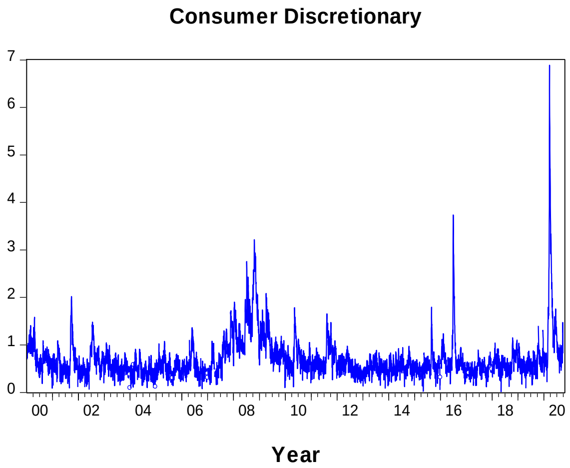

Figure 9.2

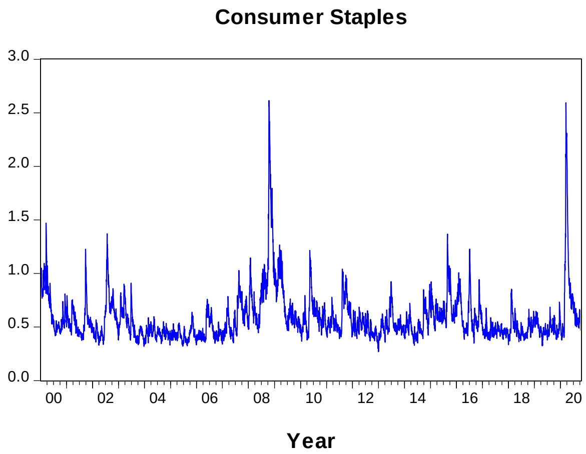

Figure 9.3

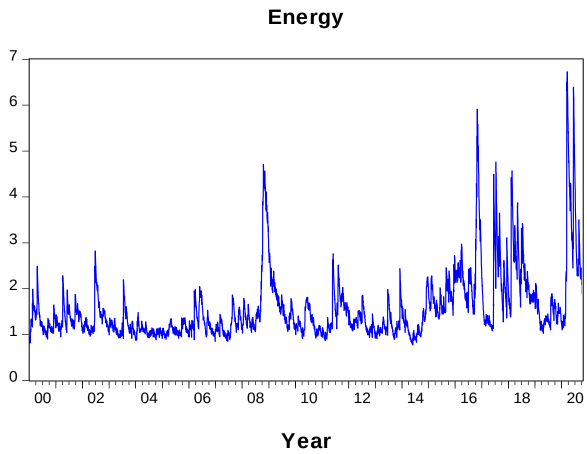

Figure 9.4

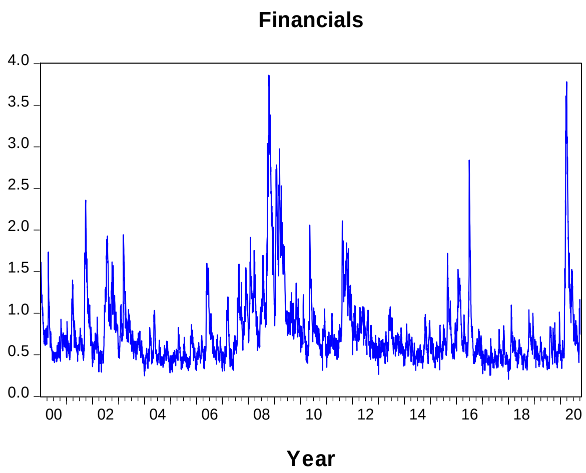

Figure 9.5

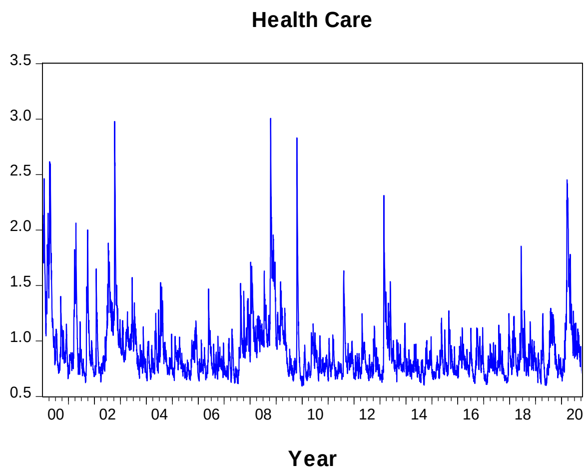

Figure 9.6

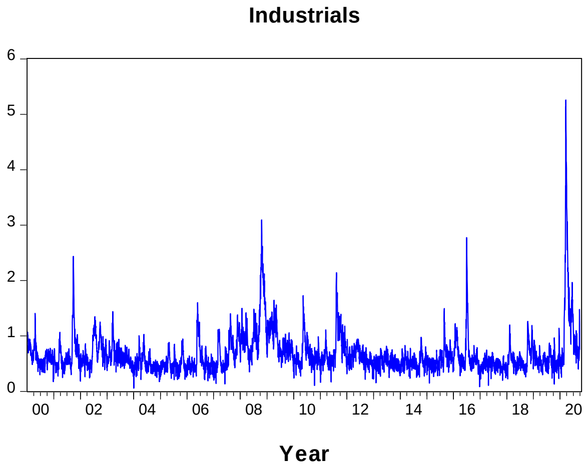

Figure 9.7

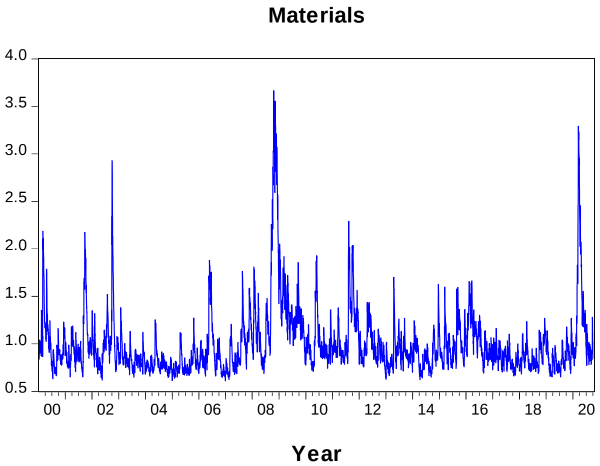

Figure 9.8

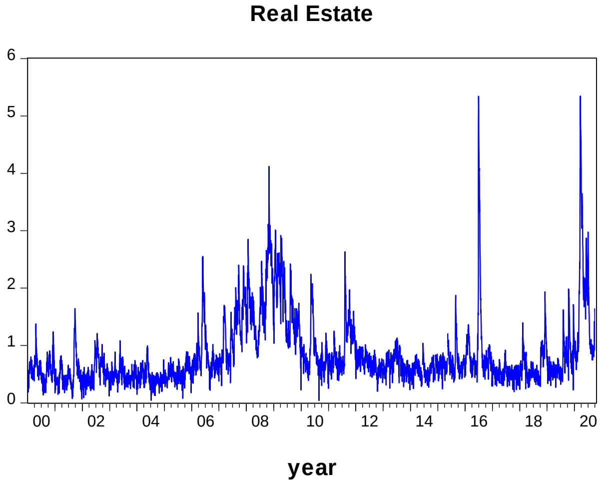

Figure 9.9

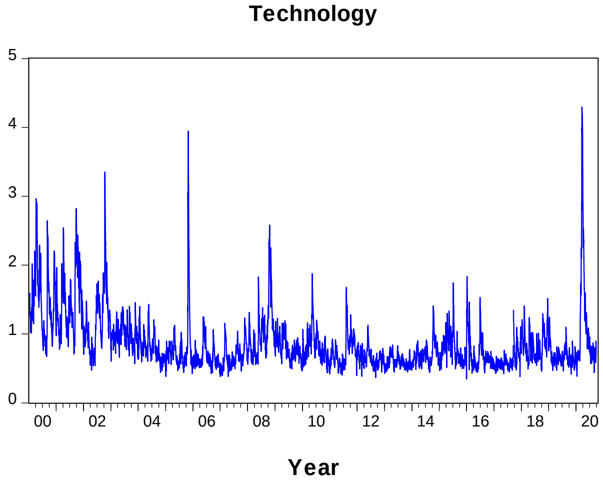

Figure 9.10

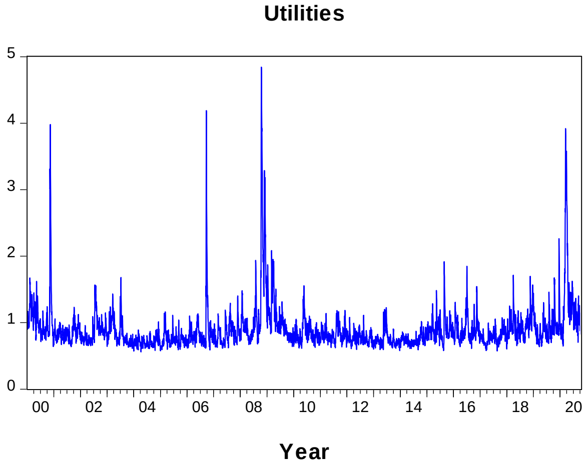

Figure 9.11

Figure 9.12 to 9.22 Standard deviation of average sector returns in the markets of Germany and France

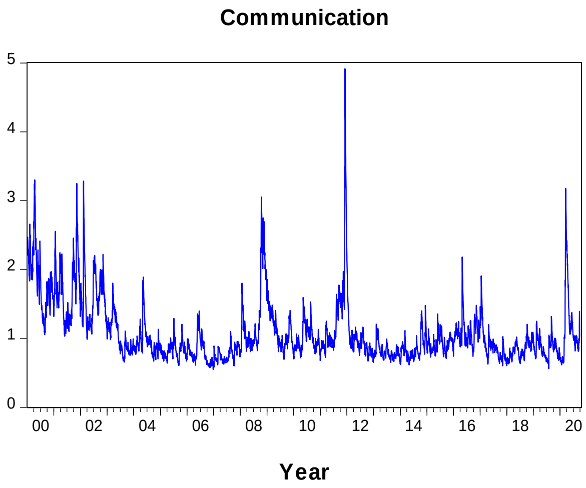

Figure 9.12

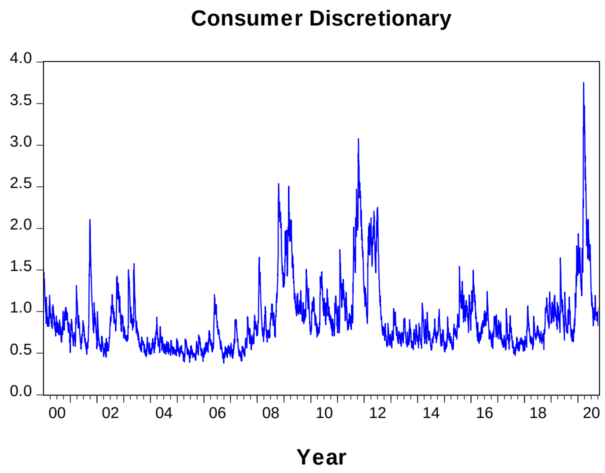

Figure 9.13

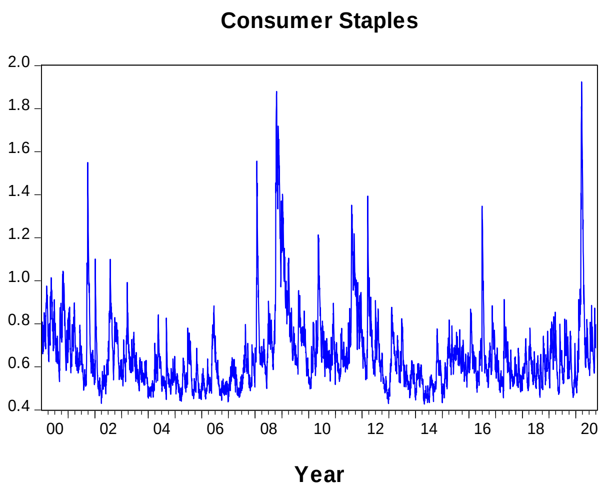

Figure 9.14

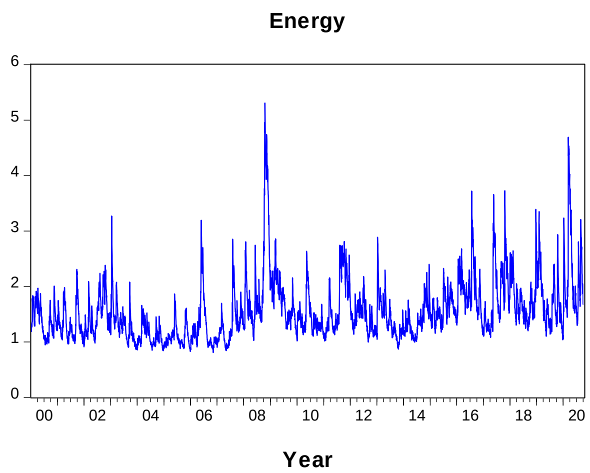

Figure 9.15

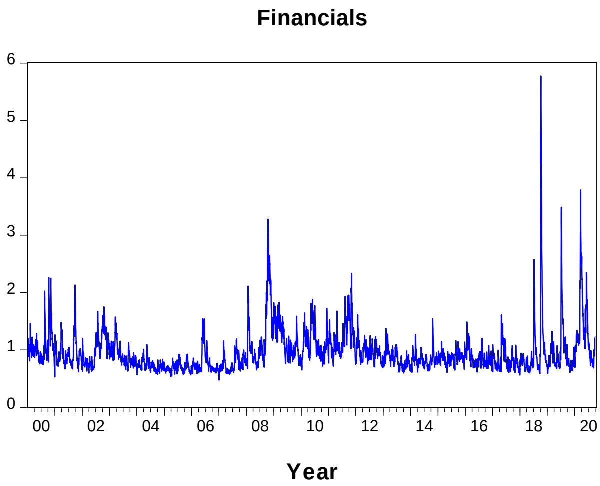

Figure 9.16

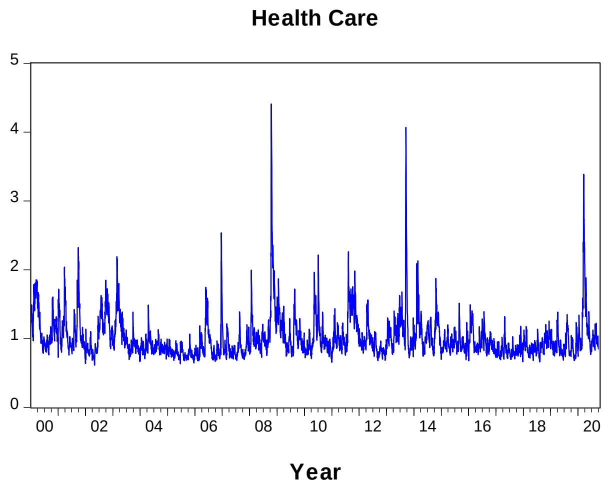

Figure 9.17

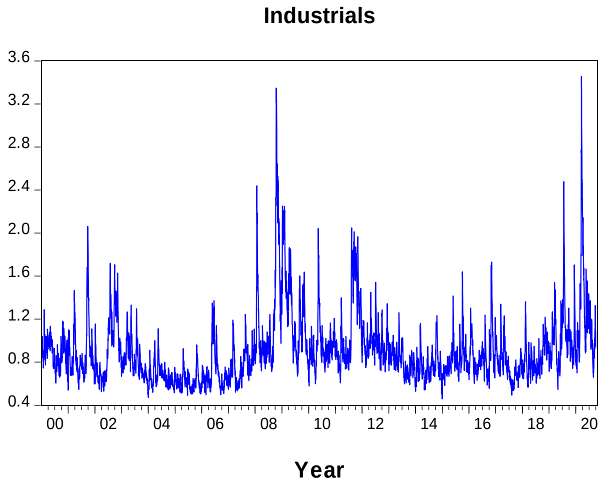

Figure 9.18

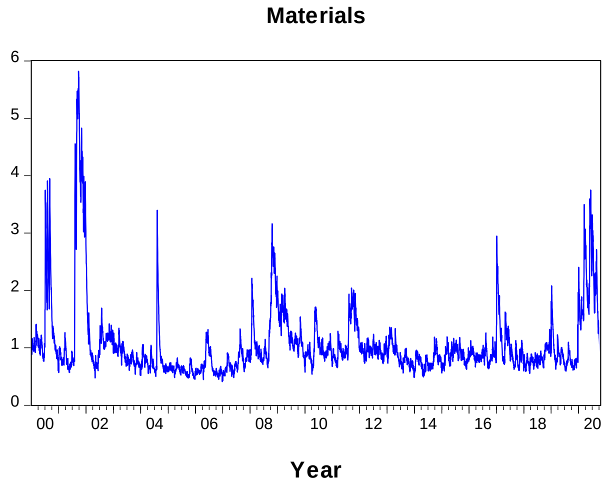

Figure 9.19

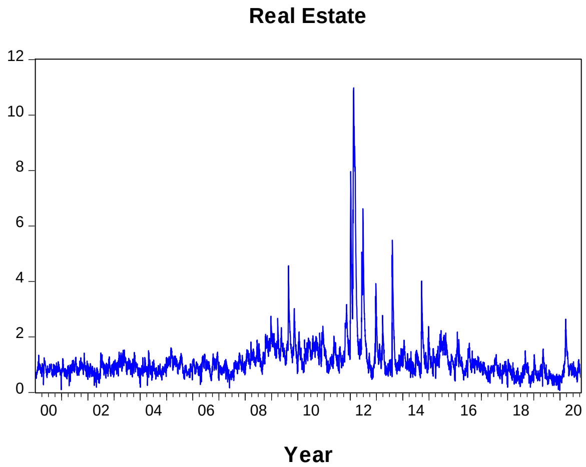

Figure 9.20

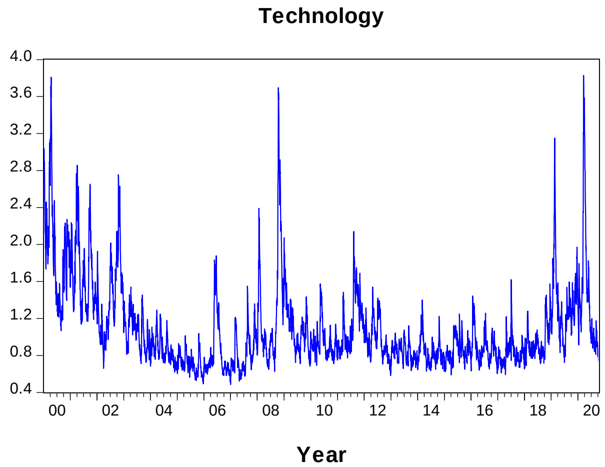

Figure 9.21

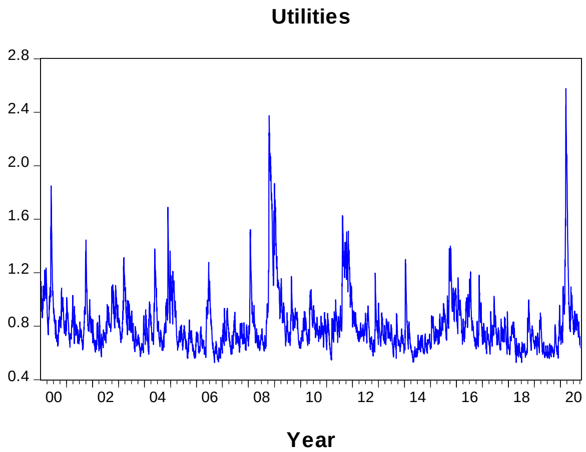

Figure 9.22

The above figures show the standard deviation of average returns in the UK, German, and French markets. We can see that during the global financial crisis period around the year 2008, and in the year 2020, we have remarkably large price movements and volatility in each sector. From these figures, we can find out that with market condition suffering larger volatility, based on above regression results, herding behaviour in the market may contribute to increase the market volatility. During the market turmoil period, the panic may have even rattled informed investors, leading to unclear market movements and diverging trading in all stocks; As a result, volatility has increased across sectors, but by varying amounts (Litimi, BenSaïda and Bouraoui, 2016).

In this section, we show the impact of herding on market volatility. Using the residual values from the various regressions as the proxy of herding, we can see that there is a mixed linear relationship between herding and market volatility. While when we fit the residual value into the model without lag, we only have partial evidence to show that herding could stimulate market volatility in several sectors, and some sector shows that herding has inhibit effect to market volatility. Using the lagged residual value from the CCK model and solution 1 as the proxy of herding to estimate market volatility, we have found that market volatility is clearly influenced by herding behaviour in the market, shown by significantly negative coefficients of residual value in most of sectors in different markets. Using a lagged independent residual variable in the equation helps us to fully capture the dynamics between herding and conditional volatility in the market.

10.0 Conclusions

Herding plays an important role in behavioural finance and has various impacts on our decision-making processes. Herding behaviour in the financial markets can be defined as a phenomenon in which an individual market participant decides to follow other investors and imitate the behaviour of the group, rather than making decisions independently based on their own private information. Herd theory perhaps originated with Keynes, who focused on imitation and the behaviour of crowds in an uncertain world (Keynes 1930). Keynes argued that herding behaviour was a response to uncertainty and an individual's perception of his own ignorance: people may follow the crowd because they believe that other market participants in the group are better informed. This can lead to instability, and in financial markets, herd behaviour is a key trigger for speculative events.

Going beyond narrow theories of herding, Keynes (1936,1937) sought to explain financial instability, especially in the stock market. Consumption comes from income and the desire to hold money, but there are also waves of optimism and pessimism, the animal spirits that influence and drive the stock market and entrepreneurship. Also, Keynes identified the social forces that impact investors, during times of uncertainty, socially driven conventions encourage speculators to believe what others believe and do what others do (Keynes 1936,1937). The work of Kindleberger and Aliber (2005) is also relevant to herding. They analysed the psychosocial impact of emotional contagion and determined that speculative mania spreading through the investor community during a mania period was the critical catalyst for economic and financial prosperity. On the contrary, excessive pessimism and extreme risk aversion can lead to bubbles bursting.

Turning to an empirical viewpoint, Christie and Huang (1995) introduced the cross-sectional standard deviation (CSSD) method in order to measure herding behaviour in the financial market, by analysing the relationship between the deviation between the average market return and the returns of the individual securities in the market. This method assumes that there should be a linear relationship between the return dispersion of individual securities and the average market return. If the market has herding behaviour, we should find that the dispersion level has a decreasing trend during periods of high market fluctuations. Chang et al. (2000) extended the previous work using a non-linear regression specification to detect herding behaviour in the market and created the cross-sectional absolute deviation (CSAD) model, also known as the CCK model. The CCK model can detect herding behaviour in the market with more accuracy, and it is less sensitive to outliers. Chang et al. (2000) indicates that if the market has herding behaviour, there should be a negative and non-linear relationship between the market return and CSAD results. Both the CSSD and CCK models are widely used in empirical research to detect the existence of herding behaviour.

Chapter 2 of the thesis gives a review of the current literature relating to behavioural finance and theoretical and empirical research on herding in different markets. In prior research, a large amount of literature relied on the CSSD model and the CCK model to detect herding behaviour in the financial market worldwide based on the log return calculation method. The mixed empirical results, from this research tend to indicate that herding behaviour is not often found in major markets but exists in emerging markets, and individual investors are more prone to herding behaviour than institutional investors. Also, most herding behaviour was detected when there were large movements in the market. In empirical chapters 3 and 4, as well as chapter

6, we use daily stock prices to construct our data sample which covers the period from 02/Jan/2002 to 31/May/2018 and includes the global financial crisis and Eurozone crisis. We chose the companies in 13 world-leading indices and collect the data from the Bloomberg database. This lets us have a view of herding behaviour in different countries over a long timeframe including some periods of market turmoil. Chapter 3 fits the standard CCK model using log returns to estimate the herding behaviour in world major stock markets. We capture clear evidence of anti-herding behaviour in most countries' stock markets, with only a few countries showing evidence of herding behaviour in their stock markets. When we consider subsamples of the data, we find more herding behaviour detected during the global financial crisis period under the market conditions associated with larger price movements. Following Hudson (2010), we estimate the herding behaviour in these major stock markets by fitting the CCK model based on the simple return calculation method in chapter 4. We found broadly similar results to those based on log return method in chapter 3. There is anti-herding in most markets, and only a few countries show herding behaviour. In both chapter 3 and chapter 4, the main findings support the prior research that herding is more likely to exists in the market under market conditions associated with larger price movements. Also, by comparing the results in both chapters, we have captured slightly more evidence of herding and anti-herding behaviour in the market with a simple return calculation method.

In chapter 5, we outline problems with the CCK model, which is the standard test for herding. The CCK model is based on the proposition that the cross-sectional absolute deviation of stock returns (CSAD) should be linearly related to overall market returns. We show that the test is highly biased against finding herding. The bias arises because the test assumes that, in the absence of herding, stock prices follow the CAPM but does not account for the implications of the CAPM not being a perfect asset pricing model. The method has the disadvantage that it is heavily influenced by the error term in the CAPM model when the average market return $R_{m,t}$ is small. Theoretical and empirical analysis shows that this problem causes the CCK approach to lose its effectiveness. We suggest three simple alternative tests for herding: estimating herding without a constant value in the regression, using the new SCSAD regression model and testing for herding by considering large market returns. The proposed methods have been designed to be very easy to apply so the finance research community can take them up without difficulty. Chapter 6 and chapter 6* (in the Appendix) fit our new solutions to estimate herding behaviour in the stock market using the log return and simple return calculation methods respectively. We observe a high level of herding behaviour in many countries during our sample period with solution 1 and solution 2. We also see herding behaviour increases and anti-herding decreases in our data sample along with the magnitude of security returns as considered in our third test. The results based on different return calculation approaches to test for herding provides similar results, whichever type of security returns are used. But we do observe somewhat more herding behaviour in the market when using a simple return calculation method.

Chapter 7 collects daily data from Bloomberg at the industry sector level for the top three economies in Europe: Germany, UK and France from 03-Jan-2000 to 20-Oct-2020. We investigated 640 companies in our sample, which provides us with a better view of herding in different industries. We conduct the standard CCK model and our three alternative solutions to estimates herding behaviour among different industries. The CCK model does not provide much evidence of herding, however, with our alternative test approaches, we detect different levels of herding in the stock markets. Each sector has its own herding triggers. As a result, we have observed more herding at the sector level than in the entire market. Also, when the market is suffering great turmoil or larger price movements, there is more chance of capturing clear evidence of herding behaviour in different sectors.

Furthermore, we compare the strength of herding in the banking industry and the Financial sector in chapter 8. The main finding is that there is more chance for capturing herding behaviour during the global financial crisis period, and herding behaviour is more evident in the Financial sector as a whole than in the banking industry. Chapter 9 investigates the impact of herding on market volatility using a GARCH (1,1) model. We use CSAD results and the residual value from CCK model and solution 1 as the proxy of herding. By using CSAD results as the proxy of herding, we have found out that there is a direct linear relationship between herding and market volatility so market volatility is positively influenced by herding behaviour in the markets. As CSAD is a measure of dispersion, we also fit the residual value from the modified CCK model as a measure of herding to forecast the market volatility. Using standard residual value, most of sectors have a significantly positive coefficient of residual value, which is indicates that herding inhibits market volatility, only afew sectors show a significantly negative coefficient of residual value, which indicates that herding contributes to market volatility. Also, when we fit the lagged residual value from modified CCK model, we have captured clear evidence among most sectors to show that herding behaviour contributes to the market volatility, and using lagged residual value from solution 1, all the sectors have a significantly negative coefficient of lagged residual value, which indicates that market volatility is significant positively influenced by herding behaviour.

In summary, this thesis initially compares the herding detection results based on different return calculation methods among the major stock markets around the world and find slightly different results by using the simple return calculation method. Then we show that the standard CCK test is highly biased against finding herding and introduce several alternative methods to detect herding. and provide theoretical and simulation evidence to support their superiority over the CCK approach. The methods we proposed have been designed to be very easy to apply so they can be taken up by the finance research community without difficulty.

We then apply the CCK method and our new approaches to a number of major world stock markets. The CCK generally provides little support for herding, which is broadly in line with the existing literature, whereas our proposed new approaches indicate a high level of herding in many of the markets. After this we use these methods to detect herding among the UK, Germany and France stock markets at the sector level, and the results show that there is more evidence of herding behaviour in different sectors than the overall markets, especially during periods of market turmoil. Also, we investigate whether market volatility is influenced by herding behaviour in the market, by fitting the CSAD results as the proxy of herding, we found a significantly positive contemporaneous relationship between herding and market volatility, that with more herding in the market, there would be more volatility in the market. These results are broadly in agreement with prior findings in the literature but there is an issue in that CSAD is not really a measure of herding but of dispersion. In contrast, using standard residual values from our solution 1, which are a more valid measure of herding, without a lag to forecast market volatility, only a few sectors in the market show that herding contributes to market volatility, while using lagged residual value from modified CCK model and residuals from solution 1 in the regression model, we have captured clear evidence that herding contributes to market volatility and that market volatility is positively influenced by herding behaviour among different sectors in different markets.

10.1 Practical implications

Because investors with herding behaviour often abandon their private information to follow others, this leads to the interruption of the market information transmission chain. However, this situation may have two effects: First, the herding behaviour may weaken the effect of market fundamentals on future price trends. When investment funds have herding behaviour, many funds will buy and sell the same stocks at the same time. The pressure of buying and selling may exceed the liquidity that the market can provide. The excess demand for stocks will have an important impact on stock prices. This may lead to discontinuities and substantial changes in stock prices, which undermine the stable operation of the market. On the other hand, if the herding behaviour is due to investors reacting quickly to the same basic information, investors' herding behaviour may accelerate the rate at which stock prices assimilate of information, prompting the market to become more efficient.

The causes of the herding effect can be divided into rational and irrational behaviour. The rational herding effect is conducive to accelerating the development of securities prices and maintaining market stability. In contrast, the irrational herding effect slows down the rate of price changes, thereby exacerbating market turbulence. If the herding behaviour exceeds a certain limit, it will induce another important market phenomenon-the emergence of overreaction. In a rising market (such as a bull market), blindly chasing profit and surpassing the limit of value can only create bubbles; in a falling market (such as a bear market), blindly selling and keeping the market falling can only deepen the crisis. In these cases, the herding behaviour of investors may cause greater volatility in stock prices and reduce the stability of the securities market.

The basis of all herding behaviour is the incompleteness of information. Therefore, once the information state of the market changes, withthe arrival of new information, the herding behaviour will collapse. At this time, the excessive rise or fall of stock prices caused by herding behaviour will stop, and even change excessively in the opposite direction. This means that herding behaviour is unstable and fragile. This has also directly led to the instability and vulnerability of financial market prices. Market participants should combine their own investment goals, risk tolerance and other factors to set profit points and stop-loss points while controlling their emotions to face market price fluctuations.

Our work also shows that based on traditional testing models, herding behaviour can only be detected when markets have larger price movements, they lose the effectiveness to detect herding when average market return become small. We have introduced several alternative approaches to detect herding, according to these approaches, we see that although herding tends to be more likely to be present during large market movements, there can still be herding behaviour in the market when average market returns are small.

10.2 Future research work

In this thesis, we have shown the drawbacks of the standard CCK model. Previously some theoretical and empirical research has introduced some very complicated methods to overcome those disadvantages. We have provided several simple and effective ways to detect herding under different market conditions more accurately and overcome the influence of the error term in the CAPM model. Our work indicates the need to revise many of the previous findings in the herding area and also to apply new and more appropriate methods to detect herding. There are some other interesting questions to address, such as, how to identify the category of herd behaviour as rational or irrational and how to quantify people's mental processes to create models that accurately reflect their behaviour. Addressing these questions may require obtaining new and relevant data, for example, to find information about the holding periods of market participants and way they change the proportion of assets they hold. These and related questions may become the directions for the development of the theory of herding behaviour in the future.

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12.0 Appendix

Material Associated with Chapter 2

2.5.6 Herding in Peer-to-Peer (P2P) Markets

A P2P market is a model which is decentralised and in which two individuals interact directly to buy and sell goods and services directly, or to produce goods and services together, without an intermediary third-party or the use of an incorporated entity or business firm. In a P2P transaction, the buyer and the seller transact directly with each other, in terms of the delivery of the goods or services and the exchange of payment. In a P2P market, the producer is usually a private individual or independent contractor who owns both their tools (or means of production) and their finished product. P2P finance refers to small loan transactions between different network nodes. It needs the help of a professional e-commerce network platform to help both borrowers and lenders establish a loan relationship and complete relevant transaction procedures. The borrower can release the loan information, including the amount, interest, repayment method and time, and decide the loan amount to realise the self-service loan. P2P lending markets differ from other electronic C2C markets in that they require some coordinated action by lenders. listing can only get funding if they are able to attract enough lenders. Herzenstein et al. (2011) suggest that if there is absolutely no herding, funds will be widely dispersed among the listings. Only a few listings will receive sufficient funds, while most of the money will be tied up in unfunded listings - wasting valuable resources for lenders. So some herding is good for both lenders and markets. But borrowers could also benefit. Lenders benefit from herding because it increases the likelihood that a loan auction will be fully funded and that they will also be among the winning applications, reducing their search and opportunity costs. In general, lenders are able to get higher interest rates because they reduce their herd behaviour after fully financing, so rates don't fall too far below the maximum the borrower is willing to pay. Several researchers have established herding behaviour amongst P2P investors.

Herzenstein et al. (2011) find evidence of strategic herding, where bidders in loan auctions have herding behaviour until the loan funds are fully available, after which the herd effect decreases. It suggests that this is the result of a highly uncertain auction environment and of an active, cohesive and well-capitalised community of lenders. There is more herding before the listing is fully funded, and less after the listing. The research reveals that strategic herding behaviour in P2P loan auction is beneficial to both individual and collective bidders. Ceyhan et al. (2011) observe herding behaviour in the bidding process, and for most bids, the number of bids they receive peaks at very similar points in time.

Zhang and Liu (2012) find evidence of rational herding behaviour among lenders. After they controlled for unobserved listing heterogeneity and return externalities, well-capitalized borrowers tended to attract more funds when they list. Moreover, lenders do not passively imitate their peers (irrational herding), but actively observe and learn (rational herding). They inferred information about borrowers' creditworthiness by looking at peer lending decisions and tempered their inferences with publicly visible borrower characteristics.

Lee and Lee (2012) research the herding effect in lender behaviour in the P2P market, and, according to their results, based on a one-year range of data from the Pop funding market, strong evidence of herding behaviour exists in the P2P market. Stebro et al. (2017) analysed herding behaviour in equity crowdfunding. In the activity of crowdfunding, backers make assurances based on historical data and their private information. As positive information emerges, they may pledge larger amounts. Thus, larger amounts of investment input for projects could provide more positive public signals, with regards to the project’s quality. Uninformed investors tend to follow the signals generated by informed investors with private information, as well as the public beliefs generated by all past commitments. The authors also find that high levels of investment provide positive public information about project quality, while low levels of investment provide negative information. A cascading display of information occurs only when there is not enough positive signals being generated.

Jiang, et al., (2018) analysed herding behaviour among P2P lending platforms in P2P lending market and whether investors' herding behaviour will be affected by their governance. Their findings suggest that herding behaviour exists at the platform level, and that several platform attributes could moderate herding behaviour, such as, participants and operating periods. Also, governance and regulation could have a significant influence on the participants in the P2P platform.

2.5.7 Herding Among Funds

Gleason, Mathur and Peterson (2004) tried to detect the existence of herding behaviour among traders by examining the Exchange Traded Funds (ETF) sector, which aids the investors in tracking a sector index performance. During both rising and falling market conditions, ETF traders tend to trade away from the market consensus, and the study did not capture any evidence to confirm herding behaviour. When the market is under stress, in both rising and falling market conditions, investors have a delayed response to good news, but have a quick reaction to bad news, as investors tend to fear potential losses in falling market conditions and enjoy potential gains in rising market conditions. This study provides support for the opinion that investors do not herd while using ETF during periods of market turmoil.

Hsieh, Yang, Yang and Lee (2011) investigate the existence of the effect of positive feedback and herding behaviour in the Asian mutual fund market. They found that positive stock returns and currency appreciation have attracted money into mutual funds in the Asian markets. The Asian market does have positive feedback effects and herding behaviour.

After Xu, et al., (2015) analysed the relationship between herding and stock price crashes, Deng, Hung and Qiao (2018) similarly analysed the relationship between herding in mutual funds and stock price crashes. The empirical results show that herding in mutual funds and stock price crashes are positively correlated, mutual fund herding magnifies the risk of a subsequent collapse in share prices. Also, herding behaviour among mutual funds could be affected by poor quality information disclosure. The herding effect in mutual funds is related to the poor information environment and the low quality of information disclosure, those firms affected by a higher level of mutual fund herding could have less available private information, lower revenue transparency and a higher probability of accounting errors, as well as lower accounting conservativeness. There is a predictive relationship concentrated in buy-herding rather than sell-herding between the mutual fund herding and stock price crashes. In the US ETF market, Rompotis (2018) did not find clear evidence of herding behaviour in the market, and also found no evidence to show that herding was influenced by high trading activity. Some results, however, confirm herding in the ETF market was induced by extreme volatility.

A study by Caglayan, Celiker and Sonaer (2018) detected herding behaviour in the hedge fund at the industry level and found that industry returns were influenced by hedge fund herding. Compared with non-hedge funds, the level of industry herding by hedge funds is much weaker. They also found that following industry herding by hedge funds, these long-term returns reversals were concentrated in sectors where non-hedge funds sold most aggressively in subsequent quarters. These phenomena are consistent with claims that non-hedge funds will be associated with clusters of hedge fund firms, particularly on the sell-side. The reason this may cause long-run return reversals in the industries is that non-hedge funds have been slow to respond to good news from the strong hedge fund selling industries in subsequent quarters.

Koetsier and Bikker (2018) examined asset herding behaviour in the Dutch pension fund market where there are a large number of pension funds. They found significant evidence of herding behaviour in this market. The herding behaviour is more intense in some sectors such as private equity and emerging markets. Herding behaviour among the pension funds is more likely to be affected by the financial market, macroeconomics circumstances and returns. For shares and private equity, they have found herding behaviour has a stabilizing effect on the buy-side and whereas for fixed interest investment there is destabilizing behaviour concentrated on the buy-side. During periods of market uncertainty, herding behaviour is more likely present for buying behaviour. Pension funds with similar characteristics herd together.

2.5.8 Herding in Cryptocurrencies Markets

Like national currencies, cryptocurrencies are a type of exchange medium, without any intrinsic value and cannot be redeemed for another commodity such as gold. Also, there has no physical form for cryptocurrencies, and they are not supported by any government or legal entity, furthermore, based on the mechanism of a completely decentralised network consensus, the complement of cryptocurrencies is not determined by a central bank, and all transactions are made by the system users (Murphy, Murphy and Seitzinger, 2015). They have become an innovative alternative investment asset class, traded in data-rich markets by investors scattered across the world.

By using a Markov-Switching approach, Poyser (2018) have found significant herding behaviour in the cryptocurrencies market and indicate that herding behaviour is a driving force of the price fluctuations of cryptocurrencies. Bouri, Gupta and Roubaud (2019) investigated herding behaviour in the cryptocurrency market. They found significant evidence of herding behaviour in the market, due to a combination of the extreme price volatility, low quality information and the fact that market participants are looking for high profitability. The results have shown that the herding behaviour changes over time and becomes stronger as market uncertainty increases. Still, in the cryptocurrency market, Vidal-Tomás, Ibáñez and Farinós (2019) analysed herding behaviour by applying both the traditional CSSD and CCK approaches. Through the CSSD method, they observed extreme price movements, which can be explained by rational asset pricing models, which indicates the cryptocurrencies tend to be inefficient and risky and this cannot be explained by herding. Through the CCK method, they found the cryptocurrency market herds during falling market conditions, at the same time they also found that smallest cryptocurrencies are more likely to herd towards the largest cryptocurrencies, which confirms the risk of investment in this market. Given these findings they could not conclude this type of market to be efficient. They proposed that governments should provide more security in the market and ensure the accuracy of asset valuation. Stavroyiannis and Babalos (2019) investigated herding behaviour in the cryptocurrency market and found evidence of herding behaviour, and they show the asymmetric nature of cryptocurrencies' returns. However, herding behaviour disappears when applying a more robust time-varying regression model. Gurdgiev and O'Loughlin (2020) use sentiment analysis to simulate the overall impact of public sentiment on the investment market. Their findings indicate that the price direction of cryptocurrencies can be predicted by the sentiments of investors, indicating the direct impact of herding and anchoring bias. Amirat and Alwafi (2020) also try to detect herding behaviour in the cryptocurrencies market among 20 large cryptocurrencies, but by applying the cross-sectional absolute standard deviation (CSAD) method. They did not initially find any significant evidence of herding behaviour. However, they then changed to using rolling window analysis and showed the existence of herding behaviour in the market. Also, they found an inverse relationship between herding behaviour and the Bloomberg Consumer Comfort

Index, which means that when investors feel uncomfortable, they are more likely to ignore their expectations and follow the market.

Ballis and Drakos (2020) have examined whether herding behaviour exists in the rapidly emerging cryptocurrency market. By investigating daily data for major cryptocurrencies from August 2015 to December 2018, they captured evidence that in the cryptocurrency market, investors act irrationally and mimic the decisions of others without considering their own beliefs. In addition, the empirical results provide evidence that market dispersion for rising events follows market movements at a faster rate than for falling events. As a result, cryptocurrencies exhibit a tendency to move in lockstep, which does not necessarily reflect their fundamentals.

Senarathne and Jianguo (2020) indicate that under normal market conditions, there is a strong tendency to herd on non-fundamental information that explains the CSAD of returns. This indicates the nature of cryptocurrency price changes is speculative and supports the argument that, as many scholars have proved, it is impossible to predict the return of cryptocurrencies based on basic economic information such as major macroeconomic announcements. Under different market conditions, the regression regarding herding also show that the accumulation of non-essential information in the cryptocurrency market is more pronounced during periods of extremely rapid price movements whether markets are rising or falling. During normal or other market periods, no evidence of herding has been found based on fundamental information such as major macroeconomic announcements.

King and Koutmos (2021) using sample price data from Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Litecoin, Stellar, Cardano, and IOTA, found that there is herd behaviour in the cryptocurrency market and it really drives the price dynamics. There was heterogeneity in herding behaviour and feedback effects. This suggests that the cryptocurrency market may be fragmented, even though they have shown themselves to be linked over time. The cryptocurrencies-related literature suggests that these currencies seem divorced from economic fundamentals and exhibit unprecedented and ironically similar price behaviour to traditional assets.

The cryptocurrency market has attracted the attention of many scholars and investors in recent years because of the success of Bitcoin. This context could have generated a herding effect which could explain the extraordinary performance of the cryptocurrency. Much of the literature has used the standard CCK model and captured clear evidence of herding behaviour in the cryptocurrency market. Similarly, to traditional financial markets, herding behaviour in the cryptocurrency markets are more likely to be present in emerging markets and under market conditions with larger price movements.

Material Associated with Chapter 3

Table 3.1.2.1 Panel B, Standard Regression

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.201	0.215	0.168	0.165	0.187	0.318
	(10.50)***	(16.97)***	(10.41)***	(13.24)***	(13.34)***	(23.57)***
$R_{m,t}^2$	0.0330	0.0111	0.0112	0.0181	0.0205	0.0157
	(8.19)***	(4.26)***	(3.49)***	(7.44)***	(7.62)***	(7.71)***
_cons	0.987	0.709	0.969	0.797	0.805	1.406
	(67.45)***	(74.04)***	(71.62)***	(75.77)***	(67.45)***	(96.61)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.174	0.309	0.290	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.1 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.229	0.179	0.322	0.311	0.177	0.173	0.263
	(18.85)***	(11.08)***	(14.49)***	(16.35)***	(12.25)***	(14.32)***	(17.44)***
$R_{m,t}^2$	0.00988	0.0219	0.000902	0.00505	0.0175	0.00747	0.0268
	(4.40)***	(6.29)***	(0.26)	(1.10)	(5.60)***	(3.81)***	(8.38)***
_cons	0.903	0.878	1.074	0.895	0.782	0.796	0.850
	(82.20)***	(69.00)***	(45.55)***	(66.20)***	(70.60)***	(67.85)***	(78.86)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.299	0.256	0.197	0.230	0.245	0.239	0.377

t statistics in parentheses
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

With the standard regression results shown in panel B, both Norway and Portugal have an insignificant positive coefficient of squared market return $R_{m,t}^2$, the rest of the countries in the data sample have a significantly positive coefficient of $R_{m,t}^2$, which is indicative of existence of anti-herding in the market. Comparing with the robust results, for some countries the significantly positive coefficient of $R_{m,t}^2$ has become insignificant, the p-value of the coefficient $R_{m,t}^2$ in Denmark is 0.109, Sweden is 0.093, in the US it has become

0.100 and 0.162 in Hong Kong, which indicates a decrease of the anti-herding in the market.

Table 3.1.2.2 Panel B, Standard Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00255	-0.00850	0.0122	0.0118	0.00789	0.00791
	(-0.36)	(-1.82)*	(2.36)**	(2.88)***	(1.62)	(1.50)
$\lvert R_{m,t} \rvert$	0.201	0.214	0.169	0.167	0.188	0.317
	(10.50)***	(16.83)***	(10.47)***	(13.33)***	(13.38)***	(23.53)***
$R_{m,t}^2$	0.0328	0.0116	0.0111	0.0179	0.0204	0.0160
	(8.08)***	(4.40)***	(3.45)***	(7.40)***	(7.61)***	(7.83)***
_cons	0.987	0.710	0.968	0.795	0.804	1.406
	(67.44)***	(74.05)***	(71.53)***	(75.68)***	(67.33)***	(96.60)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.175	0.310	0.291	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.2 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0246	0.00883	0.00669	0.0298	0.0127	0.00702	0.00344
	(5.35)***	(1.73)*	(0.93)	(4.56)***	(2.65)***	(1.64)	(0.62)
$\lvert R_{m,t} \rvert$	0.229	0.179	0.321	0.310	0.178	0.175	0.263
	(18.88)***	(11.07)***	(14.43)***	(16.31)***	(12.35)***	(14.41)***	(17.40)***
$R_{m,t}^2$	0.0101	0.0223	0.00122	0.00684	0.0175	0.00721	0.0270
	(4.50)***	(6.38)***	(0.34)	(1.48)	(5.60)***	(3.66)***	(8.41)***
_cons	0.902	0.878	1.074	0.894	0.780	0.795	0.850
	(82.38)***	(68.96)***	(45.55)***	(66.22)***	(70.43)***	(67.60)***	(78.86)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.304	0.257	0.197	0.234	0.246	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

From the results in the standard regression shown in table 3.1.2.2 panel B, we can find out the similar results compare to the robust results that only Denmark and the US have a negative coefficient of R_{mt}. The coefficient of squared market return $R_{m,t}^2$ is similar to the results in results shown in table 3.1.2.1, Norway and Portugal have an insignificant coefficient of squared market return.

Table 3.1.2.3 Panel B Standard regression in rising and falling market condition

$$\mathrm{CSAD_{i,t}} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.213	0.207	0.171	0.172	0.196	0.330
	(8.97)***	(14.52)***	(9.31)***	(11.91)***	(12.27)***	(18.27)***
$(1 - D^{up})\|R_{m,t}\|$	0.196	0.217	0.171	0.164	0.179	0.308
	(9.00)***	(13.22)***	(8.76)***	(10.92)***	(10.40)***	(20.55)***
$D^{up}(R_{m,t})^2$	0.0275	0.0109	0.0143	0.0200	0.0204	0.0148
	(4.42)***	(3.68)***	(3.66)***	(6.72)***	(6.27)***	(4.26)***
$(1 - D^{up})(R_{m,t})^2$	0.0354	0.0132	0.00680	0.0153	0.0205	0.0165
	(7.57)***	(3.16)***	(1.55)	(4.69)***	(5.47)***	(7.20)***
_cons	0.985	0.711	0.967	0.795	0.804	1.405
	(66.91)***	(73.56)***	(71.44)***	(75.63)***	(67.21)***	(95.37)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.224	0.281	0.176	0.311	0.290	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.3 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.242	0.169	0.332	0.334	0.178	0.184	0.243
	(16.64)***	(8.92)***	(12.46)***	(15.01)***	(10.82)***	(13.48)***	(12.81)***
$(1 - D^{up})\|R_{m,t}\|$	0.214	0.189	0.311	0.285	0.184	0.162	0.272
	(15.16)***	(9.96)***	(12.21)***	(12.67)***	(10.51)***	(10.27)***	(15.74)***
$D^{up}(R_{m,t})^2$	0.0137	0.0288	0.000121	0.00897	0.0221	0.00664	0.0348
	(4.55)***	(6.33)***	(0.02)	(1.46)	(5.79)***	(2.99)***	(7.30)***
$(1 - D^{up})(R_{m,t})^2$	0.00686	0.0162	0.00196	0.00498	0.0113	0.00855	0.0227
	(2.40)**	(3.67)***	(0.46)	(0.85)	(2.64)***	(2.75)***	(6.01)***
_cons	0.903	0.878	1.073	0.894	0.779	0.796	0.852
	(82.40)***	(69.01)***	(45.43)***	(66.22)***	(70.31)***	(67.14)***	(78.70)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.304	0.258	0.197	0.234	0.246	0.239	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B, both Norway and Portugal have an insignificant positive coefficient of squared market return in both up and down-market conditions, Finland has a significant positive coefficient of $D^{up}(R_{m,t})^2$ which become insignificant in

$(1 - D^{up})\left(R_{m,t}\right)^2$. The rest of the countries have significantly positive coefficients in both market conditions so we do not reject the null hypothesis that there is no herding behaviour in these stock markets during the sample period. In addition, we do not have enough evidence to prove that Norway and Portugal, as well as Finland in falling market condition, have herding behaviour.

Table 3.1.2.4 Panel B Standard regression with larger log positive returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.523	0.436	0.303	0.317	0.397	0.456
	(7.69)***	(11.16)***	(5.37)***	(6.83)***	(8.13)***	(9.20)***
$R_{m,t}^2$	-0.0186	-0.0166	-0.00279	0.00152	-0.00281	0.000989
	(-1.63)	(-3.05)***	(-0.35)	(0.24)	(-0.43)	(0.16)
_cons	0.631	0.416	0.792	0.600	0.518	1.208
	(8.27)***	(8.65)***	(10.33)***	(9.43)***	(7.69)***	(15.39)***
N	876	811	813	798	831	774
adj. R^2	0.248	0.366	0.232	0.366	0.325	0.424

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.4 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.406	0.344	0.503	0.328	0.270	0.423	0.418
	(9.32)***	(5.69)***	(5.55)***	(4.88)***	(5.73)***	(11.78)***	(7.32)***
$R_{m,t}^2$	-0.00474	0.00265	-0.0192	0.00765	0.0100	-0.0161	0.00861
	(-0.82)	(0.28)	(-1.77)*	(0.66)	(1.40)	(-4.10)***	(0.89)
_cons	0.662	0.673	0.808	0.928	0.661	0.395	0.655
	(10.83)***	(8.75)***	(5.39)***	(12.04)***	(11.40)***	(6.82)***	(10.28)***
N	826	823	817	838	854	787	768
adj. R^2	0.352	0.265	0.148	0.182	0.308	0.363	0.401

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The return we select to divide the sample was the value that was equal to the positive mean return. From the results, we find that Denmark, Finland, Germany, Norway, Sweden, US and Hong Kong have a negative but not significant coefficient of $R_{m,t}^2$, and Sweden and the US have a significantly negative coefficient of $R_{m,t}^2$, which indicates that there is herding behaviour in the market. Norway has a significantly negative coefficient of $R_{m,t}^2$ at the 10% level with p-value equal to 0.077.

Table 3.1.2.5 Panel B Standard regression with larger log negative returns

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.280	0.381	0.179	0.229	0.228	0.432
	(4.14)***	(7.04)***	(2.87)***	(4.66)***	(3.91)***	(8.96)***
$R_{m,t}^2$	0.0257	-0.0113	0.00623	0.00662	0.0151	0.00613
	(2.67)***	(-1.25)	(0.67)	(0.93)	(1.80)*	(1.32)
_cons	0.863	0.517	0.945	0.707	0.718	1.173
	(9.88)***	(8.36)***	(11.05)***	(10.30)***	(8.98)***	(12.87)***
N	716	735	725	723	730	726
adj. R^2	0.294	0.320	0.155	0.301	0.316	0.435

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1.2.5 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.342	0.107	0.460	0.233	0.269	0.199	0.377
	(8.59)***	(1.49)	(4.78)***	(3.26)***	(4.13)***	(3.28)***	(6.69)***
$R_{m,t}^2$	-0.00655	0.0275	-0.0133	0.0126	-0.00118	0.00396	0.00966
	(-1.31)	(2.51)**	(-1.25)	(1.05)	(-0.11)	(0.50)	(1.18)
_cons	0.706	0.995	0.814	0.961	0.670	0.743	0.707
	(11.68)***	(10.28)***	(4.70)***	(11.14)***	(8.03)***	(7.95)***	(9.85)***
N	707	718	720	729	705	681	664
adj. R^2	0.291	0.207	0.157	0.198	0.206	0.202	0.400

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The standard regression results has shown that, during larger negative market movement, Denmark and Italy have significantly positive coefficient of squared market return, which is indicative of anti-herding exists in their market. Also, anti-herding in Germany is significant at 10% level. There have neither herding nor anti-herding behaviour exists in the US, Finland, France, Greece, Hong Kong, Norway, Portugal, Spain, Sweden and UK markets.

3.2 First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.1

variable		mean	p50	sd	variance	skewness	kurtosis	min	max	N
Denmark	$R_{m,t}$	.024544	.059973	1.34205	1.80109	-.491661	8.60944	-10.5563	7.99761	2507
	CSAD	1.34178	1.18975	.684171	.46809	3.28632	34.6086	.330539	12.504	2507
US	$R_{m,t}$	.019281	.047404	1.39656	1.95039	.143739	7.94726	-8.06138	9.54237	2519
	CSAD	1.02739	.892154	.477616	.228117	2.26581	10.9778	.239378	4.90784	2519
Finland	$R_{m,t}$	.018787	.07339	1.60884	2.58837	-.059115	6.7655	-8.92102	8.93025	2515
	CSAD	1.27756	1.13555	.573683	.329113	1.80592	8.16712	.32942	5.02699	2515
France	$R_{m,t}$	.001346	.037492	1.63112	2.66055	-.074823	6.88196	-9.31602	8.91817	2563
	CSAD	1.10681	.952293	.528138	.278929	1.68721	6.44728	.337484	3.82925	2563
Germany	$R_{m,t}$	.011729	.066572	1.58072	2.49868	-.139862	7.53478	-9.02234	11.1545	2548
	CSAD	1.1632	.99501	.601639	.361969	1.97465	8.56218	.252214	5.52583	2548
Greece	$R_{m,t}$	-.040199	.052492	1.56038	2.43477	-.165836	7.83263	-10.9951	12.6811	2496
	CSAD	1.62505	1.51942	.52368	.27424	1.91749	11.2314	.681186	6.72324	2496
HK	$R_{m,t}$	.04466	.077325	1.57122	2.46872	-.097367	7.85493	-12.413	11.4602	2473
	CSAD	1.30579	1.1816	.537651	.289069	2.10351	11.0499	.31458	5.98583	2473
Italy	$R_{m,t}$	-.012438	.078148	1.38025	1.9051	-.287926	7.30727	-8.56588	9.27357	2542
	CSAD	1.05975	.918019	.494662	.24469	1.82363	7.44177	.26375	3.86093	2542
Norway	$R_{m,t}$	.019768	.127756	2.06155	4.24999	-.355872	6.33304	-12.3905	10.4173	2514
	CSAD	1.76188	1.4636	1.06162	1.12705	2.15295	10.3202	.321608	10.65	2514
Portugal	$R_{m,t}$	.003748	.070974	1.13936	1.29815	-.461653	8.95977	-7.98493	8.74228	2555
	CSAD	1.07216	.968459	.519049	.269412	1.59676	7.59465	.218911	4.62524	2555
Spain	$R_{m,t}$	.017687	.100505	1.36524	1.86389	-.20278	7.71397	-8.06577	9.71678	2535
	CSAD	.993562	.869908	.496395	.246408	1.95299	9.28667	.276384	4.75011	2535
Sweden	$R_{m,t}$	.03258	.090111	1.8548	3.44027	.073342	7.57361	-9.30306	13.0496	2515
	CSAD	1.15581	1.00554	.559667	.313228	2.13587	12.4044	.325067	7.36813	2515
UK	$R_{m,t}$	.008805	.073326	1.33776	1.7896	-.325794	8.67482	-9.38468	7.88027	2511
	CSAD	1.22802	1.05846	.603809	.364585	2.42693	11.3253	.370236	5.92593	2511

First time period from 02/Jan/2002 to 30/Dec/2011

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.1 Panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.256	0.232	0.182	0.204	0.249	0.225
	(3.58)***	(8.26)***	(6.77)***	(10.21)***	(7.61)***	(16.59)***
$R_{m,t}^2$	0.0226	0.00679	0.00721	0.0114	0.0108	0.0153
	(1.05)	(0.98)	(1.18)	(2.87)***	(1.46)	(6.51)***
_cons	1.061	0.783	1.053	0.842	0.861	1.336
	(31.79)***	(45.72)***	(56.24)***	(56.71)***	(42.59)***	(106.78)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.256	0.290	0.187	0.333	0.324	0.402

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.1 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.243	0.233	0.367	0.303	0.219	0.184	0.329
	(8.79)***	(11.54)***	(10.36)***	(12.30)***	(10.48)***	(7.74)***	(11.78)***
$R_{m,t}^2$	0.00633	0.00927	-0.00709	0.00663	0.00844	0.00433	0.0118
	(0.95)	(2.05)**	(-1.27)	(1.16)	(1.75)*	(1.01)	(1.86)*
_cons	1.016	0.819	1.250	0.825	0.769	0.904	0.907
	(57.33)***	(62.01)***	(40.12)***	(57.23)***	(55.39)***	(49.35)***	(57.03)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.312	0.302	0.192	0.271	0.254	0.247	0.384

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.1 Panel B, Standard regression

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.256	0.232	0.182	0.204	0.249	0.225
	(10.36)***	(13.82)***	(8.79)***	(12.32)***	(13.39)***	(15.74)***
$R_{m,t}^2$	0.0226	0.00679	0.00721	0.0114	0.0108	0.0153
	(4.73)***	(2.13)**	(1.89)*	(3.81)***	(3.28)***	(6.25)***
_cons	1.061	0.783	1.053	0.842	0.861	1.336
	(52.85)***	(55.11)***	(57.21)***	(56.00)***	(50.75)***	(95.82)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.256	0.290	0.187	0.333	0.324	0.402

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.1 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.243	0.233	0.367	0.303	0.219	0.184	0.329
	(15.76)***	(12.79)***	(12.20)***	(14.33)***	(11.84)***	(11.83)***	(16.36)***
$R_{m,t}^2$	0.00633	0.00927	-0.00709	0.00663	0.00844	0.00433	0.0118
	(2.43)**	(2.45)**	(-1.61)	(1.40)	(2.26)**	(1.85)*	(2.96)***
_cons	1.016	0.819	1.250	0.825	0.769	0.904	0.907
	(66.22)***	(58.14)***	(36.20)***	(56.32)***	(52.33)***	(54.42)***	(57.61)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.312	0.302	0.192	0.271	0.254	0.247	0.384

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In table 3.2.2.1 panel B, Norway has a negative coefficient of $R_{m,t}^2$, but it is insignificant, Finland and Sweden have a significantly positive coefficient of $R_{m,t}^2$ at the 10% level, Portugal has an insignificantly positive coefficient of $R_{m,t}^2$. The rest of the countries in our data sample have a significantly positive coefficient of $R_{m,t}^2$, which indicates that they have anti-herding behaviour during time period 1.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.2 Panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00111	-0.00251	0.0141	0.0165	0.0124	0.0157
	(-0.07)	(-0.31)	(1.65)*	(2.50)**	(1.36)	(2.49)**
$\lvert R_{m,t}\rvert$	0.256	0.231	0.185	0.207	0.251	0.229
	(3.63)***	(8.37)***	(6.91)***	(10.37)***	(7.47)***	(16.89)***
$R_{m,t}^2$	0.0225	0.00695	0.00679	0.0111	0.0106	0.0150
	(1.07)	(1.02)	(1.12)	(2.84)***	(1.39)	(6.59)***
_cons	1.061	0.783	1.050	0.840	0.859	1.333
	(31.68)***	(46.30)***	(56.35)***	(56.51)***	(42.04)***	(106.35)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.256	0.289	0.189	0.335	0.325	0.404

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.2 Panel A,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0228	0.0133	0.00465	0.0220	0.0168	0.00731	0.0127
	(2.62)***	(1.62)	(0.35)	(2.42)**	(2.03)**	(1.00)	(1.27)
$\lvert R_{m,t}\rvert$	0.242	0.235	0.366	0.305	0.222	0.186	0.328
	(9.17)***	(11.52)***	(10.36)***	(12.95)***	(11.20)***	(7.79)***	(12.09)***
$R_{m,t}^2$	0.00644	0.00940	-0.00688	0.00721	0.00830	0.00397	0.0123
	(1.02)	(2.08)**	(-1.25)	(1.41)	(1.93)*	(0.91)	(2.05)**
_cons	1.015	0.817	1.250	0.822	0.766	0.902	0.906
	(58.91)***	(61.20)***	(40.15)***	(57.74)***	(56.22)***	(49.24)***	(57.73)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.316	0.303	0.191	0.273	0.256	0.247	0.385

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.2 Panel B, Standard Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00111	-0.00251	0.0141	0.0165	0.0124	0.0157
	(-0.12)	(-0.43)	(2.20)**	(3.17)***	(1.99)**	(3.00)***
$\lvert R_{m,t}\rvert$	0.256	0.231	0.185	0.207	0.251	0.229
	(10.36)***	(13.71)***	(8.91)***	(12.48)***	(13.48)***	(15.96)***
$R_{m,t}^2$	0.0225	0.00695	0.00679	0.0111	0.0106	0.0150
	(4.67)***	(2.17)**	(1.79)*	(3.72)***	(3.24)***	(6.16)***
_cons	1.061	0.783	1.050	0.840	0.859	1.333
	(52.84)***	(55.00)***	(57.02)***	(55.90)***	(50.60)***	(95.52)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.256	0.289	0.189	0.335	0.325	0.404

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.2 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0228	0.0133	0.00465	0.0220	0.0168	0.00731	0.0127
	(4.01)***	(2.22)**	(0.50)	(2.82)***	(2.69)***	(1.39)	(1.79)*
$\lvert R_{m,t}\rvert$	0.242	0.235	0.366	0.305	0.222	0.186	0.328
	(15.79)***	(12.88)***	(12.17)***	(14.46)***	(11.98)***	(11.91)***	(16.32)***
$R_{m,t}^2$	0.00644	0.00940	-0.00688	0.00721	0.00830	0.00397	0.0123
	(2.48)**	(2.48)**	(-1.55)	(1.52)	(2.22)**	(1.69)*	(3.08)***
_cons	1.015	0.817	1.250	0.822	0.766	0.902	0.906
	(66.34)***	(57.96)***	(36.18)***	(56.05)***	(52.11)***	(54.15)***	(57.61)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.316	0.303	0.191	0.273	0.256	0.247	0.385

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B, Norway has an insignificantly negative coefficient of $R_{m,t}^2$, Finland and Sweden have a significantly positive coefficient of $R_{m,t}^2$ at the 10% level, Portugal has an insignificantly positive coefficient of $R_{m,t}^2$. Denmark, US, France, Germany, Greece, Hong Kong, Italy, Spain and the UK have a significantly positive coefficient of $R_{m,t}^2$, which indicates that they have anti-herding behaviour during the first time period.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.3 Panel A Robust regression in rising and falling market condition

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.280	0.231	0.187	0.215	0.261	0.248
	(5.96)***	(7.49)***	(5.56)***	(8.88)***	(6.08)***	(16.06)***
$(1-D^{up})\|R_{m,t}\|$	0.244	0.225	0.187	0.202	0.242	0.208
	(2.73)***	(8.54)***	(6.80)***	(9.09)***	(9.13)***	(11.42)***
$D^{up}(R_{m,t})^2$	0.0143	0.00597	0.0100	0.0135	0.0113	0.0140
	(1.05)	(0.72)	(1.15)	(2.62)***	(0.99)	(6.75)***
$(1-D^{up})(R_{m,t})^2$	0.0265	0.00939	0.00235	0.00807	0.00959	0.0165
	(0.91)	(1.35)	(0.38)	(1.71)*	(1.90)*	(3.82)***
_cons	1.058	0.784	1.050	0.840	0.859	1.334
	(36.16)***	(48.93)***	(56.30)***	(56.63)***	(43.99)***	(105.72)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.256	0.289	0.189	0.335	0.325	0.404

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.3 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.251	0.220	0.375	0.319	0.215	0.195	0.305
	(6.93)***	(7.14)***	(9.75)***	(12.42)***	(10.07)***	(7.38)***	(9.56)***
$(1-D^{up})\|R_{m,t}\|$	0.231	0.256	0.358	0.294	0.242	0.173	0.336
	(9.04)***	(11.32)***	(8.31)***	(9.34)***	(9.86)***	(7.31)***	(11.64)***
$D^{up}(R_{m,t})^2$	0.0103	0.0187	-0.00799	0.0104	0.0163	0.00349	0.0234
	(1.00)	(2.14)**	(-1.31)	(2.39)**	(3.76)***	(0.67)	(3.04)***
$(1-D^{up})(R_{m,t})^2$	0.00309	-0.000972	-0.00613	0.00361	-0.00280	0.00519	0.00602
	(0.53)	(-0.19)	(-0.81)	(0.42)	(-0.46)	(1.23)	(0.96)
_cons	1.016	0.817	1.249	0.822	0.764	0.903	0.911
	(58.40)***	(57.43)***	(40.30)***	(57.24)***	(56.80)***	(52.03)***	(59.59)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.316	0.306	0.191	0.273	0.259	0.247	0.386

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.3 Panel B Standard regression in rising and falling market condition

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.280	0.231	0.187	0.215	0.261	0.248
	(9.02)***	(12.26)***	(7.84)***	(11.17)***	(12.30)***	(14.85)***
$(1 - D^{up})\|R_{m,t}\|$	0.244	0.225	0.187	0.202	0.242	0.208
	(8.72)***	(10.44)***	(7.53)***	(10.21)***	(10.56)***	(12.05)***
$D^{up}(R_{m,t})^2$	0.0143	0.00597	0.0100	0.0135	0.0113	0.0140
	(1.94)*	(1.67)*	(2.19)**	(3.69)***	(2.88)***	(4.66)***
$(1 - D^{up})(R_{m,t})^2$	0.0265	0.00939	0.00235	0.00807	0.00959	0.0165
	(4.79)***	(1.84)*	(0.46)	(2.03)**	(2.08)**	(4.85)***
_cons	1.058	0.784	1.050	0.840	0.859	1.334
	(52.32)***	(54.63)***	(56.98)***	(55.87)***	(50.47)***	(95.41)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.256	0.289	0.189	0.335	0.325	0.404

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.3 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.251	0.220	0.375	0.319	0.215	0.195	0.305
	(13.62)***	(10.34)***	(10.39)***	(12.95)***	(10.11)***	(11.12)***	(11.98)***
$(1 - D^{up})\|R_{m,t}\|$	0.231	0.256	0.358	0.294	0.242	0.173	0.336
	(12.98)***	(11.79)***	(10.42)***	(11.52)***	(10.73)***	(8.48)***	(14.72)***
$D^{up}(R_{m,t})^2$	0.0103	0.0187	-0.00799	0.0104	0.0163	0.00349	0.0234
	(2.95)***	(3.93)***	(-1.30)	(1.72)*	(3.60)***	(1.33)	(3.99)***
$(1 - D^{up})(R_{m,t})^2$	0.00309	-0.000972	-0.00613	0.00361	-0.00280	0.00519	0.00602
	(0.94)	(-0.20)	(-1.16)	(0.57)	(-0.54)	(1.38)	(1.29)
_cons	1.016	0.817	1.249	0.822	0.764	0.903	0.911
	(66.36)***	(58.02)***	(36.07)***	(56.00)***	(52.04)***	(53.77)***	(57.61)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.316	0.306	0.191	0.273	0.259	0.247	0.386

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B with standard regression, Norway has a negative coefficient of squared market return in both rising and falling market conditions, however, they are insignificant. Italy and Spain have a negative coefficient of squared market return in a falling market, they are insignificant as well.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.4 Panel A Robust regression with larger log positive returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.621	0.495	0.306	0.390	0.488	0.284
	(5.73)***	(6.71)***	(2.92)***	(5.76)***	(5.29)***	(7.49)***
$R_{m,t}^2$	-0.0343	-0.0241	-0.00509	-0.00743	-0.0140	0.0102
	(-1.85)*	(-2.16)**	(-0.32)	(-0.86)	(-1.03)	(2.89)***
_cons	0.656	0.413	0.896	0.585	0.522	1.284
	(5.56)***	(4.77)***	(6.66)***	(6.32)***	(4.36)***	(21.17)***
N	512	483	480	476	500	470
adj. R^2	0.278	0.377	0.233	0.403	0.350	0.467

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.4 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.407	0.368	0.550	0.307	0.243	0.426	0.511
	(5.03)***	(5.25)***	(4.51)***	(4.54)***	(4.40)***	(8.46)***	(5.93)***
$R_{m,t}^2$	-0.00615	-0.00169	-0.0269	0.0110	0.0128	-0.0177	-0.00616
	(-0.50)	(-0.17)	(-2.13)**	(1.30)	(2.02)**	(-3.76)***	(-0.47)
_cons	0.771	0.639	0.965	0.852	0.726	0.490	0.666
	(7.19)***	(7.68)***	(4.69)***	(11.52)***	(10.20)***	(5.77)***	(6.96)***
N	506	477	512	509	501	466	454
adj. R^2	0.337	0.351	0.132	0.249	0.310	0.348	0.423

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.4 Panel B Standard regression with larger log positive returns

$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t} \rvert$	0.621	0.495	0.306	0.390	0.488	0.284
	(7.07)***	(9.34)***	(4.04)***	(6.35)***	(7.60)***	(6.92)***
$R_{m,t}^2$	-0.0343	-0.0241	-0.00509	-0.00743	-0.0140	0.0102
	(-2.50)**	(-3.53)***	(-0.51)	(-0.94)	(-1.75)*	(2.15)**
_cons	0.656	0.413	0.896	0.585	0.522	1.284
	(6.22)***	(5.67)***	(8.21)***	(6.42)***	(5.47)***	(20.00)***
N	512	483	480	476	500	470
adj. R^2	0.278	0.377	0.233	0.403	0.350	0.467

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.4 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t} \rvert$	0.407	0.368	0.550	0.307	0.243	0.426	0.511
	(6.88)***	(5.95)***	(4.57)***	(4.52)***	(4.06)***	(8.84)***	(6.57)***
$R_{m,t}^2$	-0.00615	-0.00169	-0.0269	0.0110	0.0128	-0.0177	-0.00616
	(-0.86)	(-0.18)	(-1.99)**	(1.03)	(1.50)	(-3.62)***	(-0.51)
_cons	0.771	0.639	0.965	0.852	0.726	0.490	0.666
	(8.46)***	(8.20)***	(4.53)***	(11.38)***	(9.47)***	(5.61)***	(6.97)***
N	506	477	512	509	501	466	454
adj. R^2	0.337	0.351	0.132	0.249	0.310	0.348	0.423

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the standard regression, Denmark, Norway, Sweden and the US have a significantly negative coefficient of $R_{m,t}^2$, which is indicative of herding behaviour. The other countries such as Finland, Germany, Italy, France, Hong Kong as well as the UK also have a negative coefficient of $R_{m,t}^2$, but they are insignificant, except Germany which is significant at the 10% level.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.5 Panel A Robust regression with larger log negative return

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.273	0.431	0.180	0.268	0.257	0.352
	(1.16)	(5.99)***	(2.37)**	(3.91)***	(3.41)***	(6.82)***
$R_{m,t}^2$	0.0233	-0.0202	0.00360	0.0000738	0.00859	0.0000659
	(0.51)	(-1.91)*	(0.33)	(0.01)	(0.90)	(0.01)
_cons	1.011	0.521	1.053	0.734	0.820	1.106
	(4.08)***	(5.94)***	(9.53)***	(7.16)***	(7.53)***	(13.59)***
N	428	472	425	437	435	451
adj. R^2	0.290	0.316	0.150	0.320	0.317	0.432

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.5 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.349	0.242	0.443	0.210	0.254	0.190	0.414
	(6.95)***	(3.77)***	(3.00)***	(2.50)**	(3.16)***	(2.15)**	(5.09)***
$R_{m,t}^2$	-0.00863	0.000258	-0.0146	0.0147	-0.00583	0.00327	-0.00320
	(-1.66)*	(0.03)	(-1.01)	(1.02)	(-0.50)	(0.33)	(-0.30)
_cons	0.821	0.849	1.100	0.946	0.771	0.875	0.792
	(9.83)***	(9.09)***	(3.98)***	(10.07)***	(6.99)***	(6.03)***	(7.41)***
N	431	410	439	403	409	431	410
adj. R^2	0.275	0.231	0.121	0.244	0.164	0.181	0.359

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 3.2.2.5 Panel B Standard regression with larger log negative returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.273	0.431	0.180	0.268	0.257	0.352
	(3.00)***	(5.89)***	(2.20)**	(4.19)***	(3.26)***	(6.34)***
$R_{m,t}^2$	0.0233	-0.0202	0.00360	0.0000738	0.00859	0.0000659
	(1.93)*	(-1.77)*	(0.32)	(0.01)	(0.81)	(0.01)
_cons	1.011	0.521	1.053	0.734	0.820	1.106
	(7.85)***	(5.65)***	(8.56)***	(7.47)***	(6.96)***	(12.46)***
N	428	472	425	437	435	451
adj. R^2	0.290	0.316	0.150	0.320	0.317	0.432

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2.2.5 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.349	0.242	0.443	0.210	0.254	0.190	0.414
	(6.61)***	(3.22)***	(3.25)***	(2.64)***	(3.04)***	(2.26)**	(5.70)***
$R_{m,t}^2$	-0.00863	0.000258	-0.0146	0.0147	-0.00583	0.00327	-0.00320
	(-1.44)	(0.02)	(-1.05)	(1.12)	(-0.47)	(0.32)	(-0.32)
_cons	0.821	0.849	1.100	0.946	0.771	0.875	0.792
	(9.20)***	(8.26)***	(4.08)***	(9.87)***	(6.80)***	(6.16)***	(7.70)***
N	431	410	439	403	409	431	410
adj. R^2	0.275	0.231	0.121	0.244	0.164	0.181	0.359

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B with standard regression. Under falling market conditions in time period 1, Norway, Spain, the US, Hong Kong and the UK have a negative coefficient of $R_{m,t}^2$, with the herding behaviour in the US market is significant at the 10% level.

3.3 Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.1

	variable	mean	p50	sd	variance	skewness	kurtosis	min	max	N
Denmark	$R_{m,t}$	.076642	.107256	.972573	.945898	-.207897	3.83086	-4.80249	3.96821	1598
	CSAD	1.00273	.926856	.408917	.167213	1.55356	6.65181	.261331	3.09517	1598
US	$R_{m,t}$	.046763	.031675	.826574	.683225	.157181	5.13001	-3.85915	4.67651	1613
	CSAD	.723001	.679416	.225744	.05096	1.59358	8.51692	.241795	2.46486	1613
Finland	$R_{m,t}$	.04521	.017727	1.19087	1.41817	-.089482	4.05707	-4.75499	4.4115	1609
	CSAD	.996004	.908376	.415343	.17251	1.56849	7.29475	.297071	3.73231	1609
France	$R_{m,t}$	.05124	.056239	1.13776	1.29449	-.025643	4.70738	-4.42802	5.72495	1639
	CSAD	.847085	.802812	.285352	.081426	1.86624	13.5978	.30269	3.90096	1639
Germany	$R_{m,t}$	.039758	.063723	1.11147	1.23537	-.094245	4.07569	-4.25979	4.80358	1623
	CSAD	.830678	.785318	.279685	.078224	1.56586	8.61985	.293355	2.91741	1623
Greece	$R_{m,t}$	.013158	.094628	1.82629	3.33535	-.645349	9.17167	-15.9129	8.37479	1567
	CSAD	2.14584	1.94566	.888963	.790256	2.39306	14.7416	.547966	10.5073	1567
HK	$R_{m,t}$	.037226	.068295	1.08146	1.16955	-.174352	4.89037	-5.29815	4.70363	1577
	CSAD	.915395	.872072	.273104	.074586	1.10937	5.25599	.333052	2.42194	1577
Italy	$R_{m,t}$	.030785	.0694	1.46374	2.14253	-.229001	5.05916	-7.77685	6.31205	1626
	CSAD	1.16929	1.05176	.590533	.348729	5.21618	55.9957	.371091	9.58212	1626
Norway	$R_{m,t}$	.036856	.052286	1.42166	2.02113	-.083898	4.29253	-5.99803	6.56769	1606
	CSAD	1.09509	.991786	.476217	.226782	1.56376	7.73361	.241345	4.72637	1606
Portugal	$R_{m,t}$	.014255	.03165	1.28704	1.65647	-.24472	4.49841	-6.523	4.86745	1639
	CSAD	1.32224	1.2086	.619735	.384072	1.62765	7.96631	.248101	5.92302	1639
Spain	$R_{m,t}$	.01707	.039684	1.23872	1.53443	-.122639	5.27172	-5.65409	5.899	1639
	CSAD	.953455	.87608	.419996	.176397	3.45852	37.9067	.244522	7.24106	1639
Sweden	$R_{m,t}$	.027335	.049893	1.14464	1.31019	-.248668	4.50812	-5.39725	4.89527	1608
	CSAD	.784083	.719219	.293554	.086174	1.7665	8.87963	.28091	3.19133	1608
UK	$R_{m,t}$	.009929	.077461	1.0823	1.17137	-.569517	8.85506	-9.38468	5.0634	1620
	CSAD	1.09797	.999234	.409631	.167797	2.17215	13.4504	.370236	4.62475	1620

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.1 Panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.0763	0.0514	0.136	0.0653	0.0935	0.427
	(1.82)*	(1.85)*	(3.69)***	(3.07)***	(4.03)***	(17.24)***
$R_{m,t}^2$	0.0379	0.0214	0.0100	0.0251	0.00710	0.0107
	(2.04)**	(1.64)	(0.77)	(3.76)***	(0.93)	(2.98)***
_cons	0.909	0.677	0.859	0.759	0.743	1.559
	(48.68)***	(64.78)***	(45.04)***	(63.87)***	(59.38)***	(64.17)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.064	0.062	0.095	0.146	0.084	0.514

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.1 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.0850	0.0501	0.166	0.244	0.0485	0.0869	0.274
	(4.05)***	(0.97)	(4.90)***	(6.11)***	(1.24)	(3.75)***	(14.47)***
$R_{m,t}^2$	0.0253	0.0531	0.00608	0.0174	0.0530	0.00536	0.0128
	(3.74)***	(3.27)***	(0.61)	(1.46)	(3.35)***	(0.71)	(4.12)***
_cons	0.817	1.001	0.904	1.057	0.828	0.702	0.876
	(71.05)***	(36.67)***	(44.15)***	(42.72)***	(46.96)***	(53.36)***	(73.94)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.180	0.214	0.133	0.169	0.238	0.068	0.369

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.1 Panel B, Standard regression

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.0763	0.0514	0.136	0.0653	0.0935	0.427
	(1.94)*	(2.39)**	(4.22)***	(3.13)***	(4.04)***	(19.76)***
$R_{m,t}^2$	0.0379	0.0214	0.0100	0.0251	0.00710	0.0107
	(2.48)**	(2.53)**	(0.99)	(3.96)***	(0.92)	(3.65)***
_cons	0.909	0.677	0.859	0.759	0.743	1.559
	(45.02)***	(66.94)***	(43.93)***	(60.18)***	(56.07)***	(60.24)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.064	0.062	0.095	0.146	0.084	0.514

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.1 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.0850	0.0501	0.166	0.244	0.0485	0.0869	0.274
	(4.11)***	(1.63)	(5.55)***	(6.38)***	(1.93)*	(3.83)***	(13.90)***
$R_{m,t}^2$	0.0253	0.0531	0.00608	0.0174	0.0530	0.00536	0.0128
	(3.94)***	(7.55)***	(0.80)	(1.66)*	(7.97)***	(0.77)	(2.74)***
_cons	0.817	1.001	0.904	1.057	0.828	0.702	0.876
	(66.99)***	(40.82)***	(40.81)***	(39.47)***	(48.64)***	(50.33)***	(65.36)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.180	0.214	0.133	0.169	0.238	0.068	0.369

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B under the standard regression approach, Denmark, Italy, Spain, US, France, Greece, Hong Kong and the UK have a significantly positive coefficient of $R_{m,t}^2$, which is indicative of anti-herding. Portugal also has indications of anti-herding with significance at the 10% level.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.2 Panel A, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00131	-0.0171	0.0108	0.00406	-0.000113	-0.0119
	(-0.11)	(-2.28)**	(1.15)	(0.52)	(-0.02)	(-0.98)
$\|R_{m,t}\|$	0.0768	0.0496	0.133	0.0655	0.0935	0.430
	(1.84)*	(1.73)*	(3.62)***	(3.05)***	(4.03)***	(16.99)***
$R_{m,t}^2$	0.0377	0.0234	0.0111	0.0250	0.00710	0.00980
	(2.04)**	(1.73)*	(0.86)	(3.66)***	(0.93)	(2.66)***
_cons	0.909	0.677	0.860	0.759	0.743	1.557
	(48.75)***	(64.01)***	(45.20)***	(63.60)***	(59.35)***	(63.74)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.064	0.065	0.096	0.146	0.084	0.514

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.2 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0287	0.00559	0.00950	0.0397	0.00623	0.00515	0.0161
	(4.33)***	(0.35)	(0.91)	(3.00)***	(0.48)	(0.66)	(1.58)
$\|R_{m,t}\|$	0.0788	0.0486	0.165	0.229	0.0487	0.0845	0.271
	(3.86)***	(0.91)	(4.88)***	(5.75)***	(1.23)	(3.62)***	(14.43)***
$R_{m,t}^2$	0.0278	0.0536	0.00641	0.0231	0.0531	0.00627	0.0145
	(4.29)***	(3.18)***	(0.64)	(1.98)**	(3.34)***	(0.81)	(4.25)***
_cons	0.818	1.002	0.904	1.061	0.828	0.702	0.876
	(71.94)***	(36.38)***	(44.21)***	(42.87)***	(46.33)***	(53.48)***	(74.30)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.192	0.214	0.133	0.175	0.238	0.068	0.370

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.2 Panel B, Standard regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	-0.00131	-0.0171	0.0108	0.00406	-0.000113	-0.0119
	(-0.13)	(-2.58)***	(1.30)	(0.71)	(-0.02)	(-1.35)
$\lvert R_{m,t}\rvert$	0.0768	0.0496	0.133	0.0655	0.0935	0.430
	(1.94)*	(2.31)**	(4.09)***	(3.14)***	(4.03)***	(19.78)***
$R_{m,t}^2$	0.0377	0.0234	0.0111	0.0250	0.00710	0.00980
	(2.45)**	(2.75)***	(1.09)	(3.94)***	(0.92)	(3.27)***
_cons	0.909	0.677	0.860	0.759	0.743	1.557
	(44.98)***	(67.10)***	(43.95)***	(60.13)***	(56.05)***	(60.17)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.064	0.065	0.096	0.146	0.084	0.514

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.2 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0287	0.00559	0.00950	0.0397	0.00623	0.00515	0.0161
	(5.00)***	(0.63)	(1.22)	(3.62)***	(0.85)	(0.82)	(2.10)**
$\lvert R_{m,t}\rvert$	0.0788	0.0486	0.165	0.229	0.0487	0.0845	0.271
	(3.83)***	(1.57)	(5.51)***	(5.96)***	(1.93)*	(3.69)***	(13.71)***
$R_{m,t}^2$	0.0278	0.0536	0.00641	0.0231	0.0531	0.00627	0.0145
	(4.34)***	(7.57)***	(0.85)	(2.20)**	(7.98)***	(0.89)	(3.06)***
_cons	0.818	1.002	0.904	1.061	0.828	0.702	0.876
	(67.58)***	(40.81)***	(40.83)***	(39.74)***	(48.60)***	(50.29)***	(65.45)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.192	0.214	0.133	0.175	0.238	0.068	0.370

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B, similarly to the regression results from equation 3.2, we find that Denmark, Italy, Portugal, Spain, the US, France, Greece and Hong Kong have a significantly positive coefficient of $R_{m,t}^2$, which means that there is evidence that anti-herding behaviour exists in these stock markets.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.3 Panel A Robust regression in rising and falling market condition

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.0978	0.0208	0.114	0.0757	0.0977	0.358
	(1.99)**	(0.71)	(2.82)***	(3.39)***	(4.28)***	(9.99)***
$(1 - D^{up})\|R_{m,t}\|$	0.0626	0.103	0.142	0.0457	0.0877	0.443
	(1.32)	(3.43)***	(3.24)***	(1.59)	(2.73)***	(15.33)***
$D^{up}(R_{m,t})^2$	0.0246	0.0317	0.0247	0.0217	0.00485	0.0249
	(1.03)	(2.17)**	(1.61)	(3.39)***	(0.70)	(2.95)***
$(1 - D^{up})(R_{m,t})^2$	0.0471	0.00149	0.00160	0.0318	0.00994	0.00833
	(2.09)**	(0.10)	(0.10)	(2.61)***	(0.79)	(2.62)***
_cons	0.907	0.674	0.862	0.760	0.743	1.575
	(48.71)***	(67.58)***	(45.47)***	(63.50)***	(58.77)***	(62.73)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.063	0.067	0.096	0.146	0.083	0.515

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.3 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.0968	0.0404	0.149	0.269	0.0779	0.0461	0.212
	(3.59)***	(0.63)	(3.66)***	(4.85)***	(2.08)**	(1.62)	(5.54)***
$(1 - D^{up})\|R_{m,t}\|$	0.0580	0.0510	0.182	0.188	0.0105	0.0976	0.257
	(2.66)***	(0.79)	(4.78)***	(4.37)***	(0.19)	(3.95)***	(10.76)***
$D^{up}(R_{m,t})^2$	0.0329	0.0585	0.0163	0.0226	0.0433	0.0270	0.0442
	(3.04)***	(2.20)**	(1.15)	(1.11)	(3.09)***	(2.11)**	(2.91)***
$(1 - D^{up})(R_{m,t})^2$	0.0239	0.0507	-0.00351	0.0233	0.0654	-0.00288	0.0109
	(3.70)***	(2.58)***	(-0.31)	(1.84)*	(2.51)**	(-0.42)	(2.00)**
_cons	0.818	1.003	0.904	1.061	0.829	0.707	0.890
	(70.97)***	(35.85)***	(44.00)***	(41.85)***	(46.22)***	(54.55)***	(66.70)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.192	0.214	0.134	0.174	0.240	0.071	0.373

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.3 Panel B Standard regression in rising and falling market condition

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.0978	0.0208	0.114	0.0757	0.0977	0.358
	(2.10)**	(0.89)	(2.97)***	(3.35)***	(3.77)***	(10.15)***
$(1 - D^{up})\|R_{m,t}\|$	0.0626	0.103	0.142	0.0457	0.0877	0.443
	(1.39)	(3.62)***	(3.86)***	(1.71)*	(3.15)***	(18.18)***
$D^{up}(R_{m,t})^2$	0.0246	0.0317	0.0247	0.0217	0.00485	0.0249
	(1.18)	(3.36)***	(1.79)*	(3.03)***	(0.52)	(3.33)***
$(1 - D^{up})(R_{m,t})^2$	0.0471	0.00149	0.00160	0.0318	0.00994	0.00833
	(2.56)**	(0.11)	(0.13)	(3.39)***	(0.97)	(2.71)***
_cons	0.907	0.674	0.862	0.760	0.743	1.575
	(44.76)***	(66.25)***	(43.98)***	(59.81)***	(56.02)***	(58.10)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.063	0.067	0.096	0.146	0.083	0.515

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.3 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.0968	0.0404	0.149	0.269	0.0779	0.0461	0.212
	(4.01)***	(1.08)	(4.38)***	(5.32)***	(2.74)***	(1.62)	(6.62)***
$(1 - D^{up})\|R_{m,t}\|$	0.0580	0.0510	0.182	0.188	0.0105	0.0976	0.257
	(2.48)**	(1.46)	(5.23)***	(4.48)***	(0.35)	(3.84)***	(11.85)***
$D^{up}(R_{m,t})^2$	0.0329	0.0585	0.0163	0.0226	0.0433	0.0270	0.0442
	(3.84)***	(5.79)***	(1.71)*	(1.31)	(5.33)***	(2.54)**	(4.12)***
$(1 - D^{up})(R_{m,t})^2$	0.0239	0.0507	-0.00351	0.0233	0.0654	-0.00288	0.0109
	(3.12)***	(6.15)***	(-0.37)	(2.02)**	(7.40)***	(-0.37)	(2.24)**
_cons	0.818	1.003	0.904	1.061	0.829	0.707	0.890
	(67.52)***	(40.71)***	(40.85)***	(39.15)***	(48.70)***	(50.31)***	(62.93)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.192	0.214	0.134	0.174	0.240	0.071	0.373

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel A, Italy, Spain, France, Greece, Hong Kong and the UK have a significantly positive coefficient of both rising $D^{up}(R_{m,t})^2$ and falling market $(1 - D^{up})(R_{m,t})^2$ terms. Denmark and Portugal have a significantly positive value of the coefficient of $(1 - D^{up})(R_{m,t})^2$, Sweden and the US has a significantly positive value of the coefficient of $D^{up}(R_{m,t})^2$. Norway and Sweden have negative coefficients of $(1 - D^{up})(R_{m,t})^2$ but they are insignificant.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.4 Panel A Robust regression with larger log positive returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.246	0.0779	0.374	0.188	0.0959	0.508
	(1.23)	(0.81)	(2.08)**	(2.69)***	(1.14)	(4.28)***
$R^2_{m,t}$	-0.0175	0.0178	-0.0332	-0.000330	0.00727	0.00678
	(-0.31)	(0.61)	(-0.78)	(-0.03)	(0.45)	(0.43)
_cons	0.800	0.632	0.616	0.650	0.731	1.330
	(5.15)***	(9.17)***	(3.66)***	(9.07)***	(8.86)***	(7.60)***
N	369	332	335	340	340	319
adj. R^2	0.036	0.100	0.115	0.176	0.068	0.484

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.4 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.202	0.242	0.215	0.272	0.333	0.143	0.365
	(2.14)**	(1.32)	(1.58)	(1.16)	(2.95)***	(1.66)*	(3.30)***
$R^2_{m,t}$	0.0116	0.0228	0.00460	0.0179	-0.000471	0.00673	0.00948
	(0.52)	(0.57)	(0.18)	(0.35)	(-0.02)	(0.33)	(0.36)
_cons	0.714	0.791	0.830	1.090	0.550	0.609	0.769
	(8.42)***	(3.82)***	(5.22)***	(4.62)***	(4.92)***	(7.37)***	(8.55)***
N	318	334	332	349	353	349	300
adj. R^2	0.246	0.185	0.109	0.113	0.287	0.100	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.4 Panel B Standard regression with larger log positive returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.246	0.0779	0.374	0.188	0.0959	0.508
	(1.25)	(1.08)	(2.30)**	(2.55)**	(1.08)	(4.35)***
$R_{m,t}^2$	-0.0175	0.0178	-0.0332	-0.000330	0.00727	0.00678
	(-0.32)	(0.97)	(-0.90)	(-0.02)	(0.36)	(0.42)
_cons	0.800	0.632	0.616	0.650	0.731	1.330
	(5.13)***	(10.80)***	(3.86)***	(8.58)***	(8.57)***	(7.60)***
N	369	332	335	340	340	319
adj. R^2	0.036	0.100	0.115	0.176	0.068	0.484

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.4 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.202	0.242	0.215	0.272	0.333	0.143	0.365
	(2.17)**	(1.59)	(1.57)	(1.21)	(3.43)***	(1.31)	(2.98)***
$R_{m,t}^2$	0.0116	0.0228	0.00460	0.0179	-0.000471	0.00673	0.00948
	(0.55)	(0.87)	(0.19)	(0.37)	(-0.03)	(0.26)	(0.33)
_cons	0.714	0.791	0.830	1.090	0.550	0.609	0.769
	(8.16)***	(4.19)***	(5.01)***	(4.72)***	(5.24)***	(6.06)***	(7.29)***
N	318	334	332	349	353	349	300
adj. R^2	0.246	0.185	0.109	0.113	0.287	0.100	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.5 Panel A Robust regression with larger log negative returns

$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	-0.192	0.152	0.0403	0.0739	0.0414	0.612
	(-1.07)	(1.54)	(0.23)	(0.60)	(0.28)	(7.40)***
$R_{m,t}^2$	0.106	-0.0107	0.0244	0.0254	0.0195	-0.00393
	(2.17)**	(-0.37)	(0.62)	(0.91)	(0.56)	(-0.69)
_cons	1.133	0.633	0.944	0.735	0.790	1.239
	(7.47)***	(9.10)***	(5.61)***	(6.51)***	(5.89)***	(7.63)***
N	288	302	305	290	293	279
adj. R^2	0.078	0.046	0.054	0.135	0.054	0.529

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.5 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	-0.0537	-0.147	0.390	0.350	-0.151	0.220	0.141
	(-0.79)	(-0.71)	(2.82)***	(2.21)**	(-0.81)	(2.77)***	(3.01)***
$R_{m,t}^2$	0.0449	0.0792	-0.0399	0.00000597	0.0971	-0.0255	0.0243
	(3.68)***	(2.17)**	(-1.57)	(0.00)	(2.03)**	(-1.85)*	(4.94)***
_cons	0.939	1.268	0.670	0.837	0.981	0.573	1.055
	(13.37)***	(5.10)***	(4.26)***	(4.67)***	(5.86)***	(6.84)***	(16.13)***
N	272	305	304	313	298	291	271
adj. R^2	0.172	0.221	0.083	0.180	0.291	0.056	0.336

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 3.3.2.5 Panel B Standard regression with larger log negative returns

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	-0.192	0.152	0.0403	0.0739	0.0414	0.612
	(-1.16)	(1.45)	(0.28)	(0.60)	(0.31)	(7.91)***
$R^2_{m,t}$	0.106	-0.0107	0.0244	0.0254	0.0195	-0.00393
	(2.53)**	(-0.33)	(0.80)	(0.90)	(0.64)	(-0.62)
_cons	1.133	0.633	0.944	0.735	0.790	1.239
	(7.85)***	(8.62)***	(6.43)***	(6.36)***	(6.32)***	(7.72)***
N	288	302	305	290	293	279
adj. R^2	0.078	0.046	0.054	0.135	0.054	0.529

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.2.5 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	-0.0537	-0.147	0.390	0.350	-0.151	0.220	0.141
	(-0.69)	(-1.06)	(2.85)***	(2.46)**	(-1.20)	(2.47)**	(2.38)**
$R^2_{m,t}$	0.0449	0.0792	-0.0399	0.00000597	0.0971	-0.0255	0.0243
	(2.72)***	(3.68)***	(-1.65)	(0.00)	(4.02)***	(-1.42)	(2.82)***
_cons	0.939	1.268	0.670	0.837	0.981	0.573	1.055
	(11.99)***	(6.88)***	(4.02)***	(4.90)***	(7.11)***	(6.21)***	(14.31)***
N	272	305	304	313	298	291	271
adj. R^2	0.172	0.221	0.083	0.180	0.291	0.056	0.336

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In table 3.3.2.5 panel B, Norway, Sweden, the US and Greece have a negative coefficient of $R^2_{m,t}$, although Norway is only significant at the 10% level, which means Norway has weak evidence of herding behaviour. Denmark, Italy, Spain, Hong Kong and the UK have a significantly positive coefficient of $R^2_{m,t}$, which means that they show strong evidence of anti-herding behaviour during the time period.

Material Associated with Chapter 4

4.0 Empirical Study 2 – Worldwide Herding Results (Simple Returns)

Full Range of Data from 02/Jan/2002 to 31/May/2018

Table 4.2.2.1 Panel B, Standard Regression (Simple returns)

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.237	0.218	0.162	0.160	0.188	0.318
	(12.21)***	(17.70)***	(9.85)***	(13.01)***	(13.78)***	(22.83)***
$R_{m,t}^2$	0.0215	0.0108	0.0150	0.0196	0.0202	0.0154
	(5.09)***	(4.38)***	(4.65)***	(8.27)***	(7.87)***	(7.00)***
_cons	0.974	0.708	0.969	0.799	0.805	1.407
	(66.61)***	(74.57)***	(69.58)***	(76.24)***	(67.87)***	(95.96)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.206	0.286	0.182	0.315	0.293	0.422

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.1 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.224	0.146	0.195	0.317	0.174	0.173	0.255
	(18.36)***	(8.92)***	(8.23)***	(16.74)***	(12.48)***	(15.03)***	(16.89)***
$R_{m,t}^2$	0.0118	0.0320	0.0347	0.00458	0.0181	0.00748	0.0282
	(5.31)***	(9.14)***	(9.58)***	(1.00)	(6.07)***	(4.14)***	(8.71)***
_cons	0.908	0.893	1.140	0.893	0.783	0.796	0.854
	(82.30)***	(68.98)***	(44.21)***	(65.79)***	(71.88)***	(69.20)***	(79.74)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.305	0.266	0.249	0.231	0.249	0.245	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

According to panel B, we can see that Denmark, US, Finland, France, Germany, Greece, Hong Kong, Italy, Norway, Spain, Sweden and UK have a significantly positive coefficient of squared market return, which is indicative that anti-herding exists in the market. The results indicate that neither herding nor anti-herding exists in the market of Portugal. Under normal regression results, Norway does not have either herding or anti-herding behaviour in the market based on the log return calculation method, but has got evidence of anti-herding behaviour with results based on the simple return calculation method. However, based on the simple return method, the regression results show that Norway have a significantly positive coefficient of squared market return, which is indicative of anti-herding, Denmark also has some evidence that anti-herding exists in the market with significance at the 10% level.

Table 4.2.2.2 Panel B, Standard Regression (Simple returns)

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0216	0.00411	0.0228	0.0238	0.0200	0.0318
	(3.11)***	(0.87)	(4.24)***	(5.79)***	(4.11)***	(6.14)***
$\|R_{m,t}\|$	0.235	0.219	0.165	0.165	0.192	0.318
	(12.10)***	(17.72)***	(10.08)***	(13.39)***	(14.03)***	(22.92)***
$R_{m,t}^2$	0.0223	0.0105	0.0140	0.0185	0.0195	0.0156
	(5.26)***	(4.21)***	(4.32)***	(7.80)***	(7.56)***	(7.13)***
_cons	0.973	0.707	0.967	0.796	0.802	1.406
	(66.63)***	(74.41)***	(69.43)***	(76.13)***	(67.67)***	(96.28)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.208	0.286	0.185	0.320	0.295	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.2 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0396	0.0301	0.0107	0.0487	0.0252	0.0219	0.0192
	(8.63)***	(5.83)***	(1.38)	(7.48)***	(5.31)***	(5.12)***	(3.50)***
$\|R_{m,t}\|$	0.225	0.149	0.194	0.318	0.179	0.179	0.255
	(18.65)***	(9.14)***	(8.15)***	(16.91)***	(12.84)***	(15.51)***	(16.88)***
$R_{m,t}^2$	0.0109	0.0316	0.0351	0.00546	0.0171	0.00613	0.0284
	(4.92)***	(9.07)***	(9.65)***	(1.20)	(5.74)***	(3.37)***	(8.78)***
_cons	0.905	0.890	1.140	0.889	0.780	0.792	0.853
	(82.80)***	(68.94)***	(44.21)***	(65.91)***	(71.64)***	(68.82)***	(79.77)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.317	0.272	0.249	0.241	0.254	0.249	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B under standard regression, compared with the log return results, Norway has a significantly positive coefficient of squared market return, which is indicative of anti-herding.

Table 4.2.2.3 Panel B Standard regression in rising and falling market condition

(Simple returns)

$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.246	0.224	0.188	0.183	0.212	0.353
	(10.85)***	(16.25)***	(10.25)***	(13.21)***	(13.92)***	(21.09)***
$(1 - D^{up})\|R_{m,t}\|$	0.223	0.212	0.144	0.153	0.170	0.284
	(9.75)***	(12.47)***	(6.89)***	(9.85)***	(9.50)***	(17.61)***
$D^{up}(R_{m,t})^2$	0.0261	0.0102	0.0142	0.0202	0.0193	0.0148
	(4.67)***	(3.79)***	(3.85)***	(7.45)***	(6.65)***	(5.00)***
$(1 - D^{up})(R_{m,t})^2$	0.0187	0.0116	0.0135	0.0149	0.0199	0.0162
	(3.47)***	(2.56)**	(2.76)***	(4.21)***	(4.85)***	(5.87)***
_cons	0.973	0.708	0.966	0.795	0.802	1.406
	(66.63)***	(73.35)***	(69.08)***	(75.74)***	(67.15)***	(96.15)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.208	0.286	0.185	0.320	0.295	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.3 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.257	0.152	0.312	0.360	0.192	0.201	0.253
	(18.60)***	(8.25)***	(11.30)***	(16.94)***	(12.32)***	(15.61)***	(14.11)***
$(1 - D^{up})\|R_{m,t}\|$	0.198	0.165	0.0881	0.280	0.183	0.157	0.255
	(13.30)***	(8.19)***	(3.19)***	(11.93)***	(10.21)***	(9.69)***	(14.28)***
$D^{up}(R_{m,t})^2$	0.0133	0.0411	0.00849	0.00816	0.0216	0.00611	0.0353
	(4.99)***	(9.92)***	(1.77)*	(1.48)	(6.35)***	(3.13)***	(8.34)***
$(1 - D^{up})(R_{m,t})^2$	0.00714	0.0172	0.0572	0.00164	0.00767	0.00620	0.0218
	(2.22)**	(3.51)***	(12.82)***	(0.26)	(1.68)*	(1.85)*	(5.24)***
_cons	0.905	0.887	1.133	0.888	0.777	0.792	0.854
	(82.71)***	(68.71)***	(44.28)***	(65.73)***	(71.04)***	(67.64)***	(79.86)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.318	0.275	0.261	0.240	0.255	0.249	0.380

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B, we using equation 3.4 and find out that every country has a positive and significant coefficient of $D^{up}(R_{m,t})^2$ except Norway and Portugal where the coefficients are positive but not significant. Which means that most of the countries show clear evidence that anti-herding exists in their stock market during rising market conditions. During falling market conditions, every country has a positive and significant coefficient of $(1 - D^{up})\left(R_{m,t}\right)^2$ except Portugal, Spain and Sweden indicating that anti-herding behaviour also exists in falling markets.

Table 4.2.2.4 Panel B Standard regression with larger simple positive returns

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.545	0.433	0.287	0.330	0.430	0.478
	(8.01)***	(10.98)***	(5.04)***	(7.36)***	(9.32)***	(10.12)***
$R_{m,t}^2$	-0.0162	-0.0138	0.00146	0.00246	-0.00418	0.00213
	(-1.49)	(-2.64)***	(0.19)	(0.42)	(-0.72)	(0.39)
_cons	0.622	0.433	0.842	0.591	0.476	1.205
	(7.91)***	(8.66)***	(10.53)***	(9.32)***	(7.20)***	(15.29)***
N	885	817	815	797	829	783
adj. R^2	0.267	0.366	0.238	0.404	0.366	0.458

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.4 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.434	0.289	0.619	0.402	0.280	0.434	0.439
	(10.47)***	(4.47)***	(6.72)***	(6.21)***	(6.20)***	(12.58)***	(8.11)***
$R_{m,t}^2$	-0.00512	0.0217	-0.0246	0.000700	0.0107	-0.0146	0.00904
	(-0.99)	(2.25)**	(-2.35)**	(0.07)	(1.65)*	(-4.11)***	(1.04)
_cons	0.632	0.722	0.643	0.858	0.658	0.385	0.634
	(10.45)***	(8.47)***	(4.03)***	(11.06)***	(11.41)***	(6.65)***	(10.09)***
N	824	826	816	838	852	789	766
adj. R^2	0.393	0.300	0.185	0.213	0.337	0.395	0.446

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B under standard regression, the top 18% of returns was used. Unlike the log return results, Denmark, Germany, Norway, Sweden, the US and Hong Kong have a negative coefficient of $R_{m,t}^2$, Norway, Sweden and the US have a significantly negative coefficient of $R_{m,t}^2$, which is indicative of herding.

Table 4.2.2.5 Panel B Standard regression with larger simple negative returns

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.373	0.359	0.167	0.220	0.218	0.381
	(5.61)***	(6.50)***	(2.25)**	(4.37)***	(3.59)***	(7.33)***
$R_{m,t}^2$	-0.00107	-0.0116	0.0113	0.00575	0.0145	0.00688
	(-0.10)	(-1.20)	(0.99)	(0.76)	(1.59)	(1.23)
_cons	0.777	0.538	0.921	0.704	0.719	1.242
	(9.46)***	(8.75)***	(9.38)***	(10.34)***	(8.93)***	(13.53)***
N	713	739	723	719	728	723
adj. R^2	0.230	0.287	0.140	0.277	0.286	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2.2.5 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.304	0.126	-0.225	0.226	0.289	0.183	0.349
	(7.43)***	(1.96)*	(-2.00)**	(3.07)***	(4.55)***	(3.11)***	(6.18)***
$R_{m,t}^2$	-0.00508	0.0228	0.0881	0.0101	-0.00824	0.00295	0.00933
	(-0.93)	(2.23)**	(7.25)***	(0.79)	(-0.78)	(0.37)	(1.07)
_cons	0.749	0.941	1.702	0.953	0.641	0.753	0.731
	(12.55)***	(11.23)***	(8.40)***	(11.11)***	(8.13)***	(8.62)***	(10.57)***
N	705	713	714	723	708	690	665
adj. R^2	0.258	0.235	0.295	0.175	0.192	0.178	0.370

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel B with standard regression results, Denmark, US and Hong Kong have negative coefficients of $R_{m,t}^2$, although all of them are insignificant. Also, Italy and Norway have a significantly positive coefficients of $R_{m,t}^2$ which is indicative of anti-herding.

4.3 First time period from 02/Jan/2002 to 30/Dec/2011

4.3.1 Descriptive statistics results (Simple returns)

Table 4.3.1

	variable	mean	p50	sd	variance	skewness	kurtosis	min	max	N
Denmark	$R_{m,t}$	.054881	.080221	1.33443	1.7807	-.23153	8.1297	-9.93637	8.38672	2507
	CSAD	1.34215	1.18854	.66479	.441946	2.20965	12.0306	.332687	7.97629	2507
US	$R_{m,t}$	.041806	.058998	1.40006	1.96016	.334195	8.38523	-7.69683	10.0664	2519
	CSAD	1.02803	.89156	.479945	.230347	2.32158	11.474	.24053	5.0172	2519
Finland	$R_{m,t}$	.047106	.087945	1.61386	2.60454	.103716	6.90952	-8.46355	9.37088	2515
	CSAD	1.28193	1.13921	.605217	.366287	3.02042	28.8232	.326121	10.5227	2515
France	$R_{m,t}$	.028099	.045514	1.63242	2.6648	.107943	7.02705	-8.84619	9.38817	2563
	CSAD	1.10772	.952334	.532011	.283036	1.76235	7.00839	.334741	4.19721	2563
Germany	$R_{m,t}$	.039787	.076159	1.58162	2.50152	.070299	7.79428	-8.52537	11.8836	2548
	CSAD	1.16436	.994993	.604283	.365158	2.01338	8.90264	.252528	5.55287	2548
Greece	$R_{m,t}$	-.000456	.077994	1.56006	2.4338	.058046	8.28301	-10.2343	13.8705	2496
	CSAD	1.62792	1.51975	.526571	.277277	2.01909	13.3768	.683347	7.68058	2496
HK	$R_{m,t}$	.076305	.090916	1.57381	2.47687	.111924	7.91056	-11.5609	12.2546	2473
	CSAD	1.30892	1.18341	.541419	.293134	2.12534	11.2966	.316465	6.30263	2473
Italy	$R_{m,t}$	.008776	.088996	1.37839	1.89996	-.119723	7.43588	-8.14261	9.82029	2542
	CSAD	1.06009	.923267	.495822	.245839	1.89367	8.09119	.263621	4.14793	2542
Norway	$R_{m,t}$	.067386	.144883	2.09596	4.39303	-.270111	6.66656	-11.9357	11.1138	2514
	CSAD	1.79166	1.47056	1.24265	1.54417	4.487	43.6528	.320766	16.9689	2514
Portugal	$R_{m,t}$	.02186	.080198	1.13742	1.29372	-.269744	9.18759	-7.55258	9.39527	2555
	CSAD	1.07331	.968663	.520417	.270834	1.62868	7.94989	.219376	4.96321	2555
Spain	$R_{m,t}$	.037994	.104361	1.36541	1.86435	-.025595	7.94616	-7.69075	10.3766	2535
	CSAD	.994391	.871213	.498257	.248261	2.00011	9.81843	.277047	5.03856	2535
Sweden	$R_{m,t}$	.065156	.095574	1.85862	3.45446	.294093	8.05007	-8.82834	14.0028	2515
	CSAD	1.15626	1.00701	.557347	.310636	1.91712	8.607	.329038	5.2127	2515
UK	$R_{m,t}$	.036773	.084096	1.33703	1.78765	-.084958	8.56549	-8.79727	8.34741	2511
	CSAD	1.2277	1.0621	.59977	.359724	2.37045	10.7251	.370533	5.40611	2511

Table 4.3.1 shows the descriptive statistics for the equally weighted average market returns and the CCK measurements for each of the total thirteen different countries based on the simple return calculation method in time period 1. The statistics shown in table 4.3.1 show that the mean returns of $R_{m,t}$ in all the countries other than Greece are positive during this time period, which indicates a positive performance of the corresponding stock markets during our first time period. The standard deviation of $R_{m,t}$ varies between countries and is particularly high in Norway and Sweden. Also, the minimum and maximum returns are substantial in all of the markets reflecting the times of financial turbulence in the sample period. Regarding the CASD results model, we find that the mean value of the CSAD results of 1.79166 in Norway is much higher than the other countries in our sample. Similarly, Norway also has the highest standard deviation of CSAD, which is 1.24265. By using the simple return calculation method, the mean value of CSAD is slightly higher than calculated by using the log return method.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.1 Panel A, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.302	0.234	0.175	0.196	0.247	0.221
	(7.87)***	(8.34)***	(5.96)***	(9.75)***	(7.09)***	(16.74)***
$R_{m,t}^2$	0.00909	0.00676	0.0114	0.0135	0.0113	0.0160
	(0.87)	(0.98)	(1.61)	(3.33)***	(1.43)	(7.49)***
_cons	1.043	0.781	1.054	0.847	0.862	1.341
	(47.67)***	(46.28)***	(53.28)***	(56.81)***	(40.31)***	(106.91)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.239	0.295	0.194	0.338	0.327	0.402

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.1 Panel A, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.235	0.223	0.219	0.304	0.210	0.181	0.314
	(8.17)***	(10.82)***	(2.68)***	(12.27)***	(10.07)***	(7.88)***	(10.89)***
$R_{m,t}^2$	0.00855	0.0118	0.0298	0.00659	0.0112	0.00482	0.0150
	(1.20)	(2.47)**	(1.72)*	(1.13)	(2.28)**	(1.15)	(2.20)**
_cons	1.022	0.825	1.333	0.825	0.773	0.905	0.915
	(56.31)***	(61.62)***	(23.92)***	(57.22)***	(56.27)***	(50.63)***	(56.12)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.318	0.303	0.246	0.269	0.261	0.254	0.387

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.1 Panel B, Standard Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.302	0.234	0.175	0.196	0.247	0.221
	(12.12)***	(14.39)***	(8.18)***	(12.00)***	(13.68)***	(16.00)***
$R^2_{m,t}$	0.00909	0.00676	0.0114	0.0135	0.0113	0.0160
	(1.82)*	(2.27)**	(2.94)***	(4.64)***	(3.61)***	(7.00)***
_cons	1.043	0.781	1.054	0.847	0.862	1.341
	(52.36)***	(55.55)***	(54.80)***	(56.40)***	(51.21)***	(96.76)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.239	0.295	0.194	0.338	0.327	0.402

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.1 Panel B, (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.235	0.223	0.219	0.304	0.210	0.181	0.314
	(15.23)***	(12.42)***	(6.66)***	(14.66)***	(11.67)***	(12.31)***	(15.56)***
$R^2_{m,t}$	0.00855	0.0118	0.0298	0.00659	0.0112	0.00482	0.0150
	(3.30)***	(3.19)***	(6.43)***	(1.43)	(3.13)***	(2.25)**	(3.73)***
_cons	1.022	0.825	1.333	0.825	0.773	0.905	0.915
	(66.40)***	(58.72)***	(34.44)***	(56.48)***	(53.04)***	(55.76)***	(58.41)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.318	0.303	0.246	0.269	0.261	0.254	0.387

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.1 panel A (with robust regression results) and panel B shows the results of the regression given in equation 3.2 based on the simple return method in time period 1. In panel A, we can see that Italy, Spain, France, the UK and Greece have significantly positive coefficients of $R^2_{m,t}$, which is indicative of anti-herding, and Norway also has significance at the 10% level, so that these countries do not have herding behaviour during the time period 1. In panel B, we can see that all the countries have a significantly positive coefficient of $R^2_{m,t}$, except Portugal, which means that there is anti-herding behaviour present in most of the markets. In Denmark the evidence of anti-herding in Denmark is only significant at the 10% level. Compared with the herding estimation results based on log returns, we have more anti-herding behaviour detected when we estimate the herding using simple returns. According to the results shown in the table compared with the results based on log return method, more anti-herding exists in Finland, Norway and Sweden in the normal regression results. Spain and UK have clear evidence of anti-herding behaviour in the robust regression results.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.2 Panel A, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0267	0.0118	0.0236	0.0300	0.0263	0.0338
	(1.96)*	(1.49)	(2.11)**	(4.55)***	(3.04)***	(5.37)***
$\|R_{m,t}\|$	0.301	0.237	0.182	0.204	0.254	0.231
	(8.10)***	(8.43)***	(6.25)***	(10.14)***	(6.98)***	(17.95)***
$R_{m,t}^2$	0.00975	0.00574	0.00982	0.0118	0.0100	0.0145
	(0.96)	(0.83)	(1.38)	(2.98)***	(1.22)	(7.55)***
_cons	1.041	0.779	1.049	0.841	0.857	1.334
	(48.59)***	(46.04)***	(53.70)***	(56.11)***	(38.98)***	(106.87)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.241	0.296	0.197	0.347	0.331	0.412

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.2 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0396	0.0272	0.00616	0.0359	0.0289	0.0241	0.0310
	(4.66)***	(3.34)***	(0.28)	(3.91)***	(3.48)***	(3.55)***	(3.16)***
$\|R_{m,t}\|$	0.237	0.229	0.218	0.311	0.217	0.190	0.315
	(8.61)***	(10.90)***	(2.70)***	(13.82)***	(11.38)***	(7.96)***	(11.76)***
$R_{m,t}^2$	0.00749	0.0110	0.0301	0.00614	0.00993	0.00308	0.0149
	(1.12)	(2.31)**	(1.76)*	(1.36)	(2.44)**	(0.71)	(2.49)**
_cons	1.019	0.820	1.333	0.819	0.767	0.899	0.913
	(57.39)***	(60.00)***	(23.74)***	(58.64)***	(57.74)***	(49.01)***	(57.89)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.331	0.308	0.245	0.275	0.267	0.260	0.392

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.2 Panel B, Standard Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0267	0.0118	0.0236	0.0300	0.0263	0.0338
	(3.08)***	(2.03)**	(3.50)***	(5.74)***	(4.23)***	(6.47)***
$\|R_{m,t}\|$	0.301	0.237	0.182	0.204	0.254	0.231
	(12.08)***	(14.53)***	(8.49)***	(12.52)***	(14.03)***	(16.74)***
$R_{m,t}^2$	0.00975	0.00574	0.00982	0.0118	0.0100	0.0145
	(1.95)*	(1.90)*	(2.53)**	(4.05)***	(3.20)***	(6.36)***
_cons	1.041	0.779	1.049	0.841	0.857	1.334
	(52.37)***	(55.29)***	(54.49)***	(56.27)***	(50.97)***	(96.73)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.241	0.296	0.197	0.347	0.331	0.412

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.2 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0396	0.0272	0.00616	0.0359	0.0289	0.0241	0.0310
	(6.97)***	(4.57)***	(0.60)	(4.63)***	(4.63)***	(4.60)***	(4.45)***
$\|R_{m,t}\|$	0.237	0.229	0.218	0.311	0.217	0.190	0.315
	(15.52)***	(12.79)***	(6.62)***	(15.02)***	(12.06)***	(12.83)***	(15.66)***
$R_{m,t}^2$	0.00749	0.0110	0.0301	0.00614	0.00993	0.00308	0.0149
	(2.92)***	(2.97)***	(6.45)***	(1.34)	(2.78)***	(1.42)	(3.72)***
_cons	1.019	0.820	1.333	0.819	0.767	0.899	0.913
	(66.83)***	(58.45)***	(34.43)***	(56.10)***	(52.73)***	(55.37)***	(58.49)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.331	0.308	0.245	0.275	0.267	0.260	0.392

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.2 panel A (with robust regression results) and panel B show the regression results for equation 3.3. In the robust regression results shown in panel A, Italy, Spain, France, Greece and the UK have significantly positive coefficients of $R_{m,t}^2$, which indicates they have anti-herding behaviour during the sample period 1, Norway have some evidence of anti-herding which is significant at the 10 % level, and the other countries do not have evidence supporting either herding or anti-herding. In panel B, we can see that both

Denmark and the US have modest evidence of anti-herding, shown by positive coefficient of squared market return, which are significantly at the 10% level. All the other countries have a significantly positive coefficient of $R_{m,t}^2$ which is indicative of anti-herding.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.3 Panel A Robust regression in rising and falling market condition

(Simple returns)

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2(1 - D^{up})\left|R_{m,t}\right| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})\left(R_{m,t}\right)^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\left\|R_{m,t}\right\|$	0.317	0.250	0.205	0.227	0.278	0.267
	(7.38)***	(8.13)***	(5.99)***	(9.34)***	(6.52)***	(17.77)***
$(1 - D^{up})\left\|R_{m,t}\right\|$	0.283	0.220	0.160	0.191	0.234	0.189
	(6.76)***	(8.42)***	(5.18)***	(8.63)***	(8.48)***	(10.19)***
$D^{up}(R_{m,t})^2$	0.0131	0.00530	0.0101	0.0140	0.0107	0.0137
	(0.99)	(0.67)	(1.18)	(2.79)***	(0.99)	(7.72)***
$(1 - D^{up})\left(R_{m,t}\right)^2$	0.00673	0.00751	0.00922	0.00737	0.00836	0.0167
	(0.53)	(1.08)	(0.91)	(1.54)	(1.53)	(3.63)***
_cons	1.042	0.780	1.048	0.839	0.856	1.335
	(49.46)***	(49.47)***	(55.40)***	(56.30)***	(42.63)***	(105.49)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.241	0.296	0.197	0.347	0.331	0.412

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.3 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\left\|R_{m,t}\right\|$	0.267	0.234	0.358	0.340	0.228	0.213	0.313
	(7.47)***	(7.58)***	(7.39)***	(13.44)***	(10.96)***	(8.03)***	(9.78)***
$(1 - D^{up})\left\|R_{m,t}\right\|$	0.212	0.246	0.0925	0.291	0.235	0.167	0.314
	(8.21)***	(10.73)***	(0.88)	(9.17)***	(9.64)***	(7.08)***	(11.24)***
$D^{up}(R_{m,t})^2$	0.0102	0.0186	0.000153	0.00895	0.0164	0.00318	0.0247
	(1.06)	(2.23)**	(0.02)	(2.41)**	(4.16)***	(0.63)	(3.25)***
$(1 - D^{up})\left(R_{m,t}\right)^2$	0.00325	-0.00243	0.0552	0.000906	-0.00430	0.00264	0.00536
	(0.51)	(-0.46)	(2.19)**	(0.10)	(-0.69)	(0.60)	(0.84)
_cons	1.018	0.816	1.322	0.818	0.762	0.898	0.915
	(57.53)***	(56.43)***	(27.07)***	(57.30)***	(57.80)***	(51.66)***	(59.27)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.332	0.311	0.262	0.275	0.270	0.260	0.394

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.3 Panel B Standard regression in rising and falling market condition (Simple returns)

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2(1 - D^{up})\left|R_{m,t}\right| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})\left(R_{m,t}\right)^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\left\|R_{m,t}\right\|$	0.317	0.250	0.205	0.227	0.278	0.267
	(10.80)***	(13.78)***	(8.48)***	(12.27)***	(13.74)***	(17.08)***
$(1 - D^{up})\left\|R_{m,t}\right\|$	0.283	0.220	0.160	0.191	0.234	0.189
	(9.69)***	(9.86)***	(5.92)***	(9.31)***	(9.79)***	(10.46)***
$D^{up}(R_{m,t})^2$	0.0131	0.00530	0.0101	0.0140	0.0107	0.0137
	(1.99)**	(1.64)	(2.30)**	(4.21)***	(3.06)***	(5.38)***
$(1 - D^{up})\left(R_{m,t}\right)^2$	0.00673	0.00751	0.00922	0.00737	0.00836	0.0167
	(1.06)	(1.37)	(1.56)	(1.70)*	(1.66)*	(4.38)***
_cons	1.042	0.780	1.048	0.839	0.856	1.335
	(52.35)***	(54.45)***	(54.26)***	(55.96)***	(50.46)***	(95.90)***
N	2507	2519	2515	2563	2548	2496
adj. R^2	0.241	0.296	0.197	0.347	0.331	0.412

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.3 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\left\|R_{m,t}\right\|$	0.267	0.234	0.358	0.340	0.228	0.213	0.313
	(15.24)***	(11.47)***	(9.38)***	(14.41)***	(11.23)***	(12.93)***	(13.04)***
$(1 - D^{up})\left\|R_{m,t}\right\|$	0.212	0.246	0.0925	0.291	0.235	0.167	0.314
	(11.34)***	(10.96)***	(2.43)**	(10.96)***	(10.14)***	(8.00)***	(13.33)***
$D^{up}(R_{m,t})^2$	0.0102	0.0186	0.000153	0.00895	0.0164	0.00318	0.0247
	(3.30)***	(4.33)***	(0.03)	(1.67)*	(4.04)***	(1.38)	(4.76)***
$(1 - D^{up})\left(R_{m,t}\right)^2$	0.00325	-0.00243	0.0552	0.000906	-0.00430	0.00264	0.00536
	(0.87)	(-0.45)	(9.70)***	(0.13)	(-0.78)	(0.65)	(1.04)
_cons	1.018	0.816	1.322	0.818	0.762	0.898	0.915
	(66.78)***	(58.16)***	(34.50)***	(55.77)***	(52.22)***	(54.38)***	(58.65)***
N	2473	2542	2514	2555	2535	2515	2511
adj. R^2	0.332	0.311	0.262	0.275	0.270	0.260	0.394

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.3 panel A (with robust regression results) and panel B shows the results calculated based on the simple return method with rising and falling market conditions during the sample time period 1 by using equation 3.4. The robust regression results shown in panel A, under rising market condition, we can see that anti-herding exists in France, Greece, Italy, Portugal, Spain and the UK market, shown by significantly positive coefficients of squared market return in rising market condition. There is neither herding nor anti-herding behaviour present in other markets under rising market conditions. Under falling market conditions, both Greece and Norway have significantly positive coefficients of squared market return, which is indicative of anti-herding. There is no evidence of either herding or anti-herding behaviour in the other countries under falling market condition during the first time period. In panel B, under rising market conditions, we find that Denmark, Finland, France, Germany, Greece, Hong Kong, Italy, Spain and the UK have significantly positive coefficients of squared market returns in rising market condition, which is indicative of anti-herding. Under falling market conditions, we have captured evidence of anti-herding in both Greece and Norway, shown by significantly positive coefficients of squared market return in falling market condition, France and Germany have some evidence of anti-herding behaviour with significance at the 10% level. Compared with the results based on the log return method, according to the results under the normal regression model, only Italy and Spain have the insignificantly negative coefficient in falling market condition with the simple return calculation method. And there is less anti-herding behaviour detected based on simple return calculation method. In the robust regression results shown in panel B, Italy, Spain, Portugal, France, Greece and UK have significantly positive coefficients of the rising market condition; Norway and Greece have the significantly positive coefficient of the falling market, and thus we can confirm these countries have anti-herding behaviour in specific market conditions.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.4 Panel A Robust regression with larger Simple positive returns

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.686	0.499	0.325	0.394	0.515	0.298
	(6.20)***	(6.57)***	(3.09)***	(5.67)***	(5.85)***	(8.20)***
$R_{m,t}^2$	-0.0363	-0.0216	-0.00442	-0.00515	-0.0140	0.0107
	(-2.01)**	(-1.96)*	(-0.28)	(-0.61)	(-1.15)	(3.51)***
_cons	0.579	0.418	0.881	0.590	0.487	1.294
	(4.73)***	(4.46)***	(6.39)***	(5.91)***	(4.13)***	(21.18)***
N	513	481	478	471	496	473
adj. R^2	0.318	0.383	0.271	0.428	0.392	0.509

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.4 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.437	0.395	0.697	0.326	0.252	0.440	0.503
	(5.71)***	(5.85)***	(5.50)***	(4.91)***	(4.66)***	(8.74)***	(5.92)***
$R_{m,t}^2$	-0.00659	-0.00205	-0.0346	0.00969	0.0135	-0.0162	-0.00141
	(-0.61)	(-0.22)	(-2.81)***	(1.28)	(2.35)**	(-3.63)***	(-0.11)
_cons	0.736	0.611	0.749	0.852	0.727	0.472	0.687
	(6.96)***	(7.41)***	(3.40)***	(11.42)***	(10.00)***	(5.44)***	(7.00)***
N	503	476	515	510	496	466	456
adj. R^2	0.381	0.392	0.170	0.270	0.340	0.388	0.457

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.4 Panel B Standard regression with larger Simple positive returns (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.686	0.499	0.325	0.394	0.515	0.298
	(7.87)***	(9.28)***	(4.44)***	(6.43)***	(8.47)***	(7.70)***
$R^2_{m,t}$	-0.0363	-0.0216	-0.00442	-0.00515	-0.0140	0.0107
	(-2.80)***	(-3.29)***	(-0.48)	(-0.69)	(-1.96)*	(2.60)***
_cons	0.579	0.418	0.881	0.590	0.487	1.294
	(5.33)***	(5.46)***	(8.04)***	(6.25)***	(5.16)***	(20.26)***
N	513	481	478	471	496	473
adj. R^2	0.318	0.383	0.271	0.428	0.392	0.509

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.4 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.437	0.395	0.697	0.326	0.252	0.440	0.503
	(7.75)***	(6.68)***	(5.66)***	(5.00)***	(4.35)***	(9.55)***	(6.78)***
$R^2_{m,t}$	-0.00659	-0.00205	-0.0346	0.00969	0.0135	-0.0162	-0.00141
	(-1.03)	(-0.24)	(-2.64)***	(1.01)	(1.73)*	(-3.68)***	(-0.13)
_cons	0.736	0.611	0.749	0.852	0.727	0.472	0.687
	(8.11)***	(7.91)***	(3.28)***	(11.38)***	(9.40)***	(5.43)***	(7.26)***
N	503	476	515	510	496	466	456
adj. R^2	0.381	0.392	0.170	0.270	0.340	0.388	0.457

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.4 panel A (with robust regression results) and panel B shows the larger positive return regression results in time period 1 based on the simple return method. In the robust regression results shown in panel A, we can see that Denmark, Norway and Sweden have a significantly negative coefficient of $R^2_{m,t}$, which means that these countries have herding behaviour in larger rising market conditions during time period 1. The US market also has some evidence of herding which is significant at the 10% level. Finland, Italy, Germany, France and Hong Kong also have negative coefficients of $R^2_{m,t}$ but they are insignificant, and so we do not have enough evidence to indicate that they have herding behaviour in the sample period. Both Greece and Spain market have significantly positive coefficients of squared market return, which is indicative of anti-herding. In panel B, by using equation 3.2, we find that Denmark, Norway, Sweden and the US have significantly negative coefficients of $R_{m,t}^2$, which indicates that there is herding behaviour in the market. Germany also has some indication of the presence of herding in the market which is significant at 10% level. Greece has clear evidence of anti-herding behaviour in the market shown by a significantly positive coefficient of squared market return. Spain has some evidence of anti-herding, which is significant at the 10% level. Other countries do not have either herding or anti-herding behaviour evident in their stock markets under market conditions with larger positive price movement. Comparing the results with the estimation of herding based on log return method, both return calculation methods have captured the evidence of herding presence in the markets of Denmark, the US, Norway and Sweden, as well as evidence that anti-herding exists in both the markets of Greece and Spain.

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.5 Panel A Robust regression with larger Simple negative return

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.379	0.424	0.184	0.242	0.240	0.327
	(4.05)***	(5.94)***	(2.26)**	(3.47)***	(3.11)***	(6.08)***
$R_{m,t}^2$	-0.00561	-0.0228	0.00664	0.000847	0.00827	-0.000233
	(-0.37)	(-2.10)**	(0.51)	(0.09)	(0.80)	(-0.03)
_cons	0.915	0.523	1.004	0.763	0.833	1.131
	(7.74)***	(6.16)***	(8.45)***	(7.48)***	(7.72)***	(13.62)***
N	427	470	422	437	435	451
adj. R^2	0.216	0.287	0.125	0.281	0.278	0.386

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.5 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.348	0.206	-0.310	0.204	0.267	0.142	0.388
	(6.88)***	(3.02)***	(-0.82)	(2.38)**	(3.38)***	(1.83)*	(5.06)***
$R_{m,t}^2$	-0.0108	0.00229	0.0932	0.0129	-0.00998	0.00564	-0.00377
	(-1.91)*	(0.24)	(1.91)*	(0.84)	(-0.83)	(0.60)	(-0.35)
_cons	0.789	0.888	2.103	0.941	0.736	0.941	0.809
	(9.89)***	(9.09)***	(3.45)***	(10.05)***	(7.09)***	(7.53)***	(8.30)***
N	427	410	426	401	407	434	410
adj. R^2	0.291	0.195	0.289	0.216	0.154	0.150	0.334

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First time period from 02/Jan/2002 to 30/Dec/2011

Table 4.3.2.5 Panel B Standard regression with larger Simple negative returns (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.379	0.424	0.184	0.242	0.240	0.327
	(4.33)***	(5.65)***	(1.76)*	(3.66)***	(2.91)***	(5.61)***
$R^2_{m,t}$	-0.00561	-0.0228	0.00664	0.000847	0.00827	-0.000233
	(-0.45)	(-1.88)*	(0.44)	(0.09)	(0.71)	(-0.03)
_cons	0.915	0.523	1.004	0.763	0.833	1.131
	(7.76)***	(5.67)***	(6.59)***	(7.77)***	(7.00)***	(12.69)***
N	427	470	422	437	435	451
adj. R^2	0.216	0.287	0.125	0.281	0.278	0.386

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3.2.5 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.348	0.206	-0.310	0.204	0.267	0.142	0.388
	(6.92)***	(2.67)***	(-1.83)*	(2.47)**	(3.18)***	(1.75)*	(5.34)***
$R^2_{m,t}$	-0.0108	0.00229	0.0932	0.0129	-0.00998	0.00564	-0.00377
	(-1.77)*	(0.19)	(5.49)***	(0.91)	(-0.77)	(0.55)	(-0.36)
_cons	0.789	0.888	2.103	0.941	0.736	0.941	0.809
	(9.65)***	(8.67)***	(6.24)***	(9.74)***	(6.64)***	(7.09)***	(8.21)***
N	427	410	426	401	407	434	410
adj. R^2	0.291	0.195	0.289	0.216	0.154	0.150	0.334

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In table 4.3.2.5 panel A (with robust regression results) and panel B show the regression results of the smaller negative returns in time period 1, which are the larger price movements in falling market condition. In panel A with robust regression results, the US market have clear evidence of herding behaviour shown by a significantly negative coefficient of squared market return, and the herding effect in the Hong Kong market is significant at the 10% level. Norway has some evidence of anti-herding as the positive coefficient of squared market return is significant at the 10% level. In panel B, by using equation 3.2, we can see that the US and Hong Kong markets have some evidence of herding behaviour, shown by the negative coefficients of squared market return which are significant at the 10% level. Also, Norway has a significantly positive coefficient of squared market return, which is indicative of anti-herding. Other countries do not have evidence of either herding or anti-herding exists. Unlike the result calculated using the log return method, Norway has a significantly positive coefficient of $R_{m,t}^2$ when applying the simple return method. In the robust regression results, Denmark, Spain, the US, Greece, Hong Kong and the UK still have negative coefficients of $R_{m,t}^2$, the US has a significantly negative coefficient of $R_{m,t}^2$. Moreover, Hong Kong is significant at the 10% level. Which means that the US has more herding behaviour detected using the simple return method. Thus both the US and Hong Kong exhibit herding behaviour under falling market condition with larger price movement in the first time period.

Within the first time period, the markets were heavily influenced by the global financial crisis, we find that, during the rising market condition with the large market movements, countries such as Norway and Sweden in northern Europe and the US market have herding behaviour, in the large market movements during falling market conditions, only US and HK have herding behaviour, the investors in the rest of the counties are more likely to hold their assets during the falling market condition. By comparing the results based on the log return and simple return calculation method, the overall results look similar between both methods. However, the simple return method has a higher chance of detecting herding behaviour in different markets.

Next we look at the results in sample period 2, which is from 02 Jan 2012 to 31 May 2018, which covers the time period after the financial crisis until recently.

4.4 Second time Period from 02/Jan/2012 to 31/May/2018

4.4.1 Descriptive statistic results (Simple returns)

Table 4.4.1

	variable	mean	p50	sd	variance	skewness	kurtosis	min	max	N
Denmark	$R_{m,t}$	.09294	.115239	.97218	.945134	-.151847	3.7783	-4.64981	4.06347	1598
	CSAD	1.00435	.930169	.410814	.168768	1.58129	6.88277	.260639	3.25351	1598
US	$R_{m,t}$	.055739	.036898	.827507	.684768	.214187	5.21919	-3.77983	4.81734	1613
	CSAD	.723071	.681934	.225294	.050758	1.6015	8.59813	.242177	2.45489	1613
Finland	$R_{m,t}$	.064149	.025044	1.19166	1.42006	-.021499	4.02099	-4.63199	4.54853	1609
	CSAD	.996932	.910465	.416995	.173885	1.57268	7.25509	.296394	3.61517	1609
France	$R_{m,t}$	.06524	.061483	1.13875	1.29675	.047852	4.76375	-4.32297	5.91751	1639
	CSAD	.847949	.80343	.28585	.08171	1.76099	11.7618	.303672	3.69809	1639
Germany	$R_{m,t}$	.05328	.067245	1.11144	1.23529	-.036438	4.0835	-4.15988	4.94011	1623
	CSAD	.831217	.786594	.279764	.078268	1.55518	8.55976	.29662	2.87128	1623
Greece	$R_{m,t}$	.0845	.127991	1.81292	3.28667	-.300921	7.77317	-14.0175	8.94898	1567
	CSAD	2.14558	1.95259	.870184	.75722	2.09098	11.215	.5503	8.79345	1567
HK	$R_{m,t}$	.051954	.076049	1.08204	1.17081	-.1006	4.85867	-5.12982	4.85558	1577
	CSAD	.9175	.872704	.276808	.076622	1.16945	5.59039	.330394	2.52306	1577
Italy	$R_{m,t}$	.059684	.085379	1.46669	2.15117	-.069821	5.08192	-7.21513	6.57863	1626
	CSAD	1.17193	1.05212	.623567	.388836	7.31568	114.201	.371945	13.5428	1626
Norway	$R_{m,t}$	.059397	.061242	1.42316	2.02539	.003948	4.31235	-5.79934	6.83945	1606
	CSAD	1.09681	.996192	.483198	.23348	1.76125	9.92854	.240526	5.47232	1606
Portugal	$R_{m,t}$	.041944	.044587	1.28759	1.65788	-.142567	4.37088	-6.16772	5.1104	1639
	CSAD	1.32484	1.20638	.628505	.395018	1.69777	8.24653	.245572	5.49308	1639
Spain	$R_{m,t}$	.035167	.046328	1.23736	1.53106	-.006296	5.28151	-5.42609	6.11187	1639
	CSAD	.953387	.877507	.408835	.167146	2.4335	17.5211	.244674	5.48169	1639
Sweden	$R_{m,t}$	.041081	.054868	1.14351	1.30763	-.183718	4.44616	-5.24693	5.03317	1608
	CSAD	.783632	.71998	.292531	.085574	1.78972	9.37742	.282288	3.33034	1608
UK	$R_{m,t}$	.030069	.09302	1.08066	1.16783	-.38375	8.22508	-8.79727	5.26235	1620
	CSAD	1.09755	1.00186	.403092	.162483	1.91976	10.5037	.370533	4.39991	1620

Table 4.4.1 shows the descriptive statistics for the equally weighted average market return and the CCK measurements for each of the thirteen different countries based on simple return calculation method in time period 2. The statistics shown in table 4.4.1 show that the mean returns of $R_{m,t}$ in all the countries are positive during this time period, which indicates a positive performance of their stock markets during our second time period. The standard deviation of $R_{m,t}$ varies between countries and is particularly high in Greece. Also, the minimum and maximum returns are substantial in all of the markets reflecting the times of financial turbulence in the sample period. Regarding the CASD results, we find that the mean value of the CSAD results of 2.14558 in Greece is much higher than for the other countries in our sample. Similarly, Greece also has the highest standard deviation of CSAD, which is 0.870184. According to Chiang and Zheng (2010), within markets with similar conditions such as in the European market, countries which have a higher standard deviation of returns may have abnormal cross-sectional variations in CSAD due to irregular fluctuations in the stock market and the statistics tend to bear this out. Comparing the results with those calculated based on the log return method, Greece still has the highest mean value of CSAD as well as the highest standard deviation of CSAD result; Portugal and Italy have the higher mean value and standard deviation of CSAD.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.1 Panel A, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.0910	0.0467	0.141	0.0674	0.0942	0.423
	(2.22)**	(1.64)	(3.99)***	(3.29)***	(4.24)***	(14.90)***
$R_{m,t}^2$	0.0320	0.0237	0.00966	0.0246	0.00691	0.0109
	(1.83)*	(1.78)*	(0.79)	(4.11)***	(0.98)	(2.11)**
_cons	0.905	0.678	0.856	0.759	0.743	1.563
	(48.25)***	(63.83)***	(46.15)***	(64.53)***	(60.28)***	(61.93)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.063	0.065	0.099	0.149	0.085	0.506

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.1 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.0852	-0.0470	0.151	0.254	0.0728	0.0835	0.266
	(3.78)***	(-0.44)	(3.88)***	(5.97)***	(2.26)**	(3.44)***	(13.44)***
$R_{m,t}^2$	0.0264	0.0825	0.0116	0.0166	0.0442	0.00673	0.0145
	(3.45)***	(2.36)**	(0.94)	(1.31)	(3.91)***	(0.80)	(3.28)***
_cons	0.817	1.045	0.910	1.050	0.819	0.702	0.879
	(69.23)***	(21.68)***	(41.77)***	(41.32)***	(49.52)***	(52.80)***	(72.72)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.183	0.257	0.139	0.171	0.230	0.069	0.371

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.1 Panel B, Standard Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	0.0910	0.0467	0.141	0.0674	0.0942	0.423
	$(2.27)^{**}$	$(2.22)^{**}$	$(4.32)^{***}$	$(3.30)^{***}$	$(4.10)^{***}$	$(18.13)^{***}$
$R^2_{m,t}$	0.0320	0.0237	0.00966	0.0246	0.00691	0.0109
	$(2.04)^{**}$	$(2.89)^{***}$	(0.94)	$(4.01)^{***}$	(0.90)	$(3.13)^{***}$
_cons	0.905	0.678	0.856	0.759	0.743	1.563
	$(44.39)^{***}$	$(67.70)^{***}$	$(43.61)^{***}$	$(60.56)^{***}$	$(56.21)^{***}$	$(59.53)^{***}$
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.063	0.065	0.099	0.149	0.085	0.506

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.1 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	0.0852	-0.0470	0.151	0.254	0.0728	0.0835	0.266
	$(4.05)^{***}$	(-1.49)	$(5.06)^{***}$	$(6.39)^{***}$	$(2.98)^{***}$	$(3.65)^{***}$	$(12.99)^{***}$
$R^2_{m,t}$	0.0264	0.0825	0.0116	0.0166	0.0442	0.00673	0.0145
	$(4.03)^{***}$	$(11.47)^{***}$	(1.54)	(1.50)	$(6.86)^{***}$	(0.95)	$(2.87)^{***}$
_cons	0.817	1.045	0.910	1.050	0.819	0.702	0.879
	$(66.07)^{***}$	$(41.52)^{***}$	$(40.75)^{***}$	$(38.37)^{***}$	$(49.35)^{***}$	$(50.36)^{***}$	$(65.63)^{***}$
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.183	0.257	0.139	0.171	0.230	0.069	0.371

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.1 panel A (with robust regression results) and panel B shows the regression result using equation 3.2 based on the simple return calculation method. In panel A, the robust regression results show that France, Greece, Hong Kong, Italy, Spain and UK have clear evidence of anti-herding, shown by significantly positive coefficients of squared market return. Both Denmark and US have some evidence of anti-herding, with significance at the 10% level. In panel B, we find that Denmark, US, France, Greece, Hong Kong, Italy, Spain and UK have significantly positive coefficients of squared market return, which indicates that anti-herding behaviour exists in their stock markets. There is neither herding nor anti-herding present in the other countries according to the estimates using the normal regression model. The regression results based on the simple return calculation method look similar to the results based on log returns, Denmark, Italy, Spain, US, France, Greece, Hong Kong and the UK have a significantly positive coefficient of $R^2_{m,t}$, and in the robust regression result, US and Denmark have significant results at the 10% level, the others results remain the same. Based on these results, we do not reject the no herding null hypothesis and the countries with a significant coefficient of $R^2_{m,t}$ do not have herding behaviour in their market during the second sample period.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.2 Panel A, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0161	-0.00906	0.0263	0.0137	0.0101	0.0185
	(1.36)	(-1.21)	(2.83)***	(1.79)*	(1.45)	(1.55)
$\|R_{m,t}\|$	0.0863	0.0456	0.134	0.0690	0.0942	0.417
	(2.08)**	(1.59)	(3.89)***	(3.27)***	(4.27)***	(15.44)***
$R^2_{m,t}$	0.0335	0.0250	0.0109	0.0237	0.00673	0.0120
	(1.87)*	(1.85)*	(0.92)	(3.71)***	(0.97)	(2.56)**
_cons	0.905	0.678	0.858	0.757	0.743	1.566
	(48.12)***	(63.51)***	(46.63)***	(63.71)***	(60.35)***	(63.46)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.064	0.065	0.104	0.151	0.086	0.508

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.2 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0397	0.0361	0.0253	0.0642	0.0190	0.0159	0.0295
	(5.99)***	(1.66)*	(2.35)**	(4.83)***	(1.69)*	(2.05)**	(3.13)***
$\|R_{m,t}\|$	0.0793	-0.0508	0.151	0.233	0.0753	0.0771	0.260
	(3.73)***	(-0.47)	(3.94)***	(5.67)***	(2.29)**	(3.27)***	(13.73)***
$R^2_{m,t}$	0.0281	0.0832	0.0112	0.0230	0.0434	0.00898	0.0171
	(4.06)***	(2.38)**	(0.93)	(1.92)*	(3.73)***	(1.11)	(4.18)***
_cons	0.818	1.046	0.909	1.057	0.818	0.704	0.880
	(71.06)***	(21.78)***	(42.00)***	(42.04)***	(49.02)***	(53.73)***	(74.20)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.206	0.264	0.144	0.188	0.233	0.072	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.2 Panel B, Standard Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0161	-0.00906	0.0263	0.0137	0.0101	0.0185
	(1.56)	(-1.36)	(3.17)***	(2.38)**	(1.69)*	(2.15)**
$\|R_{m,t}\|$	0.0863	0.0456	0.134	0.0690	0.0942	0.417
	(2.15)**	(2.16)**	(4.13)***	(3.38)***	(4.10)***	(17.73)***
$R_{m,t}^2$	0.0335	0.0250	0.0109	0.0237	0.00673	0.0120
	(2.13)**	(3.02)***	(1.06)	(3.85)***	(0.88)	(3.42)***
_cons	0.905	0.678	0.858	0.757	0.743	1.566
	(44.43)***	(67.73)***	(43.82)***	(60.52)***	(56.21)***	(59.63)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.064	0.065	0.104	0.151	0.086	0.508

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.2 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0397	0.0361	0.0253	0.0642	0.0190	0.0159	0.0295
	(6.91)***	(3.99)***	(3.22)***	(5.88)***	(2.65)***	(2.57)**	(3.99)***
$\|R_{m,t}\|$	0.0793	-0.0508	0.151	0.233	0.0753	0.0771	0.260
	(3.82)***	(-1.61)	(5.07)***	(5.90)***	(3.09)***	(3.35)***	(12.70)***
$R_{m,t}^2$	0.0281	0.0832	0.0112	0.0230	0.0434	0.00898	0.0171
	(4.36)***	(11.62)***	(1.49)	(2.09)**	(6.75)***	(1.26)	(3.37)***
_cons	0.818	1.046	0.909	1.057	0.818	0.704	0.880
	(67.11)***	(41.72)***	(40.84)***	(38.98)***	(49.29)***	(50.52)***	(65.99)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.206	0.264	0.144	0.188	0.233	0.072	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.2 panel A (with robust regression results) and panel B presents the regression results using equation 3.3, based on the simple return method in time period 2. In panel A with the robust regression results, only Italy, Spain, France, Greece, Hong Kong and the UK have a significantly positive coefficient of $R_{m,t}^2$, Denmark and the US are significant at the 10% level, which means that these countries have anti-herding behaviour in their stock market, and we do not have evidence to determine that the other countries have herding behaviour in their markets. According to the results shown in panel B, we find that all of the countries have a significantly positive coefficient of $R_{m,t}^2$ except Finland, Germany, Norway and Sweden, which is indicative of anti-herding.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.3 Panel A Robust regression in rising and falling market conditions (Simple returns)

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2(1-D^{up})\left|R_{m,t}\right| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1-D^{up})\left(R_{m,t}\right)^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\left\|R_{m,t}\right\|$	0.118	0.0274	0.130	0.0870	0.107	0.375
	(2.38)**	(0.93)	(3.25)***	(3.93)***	(4.77)***	(10.26)***
$(1-D^{up})\left\|R_{m,t}\right\|$	0.0554	0.0912	0.136	0.0401	0.0800	0.409
	(1.21)	(3.02)***	(3.36)***	(1.42)	(2.56)**	(14.71)***
$D^{up}(R_{m,t})^2$	0.0243	0.0318	0.0249	0.0213	0.00553	0.0264
	(1.02)	(2.21)**	(1.66)*	(3.43)***	(0.83)	(3.10)***
$(1-D^{up})\left(R_{m,t}\right)^2$	0.0423	0.00246	-0.00226	0.0303	0.00868	0.00831
	(2.00)**	(0.17)	(-0.15)	(2.60)***	(0.71)	(2.21)**
_cons	0.905	0.675	0.859	0.759	0.743	1.582
	(48.19)***	(66.88)***	(46.67)***	(63.53)***	(59.31)***	(63.90)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.063	0.067	0.105	0.151	0.085	0.510

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.3 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\left\|R_{m,t}\right\|$	0.110	-0.0740	0.151	0.284	0.101	0.0519	0.211
	(4.04)***	(-0.49)	(3.18)***	(5.09)***	(2.81)***	(1.78)*	(5.29)***
$(1-D^{up})\left\|R_{m,t}\right\|$	0.0490	-0.0183	0.165	0.176	0.0415	0.0842	0.239
	(2.22)**	(-0.26)	(4.29)***	(3.98)***	(1.05)	(3.43)***	(10.00)***
$D^{up}(R_{m,t})^2$	0.0326	0.104	0.0214	0.0287	0.0403	0.0285	0.0469
	(3.01)***	(1.83)*	(1.25)	(1.45)	(3.00)***	(2.16)**	(3.12)***
$(1-D^{up})\left(R_{m,t}\right)^2$	0.0236	0.0599	-0.00342	0.0200	0.0492	-0.00219	0.0108
	(3.53)***	(3.02)***	(-0.30)	(1.55)	(2.95)***	(-0.31)	(1.85)*
_cons	0.818	1.045	0.907	1.058	0.819	0.708	0.895
	(70.59)***	(22.07)***	(42.12)***	(41.40)***	(49.79)***	(54.65)***	(64.32)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.206	0.270	0.146	0.187	0.233	0.076	0.382

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.3 Panel B Standard regression in rising and falling market conditions

(Simple returns)

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	0.118	0.0274	0.130	0.0870	0.107	0.375
	(2.57)**	(1.20)	(3.48)***	(3.96)***	(4.22)***	(11.43)***
$(1 - D^{up})\|R_{m,t}\|$	0.0554	0.0912	0.136	0.0401	0.0800	0.409
	(1.19)	(3.17)***	(3.61)***	(1.47)	(2.82)***	(15.55)***
$D^{up}(R_{m,t})^2$	0.0243	0.0318	0.0249	0.0213	0.00553	0.0264
	(1.21)	(3.55)***	(1.90)*	(3.15)***	(0.62)	(4.10)***
$(1 - D^{up})(R_{m,t})^2$	0.0423	0.00246	-0.00226	0.0303	0.00868	0.00831
	(2.15)**	(0.17)	(-0.18)	(3.10)***	(0.81)	(2.20)**
_cons	0.905	0.675	0.859	0.759	0.743	1.582
	(44.36)***	(66.57)***	(43.87)***	(59.91)***	(56.07)***	(58.79)***
N	1598	1613	1609	1639	1623	1567
adj. R^2	0.063	0.067	0.105	0.151	0.085	0.510

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.3 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.110	-0.0740	0.151	0.284	0.101	0.0519	0.211
	(4.64)***	(-2.07)**	(4.55)***	(5.76)***	(3.76)***	(1.88)*	(6.99)***
$(1 - D^{up})\|R_{m,t}\|$	0.0490	-0.0183	0.165	0.176	0.0415	0.0842	0.239
	(2.03)**	(-0.49)	(4.60)***	(3.98)***	(1.36)	(3.26)***	(10.72)***
$D^{up}(R_{m,t})^2$	0.0326	0.104	0.0214	0.0287	0.0403	0.0285	0.0469
	(3.99)***	(11.71)***	(2.40)**	(1.78)*	(5.44)***	(2.83)***	(4.85)***
$(1 - D^{up})(R_{m,t})^2$	0.0236	0.0599	-0.00342	0.0200	0.0492	-0.00219	0.0108
	(2.91)***	(6.48)***	(-0.34)	(1.59)	(5.26)***	(-0.27)	(2.01)**
_cons	0.818	1.045	0.907	1.058	0.819	0.708	0.895
	(67.11)***	(41.88)***	(40.73)***	(38.76)***	(49.16)***	(50.66)***	(64.51)***
N	1577	1626	1606	1639	1639	1608	1620
adj. R^2	0.206	0.270	0.146	0.187	0.233	0.076	0.382

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

By using equation 3.4. Table 4.4.2.3 panel A (with robust regression results) and panel B shows the regression results in rising and falling market conditions based on the simple return calculation method in time period 2. In panel A with robust regression results, under market condition with positive movements, the US, France, Greece, Hong Kong, Spain, Sweden and UK have significantly positive coefficients of squared market return in rising market condition, which indicate that there is anti-herding behaviour in their stock markets. Anti-herding is also present in Finland and Italy, with significance at the 10% level. Under falling market conditions, Denmark, France, Greece, Hong Kong, Italy and Spain have clear evidence of anti-herding, shown by significantly positive coefficients of squared market return in falling market condition. Also, anti-herding in the UK market is significant at the 10% level. In panel B, we find out that in rising market conditions, the US, France, Greece, Hong Kong, Italy, Norway, Spain, Sweden and UK have significantly positive coefficients of squared market return in rising market condition, which is indicative of anti-herding. Under market conditions with negative movement, Denmark, France, Greece, Hong Kong, Italy, Spain and UK have anti-herding behaviour present in the market shown by significantly positive coefficients of squared market return in falling market condition. Compared with the log return result, Finland, Norway, and Sweden all have negative coefficients of the squared market return during falling markets but these are statistically insignificant. Italy, Spain, France, Greece, Hong Kong and the UK have significantly positive coefficients of squared market return in both rising and falling markets. The US, Norway and Sweden have significantly positive coefficients during rising market conditions and Denmark has it in falling market conditions. In the robust regression results, Italy no longer has a significant positive coefficient in the rising market, and UK only have a significant positive coefficient during the rising market. There is less evidence of anti-herding being captured based on simple return calculation method during the time period 2.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.4 Panel A Robust regression with larger simple positive returns

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.306	0.0917	0.457	0.182	0.0995	0.528
	(1.56)	(0.96)	$(2.52)^{**}$	$(2.58)^{**}$	(1.20)	$(4.46)^{***}$
$R^2_{m,t}$	-0.0273	0.0168	-0.0444	0.00275	0.00880	0.00877
	(-0.50)	(0.59)	(-1.07)	(0.24)	(0.58)	(0.57)
_cons	0.764	0.625	0.532	0.668	0.737	1.325
	$(4.97)^{***}$	$(9.11)^{***}$	$(3.11)^{***}$	$(9.03)^{***}$	$(8.95)^{***}$	$(7.29)^{***}$
N	374	333	335	343	342	323
adj. R^2	0.046	0.117	0.142	0.188	0.081	0.521

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.4 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.196	-0.282	0.216	0.401	0.358	0.157	0.318
	$(2.00)^{**}$	(-0.53)	(1.39)	$(1.68)^{*}$	$(3.19)^{***}$	$(1.83)^{*}$	$(2.56)^{**}$
$R^2_{m,t}$	0.0154	0.132	0.0105	0.00218	-0.00167	0.00696	0.0230
	(0.68)	(1.16)	(0.34)	(0.04)	(-0.07)	(0.34)	(0.76)
_cons	0.731	1.364	0.828	0.961	0.525	0.599	0.812
	$(8.07)^{***}$	$(2.52)^{**}$	$(4.75)^{***}$	$(4.00)^{***}$	$(4.64)^{***}$	$(7.27)^{***}$	$(8.24)^{***}$
N	318	333	330	350	351	347	302
adj. R^2	0.259	0.288	0.137	0.142	0.316	0.117	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.4 Panel B Standard regression with larger simple positive returns (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.306	0.0917	0.457	0.182	0.0995	0.528
	(1.56)	(1.30)	(2.81)***	(2.50)**	(1.14)	(4.70)***
$R^2_{m,t}$	-0.0273	0.0168	-0.0444	0.00275	0.00880	0.00877
	(-0.51)	(0.97)	(-1.23)	(0.19)	(0.45)	(0.60)
_cons	0.764	0.625	0.532	0.668	0.737	1.325
	(4.83)***	(10.79)***	(3.27)***	(8.79)***	(8.65)***	(7.47)***
N	374	333	335	343	342	323
adj. R^2	0.046	0.117	0.142	0.188	0.081	0.521

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.4 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.196	-0.282	0.216	0.401	0.358	0.157	0.318
	(2.10)**	(-1.70)*	(1.58)	(1.77)*	(3.76)***	(1.45)	(2.82)***
$R^2_{m,t}$	0.0154	0.132	0.0105	0.00218	-0.00167	0.00696	0.0230
	(0.75)	(4.95)***	(0.44)	(0.05)	(-0.10)	(0.28)	(0.92)
_cons	0.731	1.364	0.828	0.961	0.525	0.599	0.812
	(8.14)***	(6.27)***	(4.86)***	(3.99)***	(4.97)***	(5.87)***	(8.13)***
N	318	333	330	350	351	347	302
adj. R^2	0.259	0.288	0.137	0.142	0.316	0.117	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.4 panel A (with robust regression results) and panel B shows the larger positive, simple return regression results for time period 2. According to the results shown in panel A, Denmark, Finland and Spain have an insignificantly negative coefficient of $R^2_{m,t}$. In panel B, the standard result shows that Denmark, Finland and Spain have a negative coefficient of $R^2_{m,t}$ as well. Italy has a significantly positive coefficient of $R^2_{m,t}$, which is indicative of anti-herding. Overall, it means that all the countries except Italy do not have either herding or anti-herding behaviour in the substantially rising market during time period 2. Compared with the results based on log returns, France no longer has a negative coefficient of $R_{m,t}^2$, and all the coefficient of $R_{m,t}^2$ are insignificant, which means we do not have enough evidence to prove that there is herding behaviour in the larger rising market conditions.

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.5 Panel A Robust regression with larger simple negative returns

(Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\|R_{m,t}\|$	-0.233	0.126	-0.0112	0.0759	0.0534	0.543
	(-1.34)	(1.24)	(-0.07)	(0.60)	(0.37)	(6.20)***
$R_{m,t}^2$	0.110	-0.00628	0.0300	0.0221	0.0145	-0.00296
	(2.34)**	(-0.21)	(0.81)	(0.78)	(0.42)	(-0.44)
_cons	1.161	0.647	0.990	0.728	0.768	1.341
	(7.73)***	(9.10)***	(6.05)***	(6.31)***	(5.87)***	(7.79)***
N	287	301	304	288	291	275
adj. R^2	0.059	0.035	0.035	0.116	0.045	0.465

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.5 Panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\|R_{m,t}\|$	-0.0749	-0.119	0.366	0.323	0.0214	0.187	0.145
	(-1.09)	(-0.57)	(2.69)***	(2.05)**	(0.13)	(2.34)**	(3.10)***
$R_{m,t}^2$	0.0475	0.0746	-0.0398	-0.00219	0.0559	-0.0220	0.0227
	(3.72)***	(1.88)*	(-1.56)	(-0.08)	(1.61)	(-1.55)	(4.11)***
_cons	0.949	1.181	0.688	0.862	0.813	0.601	1.019
	(13.57)***	(5.15)***	(4.52)***	(5.06)***	(5.18)***	(7.20)***	(17.07)***
N	272	306	304	313	297	291	269
adj. R^2	0.147	0.295	0.068	0.153	0.243	0.040	0.355

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second time Period from 02/Jan/2012 to 31/May/2018

Table 4.4.2.5 Panel B Standard regression with larger simple negative returns (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	-0.233	0.126	-0.0112	0.0759	0.0534	0.543
	(-1.40)	(1.18)	(-0.08)	(0.61)	(0.40)	(6.51)***
$R_{m,t}^2$	0.110	-0.00628	0.0300	0.0221	0.0145	-0.00296
	(2.54)**	(-0.19)	(0.95)	(0.76)	(0.46)	(-0.39)
_cons	1.161	0.647	0.990	0.728	0.768	1.341
	(8.20)***	(8.79)***	(6.86)***	(6.30)***	(6.19)***	(8.32)***
N	287	301	304	288	291	275
adj. R^2	0.059	0.035	0.035	0.116	0.045	0.465

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.5 Panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	-0.0749	-0.119	0.366	0.323	0.0214	0.187	0.145
	(-0.94)	(-1.07)	(2.65)***	(2.26)**	(0.18)	(2.10)**	(2.61)***
$R_{m,t}^2$	0.0475	0.0746	-0.0398	-0.00219	0.0559	-0.0220	0.0227
	(2.76)***	(4.14)***	(-1.59)	(-0.08)	(2.33)**	(-1.19)	(2.63)***
_cons	0.949	1.181	0.688	0.862	0.813	0.601	1.019
	(12.19)***	(8.36)***	(4.20)***	(5.20)***	(6.31)***	(6.62)***	(15.28)***
N	272	306	304	313	297	291	269
adj. R^2	0.147	0.295	0.068	0.153	0.243	0.040	0.355

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4.2.5 panel A (with robust regression results) and panel B shows the larger negative simple return regression results for time period 2. In panel A with robust regression results, Denmark, Hong Kong as well as the UK have a significantly positive coefficient of $R_{m,t}^2$, which is indicative of anti-herding. Also, Italy has evidence of anti-herding in the market with significance at the 10% level. Norway, Portugal, Sweden, the US and Greece have negative coefficients of $R_{m,t}^2$.

In panel B with normal regression results, Denmark, Italy, Spain, Hong Kong and the UK have significantly positive coefficients of $R^2_{m,t}$, which means that clear evidence of anti-herding behaviour exists in these markets. Norway, Portugal, Sweden, the US and Greece have negative coefficients of $R^2_{m,t}$, but insignificant.

Material Associated with Chapter 6*

6*.0 Empirical Study 3 -- results in Simple return

6*.1.1 Full range of data

Robust Regression results by using CCK based on Simple return method.

Table 6*.1.1 panel A, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\lvert R_{m,t}\rvert$	0.237	0.218	0.162	0.160	0.188	0.318
	(6.55)***	(9.03)***	(6.72)***	(9.54)***	(5.77)***	(18.40)***
$R^2_{m,t}$	0.0215	0.0108	0.0150	0.0196	0.0202	0.0154
	(1.92)*	(1.59)	(2.28)**	(5.07)***	(2.42)**	(4.50)***
_cons	0.974	0.708	0.969	0.799	0.805	1.407
	(53.71)***	(58.08)***	(65.37)***	(73.91)***	(45.46)***	(99.89)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.206	0.286	0.182	0.315	0.293	0.422

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.1 panel A,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\lvert R_{m,t}\rvert$	0.224	0.146	0.195	0.317	0.174	0.173	0.255
	(8.32)***	(3.64)***	(2.89)***	(14.86)***	(11.38)***	(8.12)***	(9.64)***
$R^2_{m,t}$	0.0118	0.0320	0.0347	0.00458	0.0181	0.00748	0.0282
	(1.61)	(2.49)**	(2.20)**	(0.87)	(4.66)***	(1.69)*	(3.65)***
_cons	0.908	0.893	1.140	0.893	0.783	0.796	0.854
	(61.36)***	(47.78)***	(27.18)***	(68.70)***	(78.35)***	(55.86)***	(69.37)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.305	0.266	0.249	0.231	0.249	0.245	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robust regression

Table 6*.1.1 panel B, Robust Regression (Simple returns)

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0216	0.00411	0.0228	0.0238	0.0200	0.0318
	(1.93)*	(0.59)	(2.58)***	(4.23)***	(2.71)***	(3.99)***
$\lvert R_{m,t}\rvert$	0.235	0.219	0.165	0.165	0.192	0.318
	(6.66)***	(9.08)***	(6.86)***	(9.82)***	(5.69)***	(16.44)***
$R_{m,t}^2$	0.0223	0.0105	0.0140	0.0185	0.0195	0.0156
	(2.03)**	(1.56)	(2.11)**	(4.86)***	(2.26)**	(3.93)***
_cons	0.973	0.707	0.967	0.796	0.802	1.406
	(54.55)***	(58.18)***	(65.40)***	(73.34)***	(44.33)***	(94.49)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.208	0.286	0.185	0.320	0.295	0.427

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.1 panel B,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0396	0.0301	0.0107	0.0487	0.0252	0.0219	0.0192
	(5.49)***	(2.74)***	(0.61)	(6.15)***	(3.76)***	(3.70)***	(2.03)**
$\lvert R_{m,t}\rvert$	0.225	0.149	0.194	0.318	0.179	0.179	0.255
	(8.66)***	(3.67)***	(2.89)***	(16.59)***	(12.24)***	(8.09)***	(10.03)***
$R_{m,t}^2$	0.0109	0.0316	0.0351	0.00546	0.0171	0.00613	0.0284
	(1.56)	(2.43)**	(2.25)**	(1.32)	(4.84)***	(1.33)	(3.87)***
_cons	0.905	0.890	1.140	0.889	0.780	0.792	0.853
	(62.42)***	(47.46)***	(27.03)***	(70.92)***	(79.19)***	(54.13)***	(70.70)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.317	0.272	0.249	0.241	0.254	0.249	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Based on the simple return calculation method, the regression results are mainly similar to the results based on the standard log return calculation method. According to the results, most of the countries have a significantly positive coefficient of squared market return, showing the existence of anti-herding in their market. Only the US, Hong Kong, Portugal and Sweden have an insignificant coefficient of the squared market return.

6*.1.2 Solution 1 Regression results without constant

Full range of data Regression results without constant

Table 6*.1.2, Robust Regression without constant

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0284	0.0238	0.0410	0.0402	0.0383	0.0397
	(2.00)**	(2.75)***	(3.59)***	(5.08)***	(3.94)***	(2.28)**
$\lvert R_{m,t}\rvert$	1.255	0.937	1.070	0.904	0.917	1.356
	(34.06)***	(37.10)***	(42.52)***	(50.80)***	(34.37)***	(22.77)***
$R_{m,t}^2$	-0.137	-0.0926	-0.119	-0.0879	-0.0793	-0.0982
	(-8.35)***	(-8.76)***	(-12.16)***	(-13.54)***	(-8.06)***	(-5.06)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.673	0.698	0.673	0.711	0.693	0.744

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.2,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0492	0.0452	0.00970	0.0641	0.0466	0.0440	0.0272
	(4.24)***	(3.28)***	(0.52)	(3.77)***	(4.29)***	(5.93)***	(2.02)**
$\lvert R_{m,t}\rvert$	1.004	1.033	1.029	1.284	0.966	0.797	1.179
	(29.89)***	(28.28)***	(22.55)***	(22.52)***	(23.17)***	(32.35)***	(42.29)***
$R_{m,t}^2$	-0.0872	-0.111	-0.0606	-0.161	-0.107	-0.0643	-0.117
	(-6.71)***	(-7.25)***	(-4.13)***	(-6.11)***	(-6.29)***	(-8.50)***	(-9.86)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.715	0.688	0.633	0.697	0.693	0.677	0.704

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When we apply solution 1 taking out the constant value in the regression, we can find that the all the countries have a significantly negative coefficient of squared market return, and this shows significant evidence of herding behaviour in these markets within our data sample.

6*.1.3 Solution 2 Regression results by using SCSAD method based on Simple return method

Robust regression using SCSAD (equation 5.4)

Table 6*.1.3, Robust Regression (Simple returns)

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	1.003	0.767	0.835	0.727	0.749	1.087
	(48.48)***	(68.07)***	(63.27)***	(71.25)***	(62.74)***	(52.80)***
$R_{m,t}^2$	0.00417	0.0153	0.0144	0.0125	0.0141	0.000271
	(0.52)	(4.30)***	(2.79)***	(3.66)***	(4.10)***	(0.04)
$R_{m,t}^3$	-0.0111	-0.00804	-0.0105	-0.00748	-0.00586	-0.00474
	(-5.22)***	(-9.07)***	(-9.41)***	(-10.42)***	(-7.44)***	(-3.79)***
_cons	0.0253	-0.0128	0.00127	0.00643	0.00610	0.0956
	(1.51)	(-1.29)	(0.09)	(0.56)	(0.52)	(3.81)***
N	4105	4132	4124	4202	4171	4063
adj. R^2	0.642	0.671	0.640	0.683	0.669	0.713

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.3,(continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.808	0.812	0.857	1.000	0.761	0.640	0.954
	(65.59)***	(52.67)***	(37.22)***	(46.84)***	(37.18)***	(53.49)***	(66.84)***
$R_{m,t}^2$	0.00775	0.0179	-0.00899	0.0251	0.0178	0.0140	0.00386
	(1.43)	(2.73)***	(-1.33)	(2.79)***	(3.62)***	(6.69)***	(0.73)
$R_{m,t}^3$	-0.00525	-0.00924	-0.00341	-0.0136	-0.00892	-0.00437	-0.00946
	(-5.72)***	(-5.54)***	(-2.70)***	(-4.82)***	(-4.28)***	(-7.47)***	(-8.10)***
_cons	0.0486	0.00741	0.0888	0.0312	0.0194	0.00934	0.0328
	(3.32)***	(0.49)	(3.56)***	(1.96)**	(1.63)	(0.82)	(2.68)***
N	4050	4168	4120	4194	4174	4123	4131
adj. R^2	0.684	0.660	0.618	0.662	0.661	0.648	0.677

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.3 shows the results for our solution 2 - the new SCSAD method. The results show that all the countries have a significantly negative coefficient of $R_{m,t}^3$, which means we will reject the null hypothesis which there have no herding behaviour exists in the selected stock markets and confirm that these countries have herding behaviour in their stock markets. Also, the adjusted R^2 is much higher than in the traditional method makes the results have more explanation power.

6*.1.4 Solution 3 Regression considering large market returns

6*.1.4.1 market return larger than |0.5%|

Table 6*.1.4 panel A, Robust Regression with market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0230	0.00679	0.0240	0.0251	0.0216	0.0323
	(2.08)**	(0.98)	(2.71)***	(4.47)***	(2.98)***	(4.10)***
$\lvert R_{m,t}\rvert$	0.351	0.317	0.197	0.228	0.238	0.388
	(7.08)***	(8.71)***	(5.23)***	(9.29)***	(4.74)***	(15.22)***
$R^2_{m,t}$	0.00525	-0.00259	0.00958	0.00992	0.0136	0.00839
	(0.47)	(-0.35)	(1.19)	(2.28)**	(1.35)	(2.06)**
_cons	0.846	0.595	0.930	0.718	0.743	1.300
	(20.82)***	(19.97)***	(27.76)***	(31.33)***	(17.56)***	(47.11)***
N	2460	2405	2674	2699	2645	2786
adj. R^2	0.232	0.318	0.191	0.350	0.310	0.442

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4.1 panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0410	0.0319	0.0106	0.0502	0.0265	0.0245	0.0217
	(5.92)***	(2.91)***	(0.60)	(6.15)***	(3.89)***	(4.15)***	(2.30)**
$\lvert R_{m,t}\rvert$	0.297	0.203	0.234	0.365	0.219	0.234	0.339
	(9.19)***	(3.33)***	(2.40)**	(11.20)***	(9.28)***	(8.40)***	(8.61)***
$R^2_{m,t}$	0.00252	0.0233	0.0306	-0.00210	0.0114	0.000195	0.0161
	(0.38)	(1.49)	(1.63)	(-0.35)	(2.63)***	(0.04)	(1.93)*
_cons	0.810	0.829	1.081	0.840	0.732	0.713	0.761
	(28.49)***	(18.50)***	(12.06)***	(28.89)***	(32.71)***	(25.90)***	(24.13)***
N	2579	2603	2979	2424	2538	2759	2208
adj. R^2	0.341	0.294	0.251	0.238	0.269	0.270	0.405

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.2 market return larger than |1%|

Table 6*.1.4 panel B, Robust Regression with market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0302	0.0102	0.0275	0.0271	0.0256	0.0323
	(2.55)**	(1.35)	(2.96)***	(4.54)***	(3.37)***	(3.94)***
$\|R_{m,t}\|$	0.507	0.438	0.236	0.262	0.341	0.428
	(7.79)***	(7.92)***	(3.97)***	(6.89)***	(5.04)***	(11.39)***
$R_{m,t}^2$	-0.0141	-0.0167	0.00469	0.00585	0.00207	0.00481
	(-1.26)	(-1.88)*	(0.46)	(1.06)	(0.19)	(1.00)
_cons	0.621	0.413	0.871	0.667	0.578	1.227
	(8.29)***	(6.47)***	(12.08)***	(13.90)***	(7.27)***	(22.60)***
N	1332	1258	1609	1588	1566	1784
adj. R^2	0.259	0.340	0.194	0.352	0.329	0.431

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0410	0.0356	0.0107	0.0537	0.0289	0.0272	0.0235
	(5.72)***	(3.07)***	(0.58)	(6.05)***	(3.95)***	(4.36)***	(2.28)**
$\|R_{m,t}\|$	0.365	0.202	0.202	0.313	0.253	0.318	0.404
	(8.71)***	(2.19)**	(1.42)	(6.12)***	(6.38)***	(9.64)***	(6.42)***
$R_{m,t}^2$	-0.00430	0.0234	0.0337	0.00503	0.00713	-0.00786	0.00802
	(-0.64)	(1.21)	(1.47)	(0.69)	(1.23)	(-1.89)*	(0.78)
_cons	0.694	0.833	1.140	0.908	0.682	0.563	0.668
	(13.36)***	(8.82)***	(6.50)***	(14.17)***	(13.54)***	(12.42)***	(9.03)***
N	1540	1547	2012	1332	1430	1673	1105
adj. R^2	0.349	0.273	0.230	0.199	0.273	0.299	0.396

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.3 market return larger than |2%|

Table 6*.1.4 panel C, Robust Regression with market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0366	0.0209	0.0279	0.0308	0.0348	0.0326
	(2.20)**	(2.01)**	(2.36)**	(4.15)***	(3.57)***	(3.30)***
$\lvert R_{m,t}\rvert$	0.765	0.530	0.231	0.388	0.486	0.482
	(4.77)***	(4.37)***	(1.51)	(4.62)***	(3.59)***	(6.30)***
$R^2_{m,t}$	-0.0394	-0.0261	0.00429	-0.00748	-0.0115	0.000637
	(-2.38)**	(-1.81)*	(0.24)	(-0.82)	(-0.73)	(0.09)
_cons	0.0836	0.224	0.905	0.424	0.267	1.092
	(0.26)	(1.02)	(3.19)***	(2.64)***	(1.07)	(6.82)***
N	340	315	532	544	505	714
adj. R^2	0.246	0.312	0.169	0.357	0.341	0.439

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 panel C (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0437	0.0478	0.00644	0.0495	0.0346	0.0381	0.0304
	(4.86)***	(3.08)***	(0.29)	(4.09)***	(3.52)***	(5.04)***	(2.24)**
$\lvert R_{m,t}\rvert$	0.478	0.202	0.0329	0.0990	0.184	0.424	0.749
	(6.38)***	(1.04)	(0.12)	(0.80)	(2.04)**	(7.54)***	(4.60)***
$R^2_{m,t}$	-0.0140	0.0229	0.0477	0.0290	0.0134	-0.0168	-0.0268
	(-1.79)*	(0.81)	(1.42)	(2.21)**	(1.52)	(-3.32)***	(-1.55)
_cons	0.448	0.843	1.550	1.300	0.841	0.310	-0.0417
	(3.00)***	(2.59)***	(3.00)***	(5.50)***	(4.72)***	(2.57)**	(-0.13)
N	512	537	847	367	440	627	321
adj. R^2	0.357	0.231	0.198	0.206	0.257	0.296	0.390

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.4 market return larger than |3%|

Table 6*.1.4 panel D, Robust Regression with market return larger than |3%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0275	0.0311	0.0311	0.0341	0.0405	0.0346
	(1.16)	(2.29)**	(1.96)*	(3.58)***	(3.15)***	(2.61)***
$\|R_{m,t}\|$	1.569	0.770	0.757	0.489	0.899	0.476
	(3.70)***	(3.17)***	(1.99)**	(2.50)**	(4.64)***	(3.12)***
$R_{m,t}^2$	-0.109	-0.0459	-0.0407	-0.0166	-0.0433	0.00111
	(-3.02)***	(-2.01)**	(-1.17)	(-0.95)	(-2.46)**	(0.10)
_cons	-1.933	-0.420	-0.486	0.183	-0.899	1.112
	(-1.82)*	(-0.70)	(-0.53)	(0.37)	(-1.88)*	(2.63)***
N	109	112	204	221	183	278
adj. R^2	0.240	0.268	0.192	0.340	0.405	0.412

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 panel D (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0450	0.0537	-0.00575	0.0429	0.0384	0.0424	0.0295
	(3.68)***	(2.27)**	(-0.20)	(2.70)***	(2.76)***	(4.34)***	(1.69)*
$\|R_{m,t}\|$	0.767	0.436	-0.0899	0.212	0.236	0.442	1.423
	(5.56)***	(1.07)	(-0.17)	(0.73)	(1.10)	(4.16)***	(3.76)***
$R_{m,t}^2$	-0.0343	0.00238	0.0562	0.0220	0.00904	-0.0185	-0.0866
	(-3.52)***	(0.06)	(1.12)	(0.88)	(0.51)	(-2.39)**	(-2.56)**
_cons	-0.397	0.237	1.935	0.901	0.702	0.273	-1.711
	(-1.02)	(0.24)	(1.50)	(1.23)	(1.25)	(0.88)	(-1.86)*
N	167	199	379	108	149	260	126
adj. R^2	0.424	0.221	0.182	0.402	0.276	0.252	0.382

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.5 market return larger than |4%|

Table 6*.1.4 panel E, Robust Regression with market return larger than |4%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0335	0.0385	0.0317	0.0374	0.0470	0.0375
	(0.89)	(2.19)**	(1.36)	(3.13)***	(2.77)***	(2.10)**
$\lvert R_{m,t}\rvert$	1.833	0.261	1.691	0.683	0.848	0.437
	(1.50)	(0.55)	(2.15)**	(1.88)*	(2.30)**	(1.55)
$R_{m,t}^2$	-0.129	-0.0121	-0.114	-0.0315	-0.0399	0.00345
	(-1.39)	(-0.33)	(-1.79)*	(-1.10)	(-1.42)	(0.19)
_cons	-2.758	1.322	-3.237	-0.420	-0.736	1.241
	(-0.75)	(0.90)	(-1.47)	(-0.39)	(-0.63)	(1.30)
N	43	49	91	83	80	121
adj. R^2	0.055	0.107	0.125	0.426	0.274	0.372

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 panel E (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0500	0.0718	-0.0331	0.0562	0.0544	0.0487	0.0267
	(3.42)***	(1.93)*	(-0.86)	(2.41)**	(2.96)***	(4.11)***	(1.10)
$\lvert R_{m,t}\rvert$	1.482	2.076	-0.0275	0.592	0.185	0.662	1.353
	(5.16)***	(1.60)	(-0.02)	(1.07)	(0.52)	(4.59)***	(1.25)
$R_{m,t}^2$	-0.0790	-0.124	0.0519	-0.0115	0.0111	-0.0326	-0.0815
	(-4.64)***	(-1.30)	(0.61)	(-0.27)	(0.41)	(-3.76)***	(-0.94)
_cons	-2.900	-4.743	1.706	-0.0407	0.913	-0.474	-1.485
	(-2.96)***	(-1.21)	(0.50)	(-0.02)	(0.87)	(-0.91)	(-0.47)
N	62	85	178	34	60	121	46
adj. R^2	0.528	0.219	0.171	0.501	0.346	0.299	0.216

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.6 market return larger than |5%|

Table 6*.1.4 panel F, Robust Regression with market return larger than |5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0481	0.0435	0.0200	0.0364	0.0503	0.0340
	(0.79)	(2.38)**	(0.57)	(2.90)***	(3.00)***	(1.46)
$\|R_{m,t}\|$	-0.911	1.102	-1.188	2.138	2.397	0.0100
	(-0.44)	(1.48)	(-0.55)	(2.65)**	(5.11)***	(0.02)
$R_{m,t}^2$	0.0572	-0.0678	0.0869	-0.132	-0.133	0.0257
	(0.40)	(-1.31)	(0.57)	(-2.36)**	(-4.80)***	(0.90)
_cons	6.874	-1.654	6.754	-5.530	-6.689	3.055
	(0.96)	(-0.63)	(0.90)	(-1.96)*	(-3.68)***	(1.49)
N	18	23	38	41	37	56
adj. R^2	-0.163	0.178	-0.073	0.513	0.558	0.333

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 panel F (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0628	0.103	-0.0680	0.0617	0.0636	0.0512	-0.000365
	(3.36)***	(1.49)	(-1.32)	(1.78)	(2.39)**	(3.36)***	(-0.01)
$\|R_{m,t}\|$	1.788	6.184	0.770	0.881	-0.746	0.896	2.358
	(2.51)**	(1.65)	(0.35)	(0.70)	(-0.91)	(3.20)***	(0.88)
$R_{m,t}^2$	-0.0963	-0.408	0.00524	-0.0321	0.0700	-0.0452	-0.157
	(-2.44)**	(-1.55)	(0.04)	(-0.37)	(1.37)	(-3.19)***	(-0.79)
_cons	-4.177	-18.94	-1.556	-1.019	4.364	-1.465	-4.641
	(-1.47)	(-1.53)	(-0.20)	(-0.23)	(1.37)	(-1.18)	(-0.54)
N	24	31	92	14	28	59	21
adj. R^2	0.413	0.169	0.171	0.535	0.253	0.312	-0.044

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.7 market return larger than |3%| in rising and falling market condition

Table 6*.1.4 Panel G Standard regression in rising and falling market condition with market return larger than |3%|

$$\mathrm{CSAD_{i,t}} = \alpha + \gamma_1 \mathrm{D^{up}}|\mathrm{R_{m,t}}| + \gamma_2(1-\mathrm{D^{up}})|\mathrm{R_{m,t}}| + \gamma_3 \mathrm{D^{up}}(\mathrm{R_{m,t}})^2 + \gamma_4(1-\mathrm{D^{up}})(\mathrm{R_{m,t}})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$\mathrm{D^{up}}\lvert\mathrm{R_{m,t}}\rvert$	1.718	0.881	0.783	0.539	0.972	0.526
	(3.47)***	(3.40)***	(2.18)**	(2.69)***	(4.86)***	(3.87)***
$(1-\mathrm{D^{up}})\lvert\mathrm{R_{m,t}}\rvert$	1.569	0.890	0.710	0.526	0.929	0.423
	(3.68)***	(3.00)***	(2.00)**	(2.59)**	(4.49)***	(2.83)***
$\mathrm{D^{up}}(\mathrm{R_{m,t}})^2$	-0.126	-0.0510	-0.0405	-0.0161	-0.0448	-0.00204
	(-2.61)**	(-2.21)**	(-1.18)	(-0.90)	(-2.53)**	(-0.23)
$(1-\mathrm{D^{up}})(\mathrm{R_{m,t}})^2$	-0.107	-0.0662	-0.0383	-0.0273	-0.0523	0.00404
	(-3.38)***	(-2.19)**	(-1.25)	(-1.42)	(-2.55)**	(0.36)
_cons	-2.107	-0.667	-0.463	0.0921	-1.014	1.120
	(-1.84)*	(-0.98)	(-0.53)	(0.18)	(-2.05)**	(2.78)***
N	109	112	204	221	183	278
adj. R^2	0.237	0.265	0.188	0.340	0.402	0.411

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 Panel G (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$\mathrm{D^{up}}\lvert\mathrm{R_{m,t}}\rvert$	0.804	0.547	0.277	0.178	0.423	0.487	1.436
	(5.55)***	(1.12)	(0.66)	(0.50)	(1.85)*	(4.04)***	(3.54)***
$(1-\mathrm{D^{up}})\lvert\mathrm{R_{m,t}}\rvert$	0.761	0.520	-0.210	0.0388	0.498	0.404	1.394
	(4.92)***	(0.92)	(-0.41)	(0.09)	(1.91)*	(2.84)***	(3.65)***
$\mathrm{D^{up}}(\mathrm{R_{m,t}})^2$	-0.0315	0.000682	0.00134	0.0265	0.000905	-0.0186	-0.0842
	(-2.72)***	(0.02)	(0.04)	(0.95)	(0.05)	(-2.30)**	(-2.17)**
$(1-\mathrm{D^{up}})(\mathrm{R_{m,t}})^2$	-0.0404	-0.0166	0.0878	0.0384	-0.0312	-0.0190	-0.0876
	(-3.58)***	(-0.27)	(1.57)	(0.90)	(-1.15)	(-1.38)	(-2.67)***
_cons	-0.435	0.0155	1.609	1.139	0.197	0.266	-1.692
	(-1.05)	(0.01)	(1.41)	(1.20)	(0.32)	(0.75)	(-1.78)*
N	167	199	379	108	149	260	126
adj. R^2	0.424	0.219	0.228	0.398	0.284	0.249	0.377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.4.8 market return larger than |4%| in rising and falling market condition

Table 6*.1.4 Panel H Standard regression in rising and falling market condition with market return larger than |4%|

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	2.614	0.261	1.785	0.773	0.810	0.512
	(1.87)*	(0.50)	(2.15)**	(2.06)**	(1.90)*	(2.01)**
$(1-D^{up})\|R_{m,t}\|$	2.209	0.162	1.776	0.773	0.657	0.363
	(1.68)	(0.26)	(1.94)*	(1.95)*	(1.30)	(1.36)
$D^{up}(R_{m,t})^2$	-0.205	-0.00967	-0.118	-0.0334	-0.0351	-0.00232
	(-1.78)*	(-0.25)	(-1.77)*	(-1.14)	(-1.18)	(-0.16)
$(1-D^{up})(R_{m,t})^2$	-0.148	-0.00548	-0.127	-0.0457	-0.0248	0.00870
	(-1.61)	(-0.10)	(-1.66)	(-1.41)	(-0.58)	(0.53)
_cons	-4.387	1.452	-3.474	-0.672	-0.422	1.246
	(-1.09)	(0.83)	(-1.43)	(-0.58)	(-0.29)	(1.38)
N	43	49	91	83	80	121
adj. R^2	0.073	0.087	0.116	0.423	0.266	0.371

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.4 Panel H (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	1.523	2.242	0.504	0.275	0.362	0.697	1.286
	(5.25)***	(1.36)	(0.53)	(0.43)	(0.88)	(3.81)***	(1.09)
$(1-D^{up})\|R_{m,t}\|$	1.483	2.168	-0.119	-0.000420	0.352	0.586	1.294
	(4.78)***	(1.18)	(-0.11)	(-0.00)	(0.75)	(2.44)**	(1.14)
$D^{up}(R_{m,t})^2$	-0.0763	-0.129	-0.0175	0.0134	0.00393	-0.0319	-0.0712
	(-4.62)***	(-1.14)	(-0.27)	(0.28)	(0.13)	(-3.13)***	(-0.73)
$(1-D^{up})(R_{m,t})^2$	-0.0855	-0.142	0.0860	0.0436	-0.0139	-0.0296	-0.0812
	(-4.16)***	(-0.88)	(0.96)	(0.70)	(-0.33)	(-1.42)	(-0.93)
_cons	-2.954	-5.089	1.051	1.204	0.462	-0.416	-1.312
	(-2.93)***	(-1.00)	(0.34)	(0.61)	(0.37)	(-0.61)	(-0.39)
N	62	85	178	34	60	121	46
adj. R^2	0.524	0.210	0.226	0.496	0.338	0.293	0.198

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We assume that herding tends to be present during periods when markets have larger movements such as in periods of financial turmoil. In this section, we detect herding behaviour based on the simple return calculation method with market returns larger than |0.5%|, |1%|, |2%|, |3%|, |4%| and |5%| using the standard regression equation 3.3. According to the results shown in table 6*.1.4 panel A, focusing on the coefficient of squared market returns, we find no evidence of herding behaviour in the market as do not see any significantly negative coefficients. In table 6*.1.4 panel B, we only see US and Sweden with evidence of herding behaviour in their market and these are only significant at the 10% level. In table 6*.1.4 panel C, Denmark and Sweden show significant evidence of herding behaviour, US and Hong Kong also have herding behaviour significant at the 10% level. In the last table with market returns larger than |3%|, Denmark, US, Germany, Hong Kong, Sweden and UK show clear evidence of herding behaviour. In panel E and F, with increase of absolute average market return, we have less observation in data sample, so we may have some bias to detect herding behaviour in the stock markets. In the rising and falling market condition with absolute market return larger than |3%|, results shown in panel G, we have found Denmark, US, Germany, Hong Kong, Sweden and UK have clear evidence of herding behaviour in rising market condition, and in the falling market condition, herding behaviour exists in the market of Denmark, US, Germany, Hong Kong and UK. Compare with results based on the log return calculation methos shown in table 6.1.4 panel G, we have more evidence of herding behaviour captured in the results based on simple return calculation method, such as Denmark in falling market condition, Germany and UK in both rising and falling market condition. With absolute market return larger than 4%, compare with the results based on log return calculation method, we also found some more evidence of herding behaviour in the market, such as Denmark, Finland have some evidence of herding behaviour in rising market condition which is significant at 10% level. From the results above, we can deduce that, with the increase of value of absolute return, herding behaviour is more likely to be detected. Also, compared with the regression results based on log return calculation method, it seems that herding behaviour has more likelihood of being detected when applying the simple return calculation method, especially when the market has larger movements.

6*.1.5 Larger market movements based on a proportion of the data condition

6*.1.5.1 Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

Regression results by using CCK based on the standard regression method
Table 6*.1.5, panel A Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0226	0.00674	0.0259	0.0259	0.0210	0.0319
	(2.01)**	(0.96)	(2.86)***	(4.53)***	(2.85)***	(3.95)***
$\|R_{m,t}\|$	0.378	0.341	0.207	0.243	0.273	0.414
	(6.95)***	(8.45)***	(4.38)***	(8.09)***	(4.66)***	(12.41)***
$R_{m,t}^2$	0.00178	-0.00555	0.00820	0.00813	0.00961	0.00599
	(0.15)	(-0.72)	(0.91)	(1.68)*	(0.90)	(1.32)
_cons	0.811	0.562	0.916	0.696	0.689	1.255
	(16.47)***	(15.35)***	(18.42)***	(21.44)***	(11.80)***	(28.06)***
N	2052	2066	2062	2102	2086	2032
adj. R^2	0.239	0.320	0.193	0.355	0.316	0.433

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5, panel A (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0406	0.0336	0.0107	0.0514	0.0261	0.0251	0.0213
	(5.79)***	(3.01)***	(0.58)	(6.25)***	(3.78)***	(4.18)***	(2.25)**
$\|R_{m,t}\|$	0.316	0.209	0.207	0.334	0.226	0.288	0.340
	(8.40)***	(2.86)***	(1.52)	(9.48)***	(8.13)***	(9.65)***	(8.30)***
$R_{m,t}^2$	0.000556	0.0225	0.0332	0.00225	0.0105	-0.00500	0.0160
	(0.08)	(1.31)	(1.49)	(0.38)	(2.24)**	(-1.20)	(1.88)*
_cons	0.780	0.822	1.130	0.879	0.722	0.619	0.759
	(19.76)***	(13.13)***	(6.91)***	(25.27)***	(24.57)***	(17.29)***	(22.21)***
N	2026	2084	2060	2098	2088	2062	2066
adj. R^2	0.336	0.289	0.232	0.223	0.271	0.297	0.403

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.5.2 Largest 10% (10% of absolute value (above 5% and 5% below 0))

Regression results by using CCK based on the standard regression method
Table 6*.1.5 panel B, Robust Regression

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0394	0.0196	0.0291	0.0310	0.0345	0.0315
	(2.51)**	(1.99)**	(2.31)**	(3.89)***	(3.36)***	(2.69)***
$\lvert R_{m,t}\rvert$	0.664	0.491	0.281	0.454	0.544	0.478
	(4.85)***	(4.61)***	(1.45)	(4.38)***	(3.73)***	(4.14)***
$R_{m,t}^2$	-0.0298	-0.0227	-0.000248	-0.0134	-0.0163	0.000976
	(-1.96)*	(-1.72)*	(-0.01)	(-1.28)	(-1.01)	(0.11)
_cons	0.310	0.323	0.785	0.270	0.119	1.100
	(1.23)	(1.79)*	(2.02)**	(1.25)	(0.42)	(3.78)***
N	410	414	412	420	418	406
adj. R^2	0.241	0.299	0.173	0.357	0.351	0.413

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5 panel B (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0468	0.0487	-0.00243	0.0514	0.0349	0.0403	0.0311
	(4.85)***	(2.79)***	(-0.09)	(4.34)***	(3.49)***	(4.71)***	(2.44)**
$\lvert R_{m,t}\rvert$	0.462	0.242	-0.00372	0.135	0.223	0.457	0.608
	(5.27)***	(1.05)	(-0.01)	(1.15)	(2.37)**	(6.16)***	(4.73)***
$R_{m,t}^2$	-0.0129	0.0190	0.0502	0.0254	0.00974	-0.0193	-0.0132
	(-1.50)	(0.63)	(1.05)	(2.00)**	(1.04)	(-3.27)***	(-0.89)
_cons	0.494	0.752	1.665	1.223	0.752	0.224	0.268
	(2.63)***	(1.72)*	(1.42)	(5.58)***	(4.06)***	(1.20)	(1.16)
N	406	416	412	420	418	412	414
adj. R^2	0.349	0.224	0.189	0.196	0.266	0.274	0.383

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.5.3 Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

Regression results by using CCK based on the standard regression method

Table 6*.1.5 panel C, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0343	0.0300	0.0305	0.0370	0.0399	0.0344
	(1.81)*	(2.54)**	(1.96)*	(3.83)***	(3.22)***	(2.36)**
$\|R_{m,t}\|$	1.156	0.652	0.793	0.582	0.882	0.466
	(4.90)***	(4.17)***	(2.17)**	(2.85)***	(4.86)***	(2.50)**
$R_{m,t}^2$	-0.0742	-0.0370	-0.0436	-0.0244	-0.0420	0.00179
	(-3.40)***	(-2.20)**	(-1.29)	(-1.35)	(-2.49)**	(0.14)
_cons	-0.865	-0.0672	-0.586	-0.0730	-0.850	1.137
	(-1.64)	(-0.21)	(-0.67)	(-0.14)	(-1.96)*	(2.05)**
N	206	208	206	210	208	204
adj. R^2	0.280	0.300	0.195	0.354	0.416	0.408

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5 panel C (continued)

	(1) Hong Kong	(2) Italy	(3) Norway	(4) Portugal	(5) Spain	(6) Sweden	(7) UK
$R_{m,t}$	0.0500	0.0574	-0.0250	0.0530	0.0372	0.0498	0.0310
	(4.28)***	(2.31)**	(-0.68)	(3.75)***	(2.93)***	(5.01)***	(2.08)**
$\|R_{m,t}\|$	0.643	0.325	-0.0553	0.121	0.184	0.621	1.077
	(4.84)***	(0.77)	(-0.06)	(0.66)	(1.17)	(6.14)***	(4.43)***
$R_{m,t}^2$	-0.0261	0.0114	0.0540	0.0277	0.0134	-0.0301	-0.0566
	(-2.61)***	(0.28)	(0.72)	(1.56)	(1.00)	(-4.43)***	(-2.42)**
_cons	-0.0100	0.549	1.792	1.226	0.838	-0.329	-0.826
	(-0.03)	(0.54)	(0.64)	(3.07)***	(2.20)**	(-1.06)	(-1.55)
N	202	208	206	210	208	206	206
adj. R^2	0.380	0.209	0.175	0.255	0.262	0.343	0.415

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.5.4 Largest 3% (3% of absolute value)

Regression results by using CCK based on the standard regression method

Table 6*.1.5 panel D, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0255	0.0267	0.0299	0.0446	0.0462	0.0364
	(1.14)	(1.93)*	(1.44)	(4.04)***	(3.13)***	(2.05)**
$\lvert R_{m,t}\rvert$	1.608	0.633	1.503	0.620	0.699	0.467
	(4.26)***	(2.58)**	(2.32)**	(2.30)**	(2.48)**	(1.66)*
$R_{m,t}^2$	-0.112	-0.0353	-0.0996	-0.0282	-0.0297	0.00181
	(-3.41)***	(-1.53)	(-1.85)*	(-1.26)	(-1.23)	(0.10)
_cons	-2.047	-0.0203	-2.677	-0.159	-0.248	1.123
	(-2.23)**	(-0.03)	(-1.53)	(-0.21)	(-0.32)	(1.18)
N	123	123	123	126	125	122
adj. R^2	0.281	0.219	0.190	0.385	0.317	0.374

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5 panel D (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0438	0.0714	-0.0498	0.0451	0.0461	0.0493	0.0310
	(3.24)***	(2.28)**	(-1.08)	(2.77)***	(3.13)***	(4.19)***	(1.76)*
$\lvert R_{m,t}\rvert$	0.828	0.852	-0.186	-0.144	-0.0268	0.678	1.472
	(4.21)***	(1.14)	(-0.11)	(-0.48)	(-0.10)	(4.85)***	(3.83)***
$R_{m,t}^2$	-0.0383	-0.0319	0.0614	0.0513	0.0286	-0.0335	-0.0907
	(-2.97)***	(-0.53)	(0.54)	(1.88)*	(1.40)	(-3.98)***	(-2.65)***
_cons	-0.595	-0.932	2.303	1.881	1.497	-0.534	-1.846
	(-0.98)	(-0.45)	(0.42)	(2.58)**	(2.07)**	(-1.06)	(-1.96)*
N	122	125	124	126	125	124	124
adj. R^2	0.396	0.207	0.147	0.295	0.249	0.313	0.384

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.5.5 Largest 2% (2% of absolute value)

Regression results by using CCK based on the standard regression method

Table 6*.1.5 panel E, Robust Regression

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$R_{m,t}$	0.0373	0.0365	0.0309	0.0359	0.0470	0.0320
	(1.37)	(2.45)**	(1.25)	(2.98)***	(2.81)***	(1.50)
$\|R_{m,t}\|$	1.596	0.702	1.597	0.540	0.854	0.120
	(2.82)***	(2.51)**	(1.91)*	(1.40)	(2.44)**	(0.29)
$R_{m,t}^2$	-0.111	-0.0416	-0.107	-0.0209	-0.0403	0.0202
	(-2.37)**	(-1.65)	(-1.60)	(-0.69)	(-1.49)	(0.86)
_cons	-2.008	-0.192	-2.936	0.0413	-0.760	2.554
	(-1.34)	(-0.26)	(-1.24)	(0.04)	(-0.70)	(1.63)
N	82	82	82	84	83	81
adj. R^2	0.195	0.220	0.097	0.392	0.287	0.304

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5 panel E (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$R_{m,t}$	0.0450	0.0719	-0.0791	0.0408	0.0531	0.0472	0.0378
	(3.31)***	(1.88)*	(-1.43)	(2.71)***	(3.34)***	(3.60)***	(1.86)*
$\|R_{m,t}\|$	1.257	2.085	1.902	0.741	0.465	0.823	1.575
	(5.35)***	(1.52)	(0.77)	(2.51)**	(1.49)	(4.64)***	(2.79)***
$R_{m,t}^2$	-0.0653	-0.125	-0.0600	-0.0209	-0.00842	-0.0411	-0.0992
	(-4.57)***	(-1.24)	(-0.37)	(-0.85)	(-0.34)	(-4.19)***	(-2.08)**
_cons	-2.078	-4.770	-6.229	-0.585	-0.0226	-1.151	-2.128
	(-2.70)***	(-1.16)	(-0.70)	(-0.77)	(-0.03)	(-1.63)	(-1.43)
N	81	83	82	84	83	82	83
adj. R^2	0.508	0.211	0.196	0.563	0.406	0.324	0.336

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.5.6 Largest 3% (3% of absolute value) in rising and falling market condition

Regression results by using CCK based on the Normal regression method

Table 6*.1.5 panel F, Robust Regression

$$CSAD_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1-D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.723	0.744	1.589	0.664	0.683	0.540
	(3.97)***	(3.00)***	(2.43)**	(2.44)**	(2.34)**	(2.12)**
$(1-D^{up})\|R_{m,t}\|$	1.597	0.771	1.577	0.575	0.542	0.398
	(4.26)***	(2.87)***	(2.24)**	(2.07)**	(1.68)*	(1.49)
$D^{up}(R_{m,t})^2$	-0.125	-0.0407	-0.103	-0.0282	-0.0263	-0.00363
	(-2.88)***	(-1.80)*	(-1.88)*	(-1.25)	(-1.11)	(-0.25)
$(1-D^{up})(R_{m,t})^2$	-0.110	-0.0580	-0.112	-0.0281	-0.0173	0.00660
	(-3.86)***	(-2.11)**	(-1.88)*	(-1.16)	(-0.59)	(0.40)
_cons	-2.162	-0.280	-2.885	-0.158	-0.0251	1.121
	(-2.21)**	(-0.44)	(-1.57)	(-0.21)	(-0.03)	(1.24)
N	123	123	123	126	125	122
adj. R^2	0.278	0.217	0.184	0.380	0.312	0.373

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5 panel F (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	0.868	0.908	0.283	-0.238	0.118	0.707	1.496
	(4.23)***	(1.06)	(0.19)	(-0.74)	(0.40)	(3.92)***	(3.58)***
$(1-D^{up})\|R_{m,t}\|$	0.843	0.744	-0.425	-0.439	0.109	0.591	1.441
	(3.72)***	(0.77)	(-0.26)	(-1.22)	(0.33)	(2.47)**	(3.70)***
$D^{up}(R_{m,t})^2$	-0.0353	-0.0314	-0.00669	0.0589	0.0228	-0.0325	-0.0896
	(-2.47)**	(-0.51)	(-0.07)	(2.24)**	(1.05)	(-3.24)***	(-2.25)**
$(1-D^{up})(R_{m,t})^2$	-0.0463	-0.0271	0.106	0.0841	0.00582	-0.0295	-0.0911
	(-2.90)***	(-0.29)	(0.88)	(2.27)**	(0.18)	(-1.42)	(-2.73)***
_cons	-0.667	-0.872	2.090	2.312	1.164	-0.455	-1.836
	(-1.02)	(-0.35)	(0.40)	(2.80)***	(1.43)	(-0.67)	(-1.87)*
N	122	125	124	126	125	124	124
adj. R^2	0.397	0.201	0.203	0.296	0.246	0.307	0.379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6*.1.5.7 Largest 2% (2% of absolute value) in rising and falling market condition

Regression results by using CCK based on the Normal regression method

Table 6*.1.5 panel G, Robust Regression

$$\mathrm{CSAD}_{i,t} = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}(R_{m,t})^2 + \gamma_4(1 - D^{up})(R_{m,t})^2 + \varepsilon_t$$

	(1) Denmark	(2) US	(3) Finland	(4) France	(5) Germany	(6) Greece
$D^{up}\|R_{m,t}\|$	1.893	0.773	1.715	0.641	0.821	0.193
	(3.09)***	(2.68)***	(1.89)*	(1.62)	(2.04)**	(0.48)
$(1 - D^{up})\|R_{m,t}\|$	1.625	0.727	1.720	0.656	0.671	0.0571
	(2.94)***	(2.22)**	(1.69)*	(1.60)	(1.41)	(0.15)
$D^{up}(R_{m,t})^2$	-0.145	-0.0438	-0.112	-0.0233	-0.0358	0.0148
	(-2.54)**	(-1.75)*	(-1.57)	(-0.75)	(-1.26)	(0.67)
$(1 - D^{up})(R_{m,t})^2$	-0.108	-0.0494	-0.124	-0.0379	-0.0259	0.0246
	(-2.72)***	(-1.55)	(-1.45)	(-1.13)	(-0.64)	(1.15)
_cons	-2.394	-0.303	-3.267	-0.265	-0.463	2.539
	(-1.57)	(-0.37)	(-1.20)	(-0.22)	(-0.34)	(1.66)
N	82	82	82	84	83	81
adj. R^2	0.203	0.210	0.087	0.391	0.279	0.299

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6*.1.5 panel G (continued)

	(7) Hong Kong	(8) Italy	(9) Norway	(10) Portugal	(11) Spain	(12) Sweden	(13) UK
$D^{up}\|R_{m,t}\|$	1.297	2.246	2.500	0.859	0.625	0.900	1.658
	(5.37)***	(1.32)	(1.15)	(2.37)**	(1.73)*	(3.77)***	(2.85)***
$(1 - D^{up})\|R_{m,t}\|$	1.281	2.172	1.721	0.826	0.614	0.832	1.539
	(4.91)***	(1.15)	(0.73)	(2.02)**	(1.48)	(2.57)**	(2.67)***
$D^{up}(R_{m,t})^2$	-0.0621	-0.129	-0.139	-0.0257	-0.0146	-0.0427	-0.105
	(-4.24)***	(-1.11)	(-1.04)	(-0.90)	(-0.55)	(-3.43)***	(-2.03)**
$(1 - D^{up})(R_{m,t})^2$	-0.0740	-0.142	-0.0172	-0.0359	-0.0327	-0.0468	-0.0973
	(-4.16)***	(-0.87)	(-0.11)	(-0.85)	(-0.85)	(-1.77)*	(-2.03)**
_cons	-2.164	-5.103	-6.707	-0.827	-0.401	-1.278	-2.188
	(-2.69)***	(-0.98)	(-0.81)	(-0.87)	(-0.38)	(-1.29)	(-1.44)
N	81	83	82	84	83	82	83
adj. R^2	0.509	0.201	0.247	0.559	0.403	0.315	0.328

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

By using different proportions of observations in the datasets, we can determine that under the condition with the largest 50% of returns in absolute value, we do not have clear evidence of herding behaviour in the stock markets. With the largest 10% returns by absolute return value, the results shown in table 6*.1.5 panel B reveal that Sweden has significant evidence of herding behaviour in its stock market, and Denmark and the US markets have evidence of herding which is significant at the 10% level. In table 6*.1.5 panel C, we capture significant evidence of the presence of herding behaviour in Denmark, the US, Germany, Hong Kong, Sweden and the UK. In panel D and panel E, we have got similar results, that Denmark, Hong Kong, Sweden and UK have clear evidence of herding behaviour in their stock markets. Compared with the results using log return, the regression results using the simple return method shows the presence of more herding behaviour in the stock market, particularly during periods where the market has larger movements. In panel F and panel G, we detect herding behaviour in rising and falling market condition with selection of different proportion of observations. When we have largest 3% of the observation, we have largest 3% of the observation, we have Denmark, Hong Kong, Portugal, Sweden and UK have clear evidence of herding behaviour in the rising market condition, and herding in US and Finland is significant at 10% level. While in the falling market condition, Denmark, US, Hong Kong, Portugal and UK have herding behaviour presence in their stock markets, and herding in Finland is significant at 10% level. When we select largest 2% of the observation, we have captured evidence of herding behaviour in Denmark, Hong Kong, Sweden and UK in rising market condition, and in falling market condition, we have captured evidence of herding behaviour in stock market of Denmark, Hong Kong and UK.

6*.1.6 Fitted line for CSAD based on simple returns for the full range of data

When we fit the regressions based on the simple return calculation method and apply solution 2 the new SCSAD method, we have similar results to those found for log returns. The traditional CCK method does not indicate any herding behaviour (table 6*.1.1 panel A and panel B). Then in solution 1 regression without a constant value (table 6*.1.2), and the new SCSAD method (table 6*.1.3), with the significantly negative coefficient of $R_{m,t}^2$ and $R_{m,t}^3$ for each country, we can confirm that the regressions for all the countries indicate herding behaviour.

The following figures shows the scatter distribution of CSAD results and predicted regression line based on regression results in table 6*.1.1 panel B for each country. According to the regression results, we do not have any evidence of the presence of herding behaviour, and as shown in following figures, the regression lines are mostly curved upwards although some of them tend to be linear such as Portugal, which indicates that there is no evidence of the existence of herding behaviour in these stock markets.

Figure 6*.1 to 6*.13 Fitted line for CSAD results

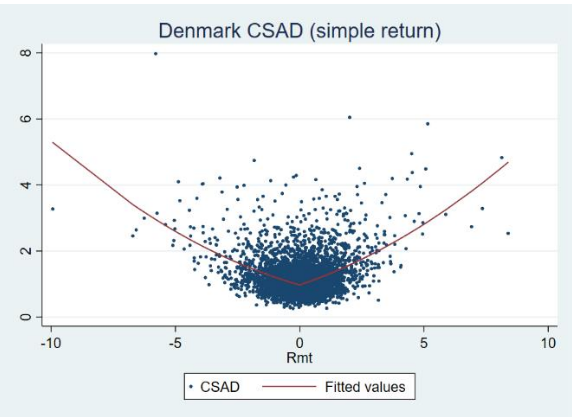


Figure 6*.1

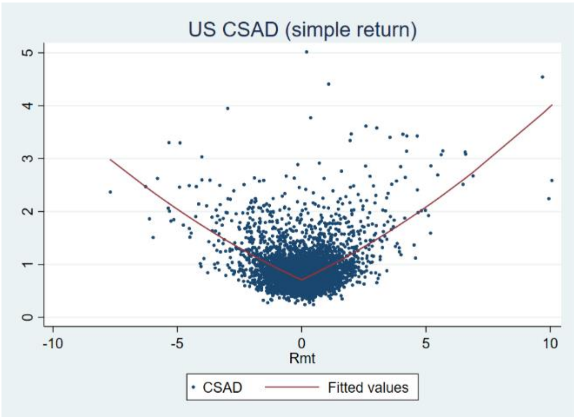


Figure 6*.2

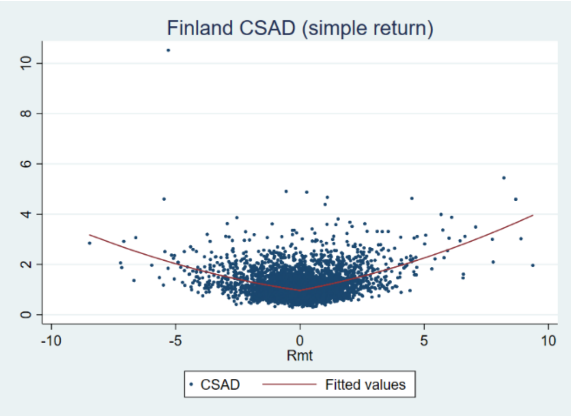


Figure 6*.3

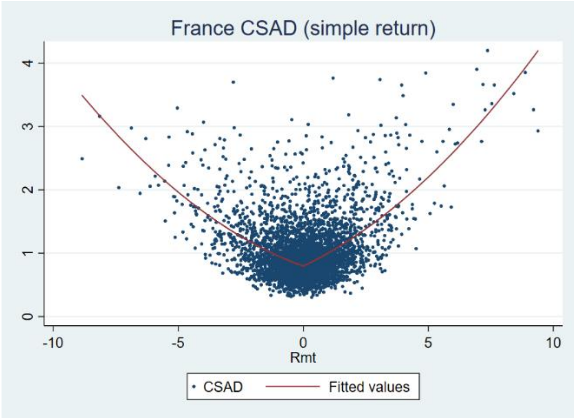


Figure 6*.4

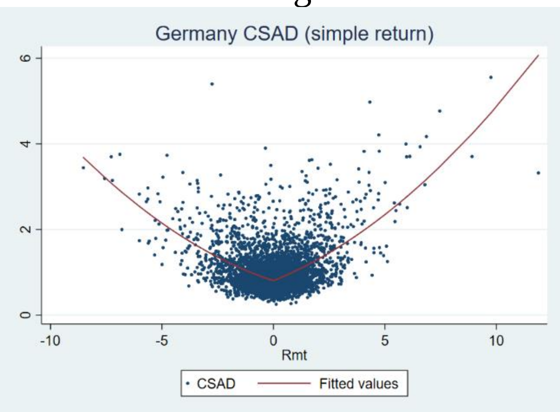


Figure 6*.5

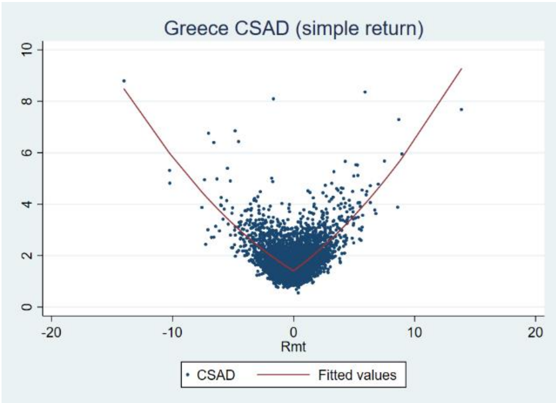


Figure 6*.6

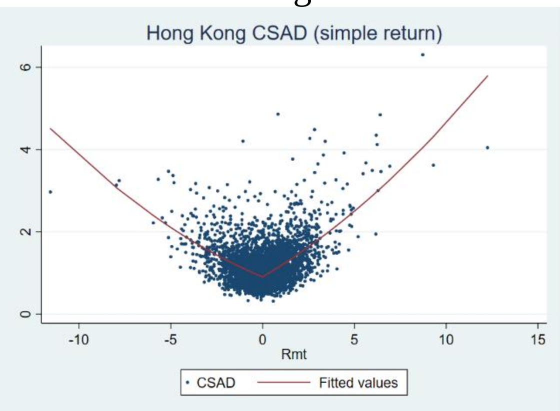


Figure 6*.7

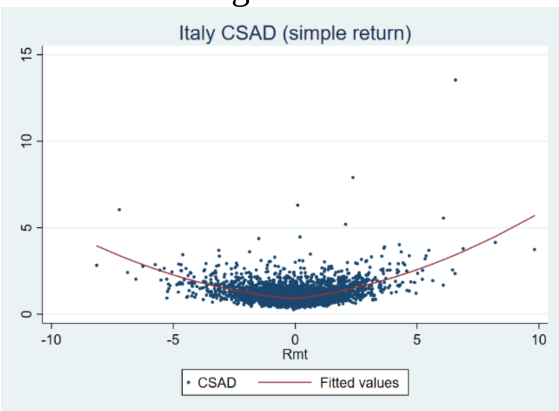


Figure 6*.8

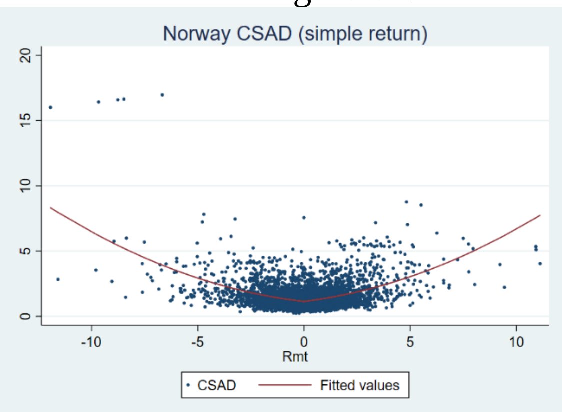


Figure 6*.9

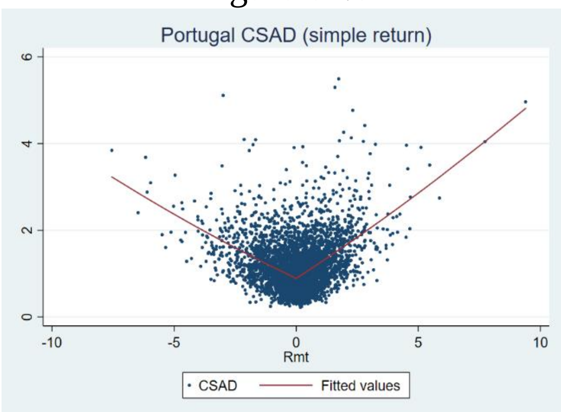


Figure 6*.10

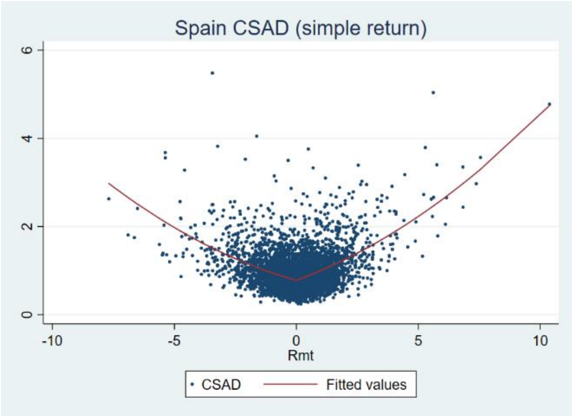


Figure 6*.11

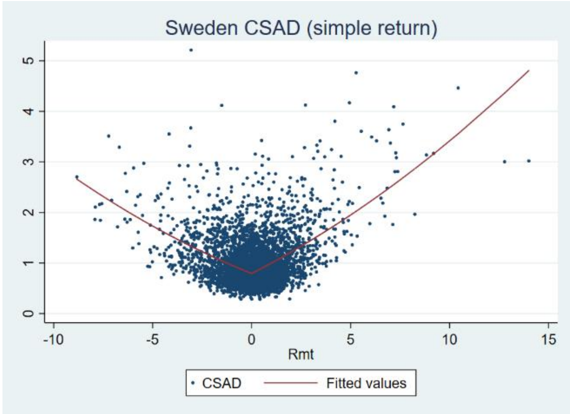


Figure 6*.12

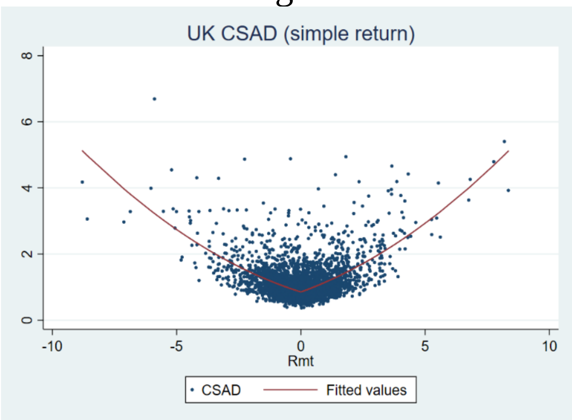


Figure 6*.13

6*.1.7 Fitted line for CSAD without constant based on simple returns for the full range of data

Applying solution 1 regression without a constant value, with results shown in table 6*.1.2, the coefficients of the squared market returns indicate that all countries have evidence of herding behaviour in their stock markets. Also, from the following figures, the fitted regression lines are curved downwards, and this also indicates presence of herding in each stock market.

Figure 6*.14 to 6*.26 Fitted line for CSAD without constant

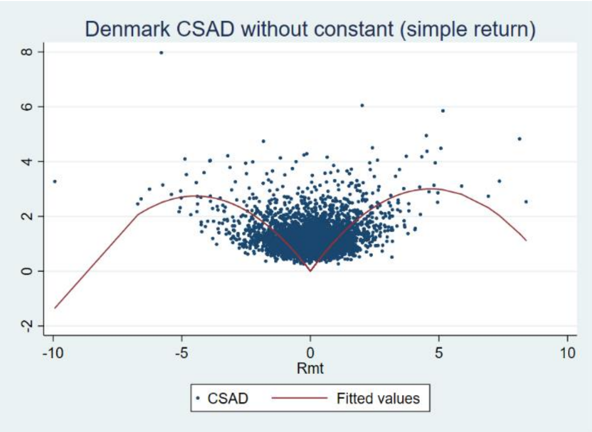


Figure 6*.14

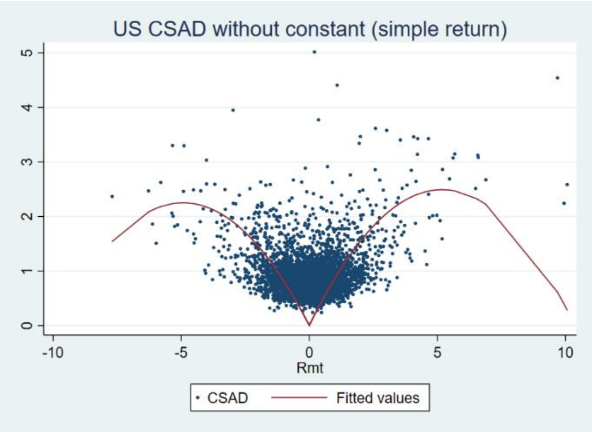


Figure 6*.15

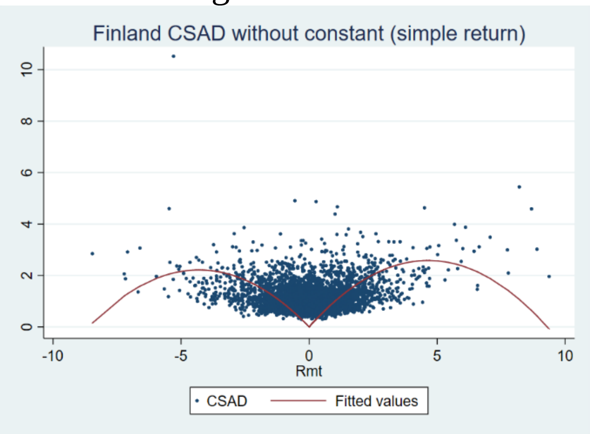


Figure 6*.16

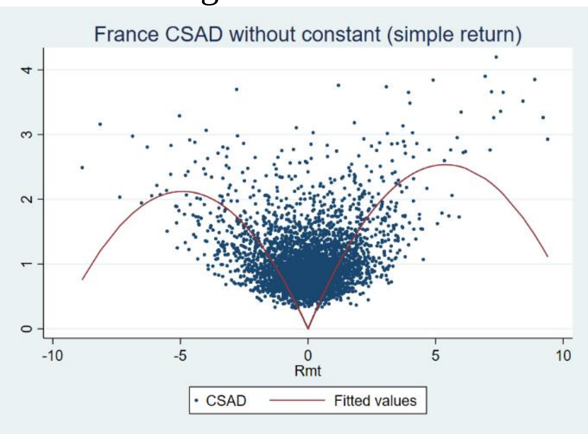


Figure 6*.17

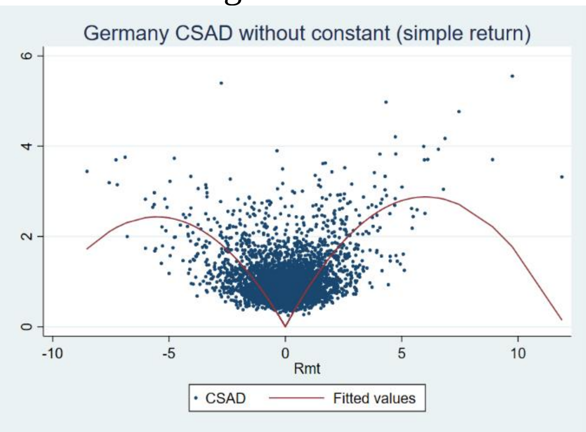


Figure 6*.18

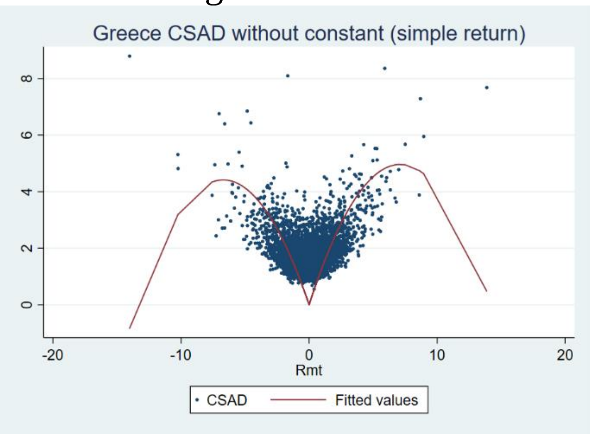


Figure 6*.19

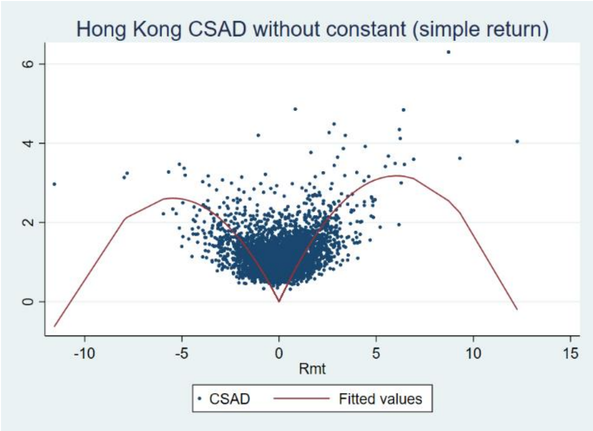


Figure 6*.20

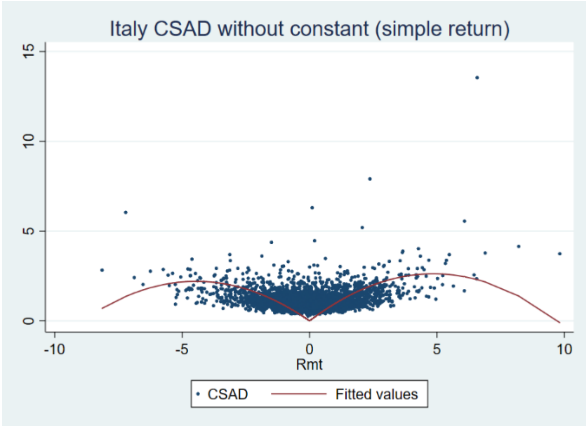


Figure 6*.21

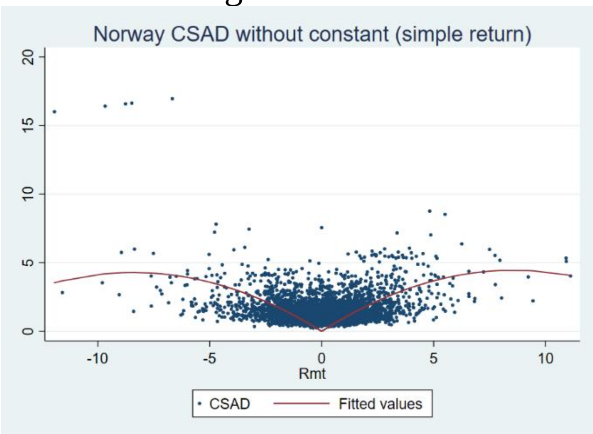


Figure 6*.22

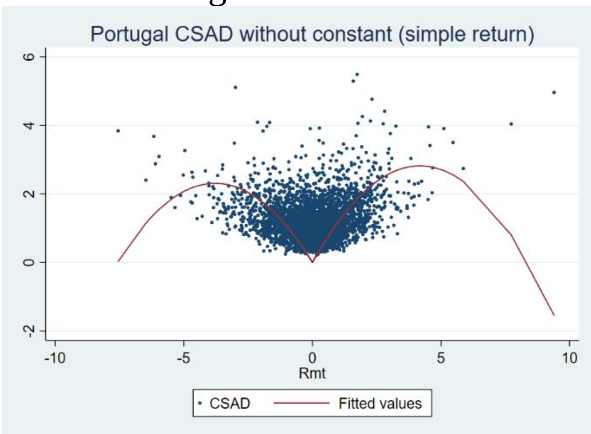


Figure 6*.23

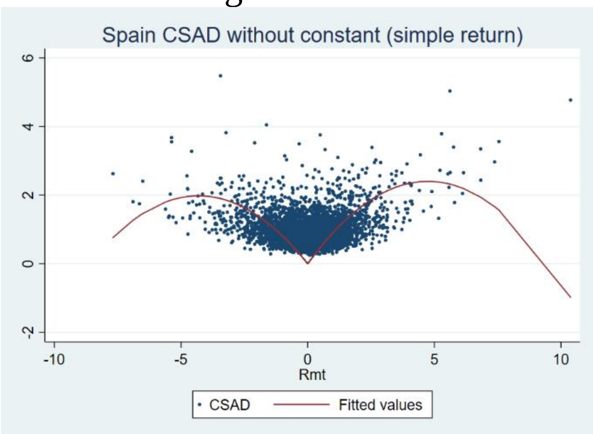


Figure 6*.24

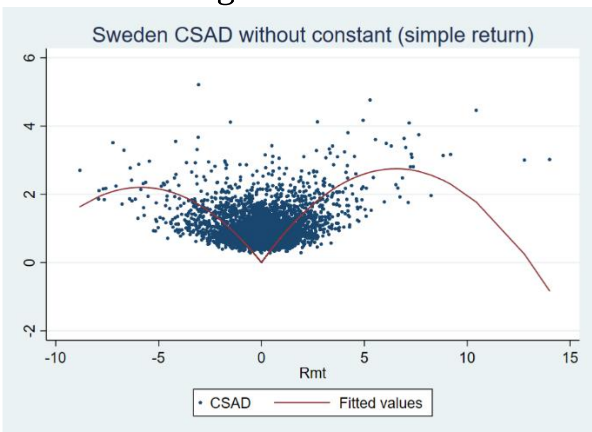
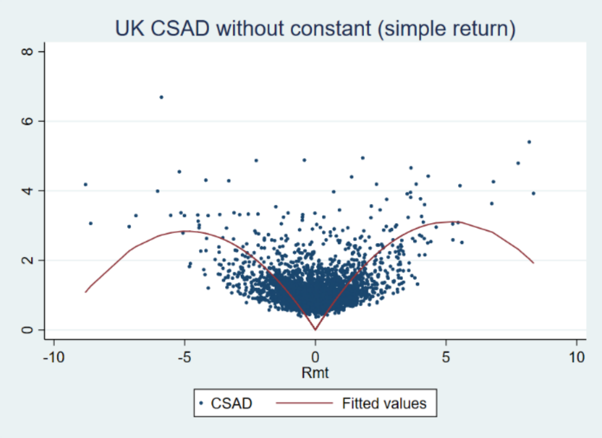


Figure 6*.25


UK CSAD without constant (simple return)
8
6
4
2
0
-10
-5
0
5
10
Rmt
CSAD
Fitted values
Figure 6*.26

6*.1.8 Fitted line for SCSAD based on simple returns for the full range of data

Applying the SCSAD regression model, we have captured significant evidence of herding behaviour in all the countries in our data sample. From the following figures, similar to the results found by using log return method, we can see that by using the simple return method, the predicted fit regression line is curved into different directions which indicates that herding behaviour exists in these markets.

Figure 6*.27 to 6*.39 Fitted line for SCSAD results

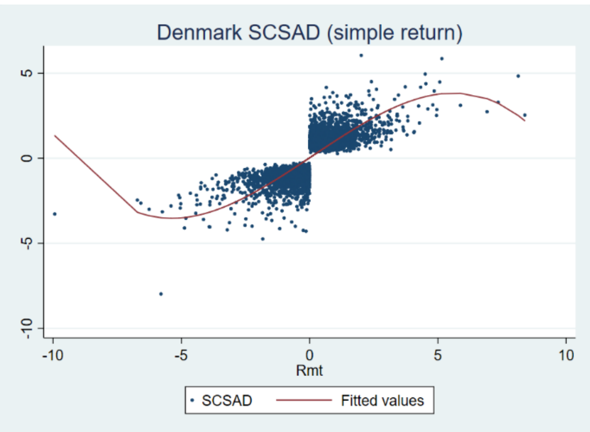


Figure 6*.27

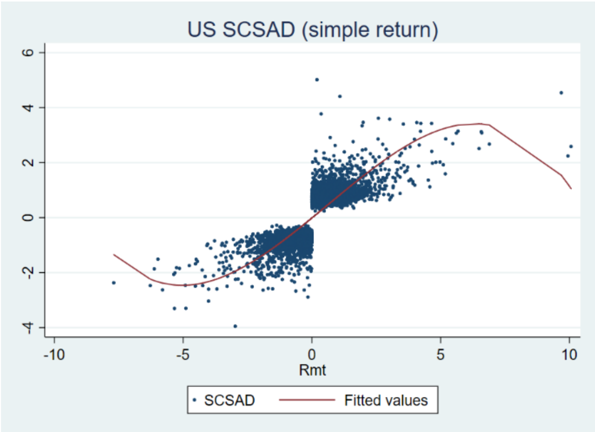


Figure 6*.28

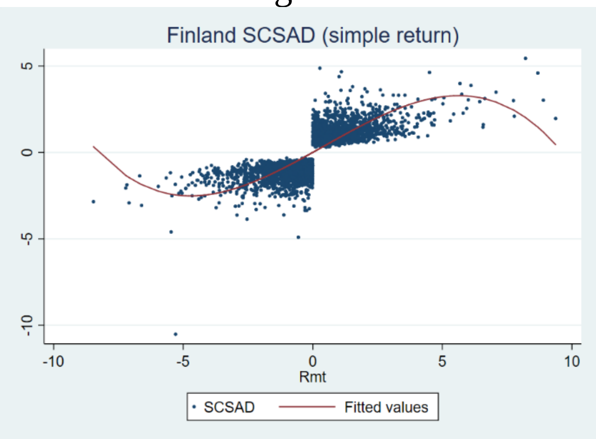


Figure 6*.29

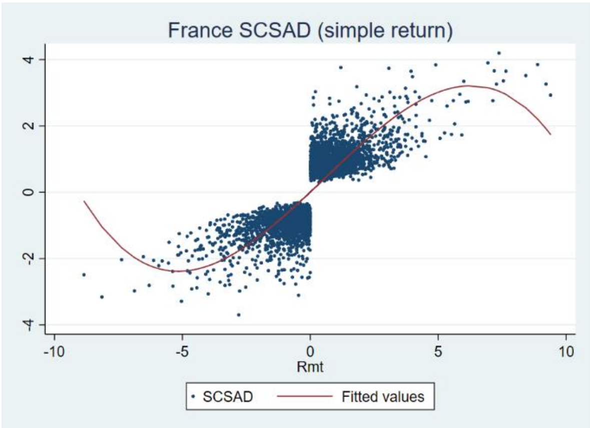


Figure 6*.30

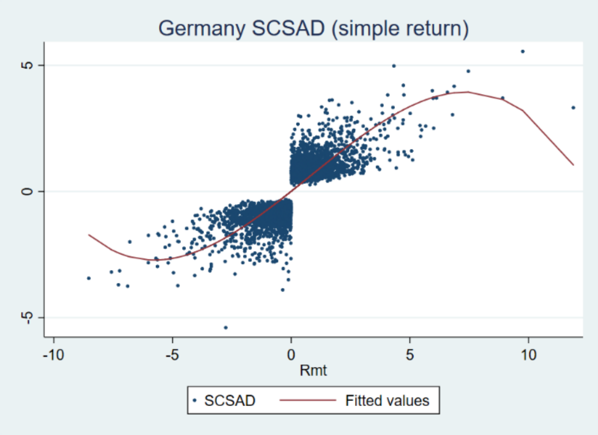


Figure 6*.31

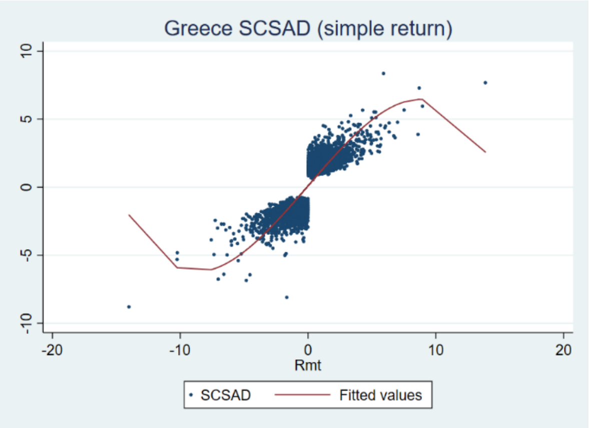


Figure 6*.32

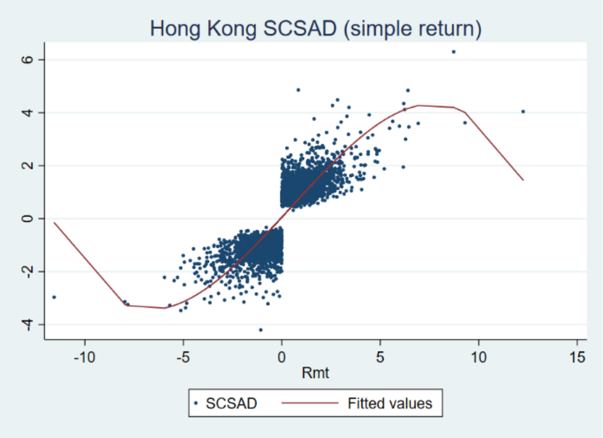


Figure 6*.33

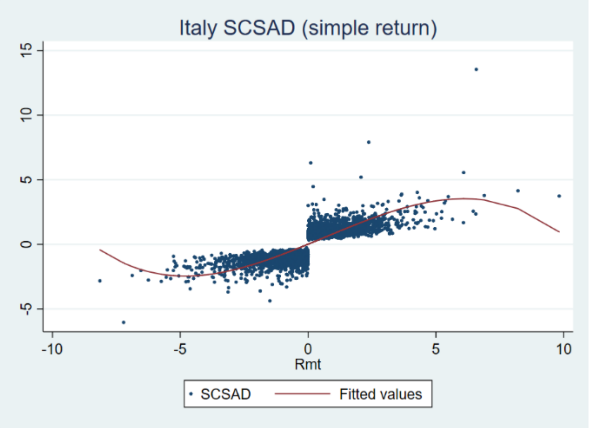


Figure 6*.34

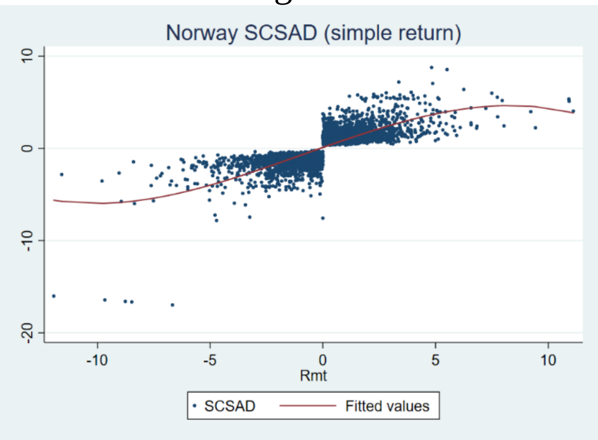


Figure 6*.35

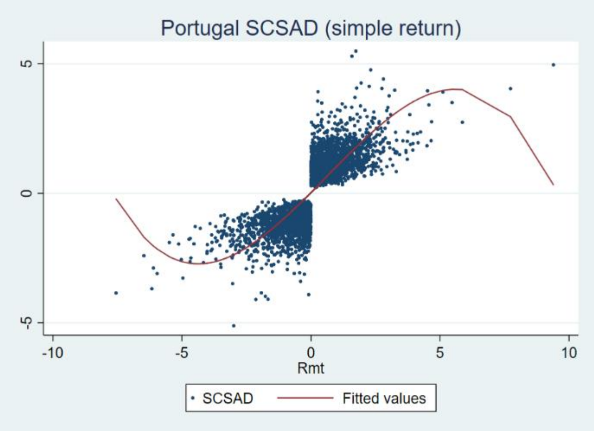


Figure 6*.36

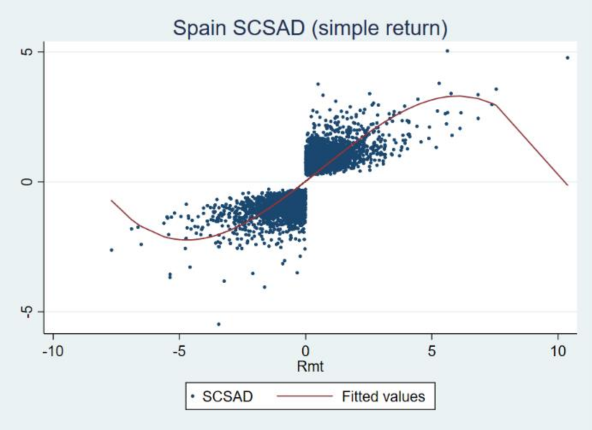


Figure 6*.37

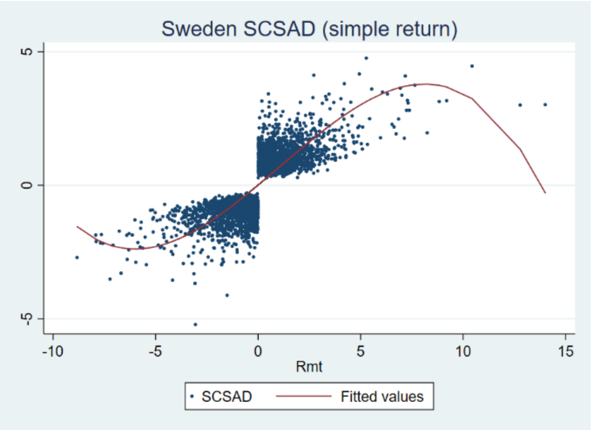


Figure 6*.38

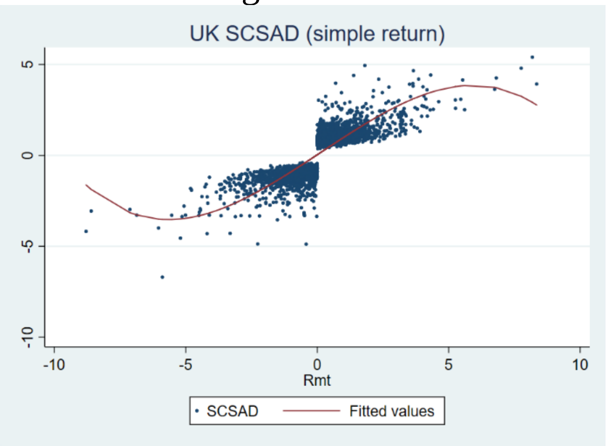


Figure 6*.39

6*.2 Conclusion

As a phenomenon in behavioural finance, herding behaviour reflects investors' investment under uncertainty. The existence of non-rational investor behaviour has a number of important features, for example, it may cause a financial crisis. During a period when the market is rising, investors may be optimistic about the market, and herding behaviour will promote the formation of an economic bubble. When the bubble gets bigger and bigger, there may be a crisis, when herd behaviour will accelerate the collapse of the market. During the market downturn period, herding behaviour may have some advantages if investors enter the market at this time and make investments, which may help the economy to improve again. However, during this downturn period, it is likely the investors are losing their confidence in the market and have unclear investment plans. If herding behaviour exists in the market, whereby, investors just follow and mimic the investment behaviour of others and this could be a bad signal to the market.

Our empirical findings show that with the traditional CCK method, the markets we study have partial herding behaviour during rising market conditions, and very little during falling market condition, especially in the northern European countries such as Sweden. However, the traditional CCK method has the disadvantage that it will be influenced by the error term in the CAPM model when the average market return $R_{m,t}$ is small. Theoretical and empirical analysis shows that, the CCK approach is not very effective. We introduce several alternative methods including the new SCSAD method. These new methods can clearly detect herding behaviour in all kinds of market conditions. We see that all the countries in our data sample have herding behaviour during the sample period. The results of the different approaches to testing for herding give very similar results whichever type of security returns (simple or log) are used, but using simple returns with the traditional CCK method, seems to give more likelihood of detecting herding behaviour in the market.

Material Associated with Chapter 7

7.2.2 The First Time period from 2001 to 2010

Regression results of sectors in the UK using the CCK model

Table 7.2.2.2 panel A UK regression results under CCK model

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0506***	0.0586***	0.0472***	-0.0055	0.0580*	0.0300*
	(3.4683)	(3.7314)	(3.5257)	(-0.3688)	(1.8837)	(1.8651)
$\|R_{m,t}\|$	0.8569***	0.8104***	0.8541***	0.6758***	0.6626***	0.7259***
	(25.6116)	(13.7932)	(21.8129)	(18.2749)	(6.6863)	(14.9963)
$R_{m,t}^2$	-0.0258***	0.0114	-0.0185	-0.0077	0.0339	0.0097
	(-2.1441)	(0.4970)	(-1.4420)	(-0.4846)	(1.2546)	(0.5727)
_cons	1.1094***	1.1663***	1.0185***	0.8705***	1.4057***	0.7573***
	(79.8713)	(47.3451)	(63.6858)	(65.8711)	(28.1622)	(41.1701)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.4921	0.4399	0.5190	0.3736	0.4663	0.6047

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0572***	0.0318***	0.0733***	0.0119	0.0681***	0.0027
	(2.2573)	(2.4765)	(2.2601)	(0.9528)	(3.4111)	(0.0472)
$\|R_{m,t}\|$	0.7397***	0.8139***	0.7467***	0.7793***	0.7466***	0.2402***
	(9.8150)	(26.3806)	(8.1546)	(19.3140)	(11.0129)	(2.1744)
$R_{m,t}^2$	0.0953***	-0.0377***	0.0459	-0.0434***	0.0788***	0.0910***
	(3.3162)	(-3.4887)	(1.4025)	(-3.7728)	(3.3662)	(2.2842)
_cons	1.2989***	1.0478***	1.3332***	0.7121***	1.3482***	0.7509***
	(41.6218)	(75.7761)	(37.2869)	(43.0924)	(47.4782)	(19.2347)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.5690	0.4716	0.5176	0.5123	0.6085	0.4765

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.2 panel B the markets of Germany and France regression results under CCK model

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0345***	0.0372	0.0624***	-0.0043	0.0111	0.0435***
	(2.5417)	(1.5608)	(2.6746)	(-0.2705)	(0.4226)	(2.5070)
$\|R_{m,t}\|$	0.7307***	0.4888***	0.6180***	0.5351***	0.5514***	0.6555***
	(17.3488)	(5.6505)	(10.8975)	(13.2270)	(6.9823)	(10.1174)
$R_{m,t}^2$	0.0057	0.0854***	0.1418***	0.0264	0.0328	0.0601***
	(0.3612)	(3.0692)	(5.8767)	(1.3501)	(1.4837)	(2.3505)
_cons	1.5205***	1.6526***	1.3670***	1.0127***	1.2351***	1.4335***
	(77.0176)	(41.5720)	(60.3766)	(64.3773)	(30.6336)	(54.1162)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.3933	0.4704	0.4780	0.2888	0.4444	0.4422

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0352	0.0344*	0.0681***	0.0029	0.0754***	-0.0065
	(1.3570)	(1.7699)	(2.4665)	(0.1309)	(5.6976)	(-0.2928)
$\|R_{m,t}\|$	0.6587***	0.7044***	0.3935***	0.9966***	0.7653***	0.6108***
	(9.2500)	(12.1375)	(6.9396)	(16.2858)	(17.8321)	(6.6547)
$R_{m,t}^2$	0.0327	0.0259	0.1672***	0.0940***	-0.0209*	0.0721
	(1.2160)	(1.1501)	(19.0570)	(4.6148)	(-1.8323)	(1.6343)
_cons	1.6147***	1.4925***	1.2040***	1.6178***	1.7400***	0.8532***
	(51.1539)	(60.2850)	(41.3491)	(51.8065)	(67.1831)	(29.2003)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.3812	0.4068	0.8543	0.5756	0.4155	0.4487

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.2.3 Solution 1 Regression without constant value over the first time period

Table 7.2.2.3 Panel A regression results without constant in the UK market

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0758***	0.0587***	0.0488***	0.0098	0.0609*	0.0482***
	(3.6635)	(3.1092)	(2.5856)	(0.3250)	(1.8570)	(2.5368)
$\|R_{m,t}\|$	2.7897***	2.5169***	2.3734***	2.3054***	1.9763***	1.7095***
	(31.6227)	(42.6697)	(27.8564)	(23.8928)	(42.8742)	(46.6004)
$R_{m,t}^2$	-0.5141***	-0.4111***	-0.3482***	-0.4388***	-0.1337***	-0.1670***
	(-8.4959)	(-12.5999)	(-7.1855)	(-5.9075)	(-7.1208)	(-9.5669)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7612	0.7787	0.7693	0.7304	0.7465	0.7888

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1119***	0.0292*	0.0972***	0.0213	0.1043***	0.0366
	(3.0862)	(1.7174)	(2.3183)	(1.1039)	(2.3192)	(0.6034)
$\|R_{m,t}\|$	2.2893***	2.6070***	2.2707***	1.6715***	2.2761***	1.0742***
	(23.0442)	(33.9702)	(32.0893)	(16.7539)	(21.3762)	(15.8942)
$R_{m,t}^2$	-0.1687***	-0.5086***	-0.2021***	-0.2046***	-0.1684***	-0.0082
	(-3.3313)	(-9.5920)	(-5.7731)	(-4.8218)	(-3.2781)	(-0.2330)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7776	0.7704	0.7669	0.7565	0.7753	0.6528

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.3 Panel B regression results without constant in the markets Germany and France

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0823*	0.0735*	0.0409	-0.0386*	0.0410	0.0514***
	(1.8335)	(1.8726)	(1.3703)	(-1.7834)	(1.3021)	(1.9980)
$\lvert R_{m,t}\rvert$	3.1338***	2.1947***	2.7841***	2.4674***	1.6413***	2.6221***
	(27.1475)	(21.0708)	(42.7734)	(32.0947)	(29.0317)	(35.5801)
$R_{m,t}^2$	-0.5803***	-0.1853***	-0.4033***	-0.5713***	-0.1075***	-0.3635***
	(-7.1978)	(-4.0618)	(-9.7140)	(-8.7967)	(-4.8928)	(-8.5506)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7562	0.7377	0.7610	0.7375	0.7416	0.7606

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0879***	0.0487	0.0819***	0.0471	0.1173***	-0.0210
	(2.2404)	(1.4265)	(3.0584)	(1.1216)	(4.4830)	(-0.8464)
$\lvert R_{m,t}\rvert$	2.3964***	2.7583***	1.6761***	2.7562***	2.6603***	1.8397***
	(25.2339)	(30.1705)	(47.4694)	(24.7417)	(45.8255)	(31.7869)
$R_{m,t}^2$	-0.2278***	-0.4142***	0.0176***	-0.1667***	-0.3410***	-0.1955***
	(-4.8214)	(-7.6354)	(2.8474)	(-2.9428)	(-13.6829)	(-4.9554)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7229	0.7546	0.8408	0.7817	0.7615	0.7596

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.2.4 Solution 2 Regression results in SCSAD over the first time period

Table 7.2.2.4 Panel A Regression results under SCSAD model in the UK market

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	2.1816***	1.9923***	1.8891***	1.8199***	1.6802***	1.4324***
	(44.3628)	(49.7027)	(42.7295)	(42.0691)	(59.3103)	(60.3216)
$R_{m,t}^2$	-0.0005	-0.0054	-0.0126	-0.0105	0.0076	0.0038
	(-0.0332)	(-0.4471)	(-1.1439)	(-0.3888)	(0.6077)	(0.4489)
$R_{m,t}^3$	-0.0719***	-0.0609***	-0.0422***	-0.0584***	-0.0092***	-0.0162***
	(-5.5671)	(-7.6433)	(-5.3056)	(-4.4122)	(-5.2228)	(-6.7855)
_cons	0.1115***	0.0913***	0.0912***	0.0435***	0.0545***	0.0660***
	(6.2774)	(4.1866)	(5.2094)	(2.5417)	(2.0148)	(4.7629)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7226	0.7547	0.7356	0.6916	0.7280	0.7698

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.9955***	2.0259***	1.9168***	1.2854***	1.9280***	1.0209***
	(50.3439)	(49.0949)	(60.8647)	(25.9545)	(48.5540)	(29.4394)
$R_{m,t}^2$	0.0473***	-0.0316***	0.0403***	-0.0120	0.0291	0.0041
	(2.2124)	(-2.3051)	(2.2948)	(-1.2237)	(1.4337)	(0.1650)
$R_{m,t}^3$	-0.0145***	-0.0796***	-0.0175***	-0.0179***	-0.0101***	0.0011
	(-2.5355)	(-6.9143)	(-4.6908)	(-3.2251)	(-2.1088)	(0.3121)
_cons	-0.0026	0.1010***	0.0408	0.0643***	0.0516*	0.0021
	(-0.0955)	(5.9420)	(1.5487)	(3.9318)	(1.8293)	(0.0904)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7642	0.7323	0.7476	0.7169	0.7561	0.6527

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.4 Panel B Regression results under SCSAD model in the markets of Germany and France

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	2.4257***	1.8036***	2.2807***	1.9260***	1.3993***	2.1090***
	(54.8029)	(37.5895)	(61.9808)	(59.2219)	(55.5707)	(58.9331)
$R_{m,t}^2$	0.0382	0.0186	0.0189	-0.0608***	0.0134	0.0043
	(1.0151)	(0.9045)	(0.9998)	(-3.0028)	(1.1728)	(0.2751)
$R_{m,t}^3$	-0.0721***	-0.0129***	-0.0538***	-0.1014***	-0.0074***	-0.0419***
	(-5.2976)	(-2.3884)	(-6.5934)	(-8.1640)	(-3.8251)	(-6.5146)
_cons	0.0812***	0.0414	0.0367	0.0412***	0.0395	0.0666***
	(2.7428)	(1.1175)	(1.5959)	(2.4317)	(1.4610)	(2.7311)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.7163	0.7151	0.7395	0.7040	0.7256	0.7339

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.9958***	2.1759***	1.6525***	2.4289***	2.0726***	1.5838***
	(73.5440)	(53.9251)	(47.5710)	(74.7898)	(63.5516)	(68.9230)
$R_{m,t}^2$	0.0445***	0.0152	0.0104***	0.0054	0.0330***	-0.0202
	(2.9373)	(0.6019)	(2.2797)	(0.2420)	(2.6620)	(-1.1442)
$R_{m,t}^3$	-0.0171***	-0.0456***	0.0032***	-0.0091***	-0.0351***	-0.0218***
	(-7.4265)	(-5.4694)	(4.7471)	(-2.4854)	(-10.0675)	(-4.4606)
_cons	0.0167	0.0505*	0.0538***	0.0136	0.0836***	0.0076
	(0.5921)	(1.7663)	(2.9005)	(0.4105)	(2.7544)	(0.4336)
N	2869	2869	2869	2869	2869	2869
adj. R^2	0.6995	0.7221	0.8420	0.7692	0.7252	0.7459

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.2.5 Solution 3 Regression considering large market returns

In the UK market

Table 7.2.2.5 panel A Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0682***	0.0610***	0.0513***	0.0005	0.0613*	0.0336***
	(4.4480)	(3.7772)	(3.6668)	(0.0281)	(1.9561)	(2.0390)
$\|R_{m,t}\|$	0.9048***	0.8444***	0.8311***	0.7448***	0.7117***	0.8338***
	(12.8911)	(6.8895)	(10.6589)	(9.4461)	(4.4587)	(9.8776)
$R_{m,t}^2$	-0.0316*	0.0042	-0.0134	-0.0217	0.0284	-0.0069
	(-1.8834)	(0.1180)	(-0.7098)	(-1.0087)	(0.8603)	(-0.3412)
_cons	1.0603***	1.1369***	1.0370***	0.8128***	1.3380***	0.6427***
	(21.0006)	(13.5135)	(18.8665)	(15.5406)	(10.2595)	(10.6630)
N	968	1472	1161	921	1726	1254
adj. R^2	0.5088	0.4063	0.4932	0.4007	0.4647	0.6255

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0603***	0.0393***	0.0731***	0.0182	0.0675***	0.0005
	(2.3434)	(2.8937)	(2.2252)	(1.4350)	(3.6346)	(0.0087)
$\|R_{m,t}\|$	0.7046***	0.7836***	0.7103***	0.6886***	0.4938***	0.1311
	(5.4461)	(13.0289)	(4.3367)	(11.8658)	(4.8652)	(0.6403)
$R_{m,t}^2$	0.1012***	-0.0272*	0.0522	-0.0276***	0.1163***	0.1034***
	(2.8047)	(-1.9028)	(1.2130)	(-2.3402)	(4.6224)	(2.0735)
_cons	1.3295***	1.0573***	1.3611***	0.7953***	1.6191***	0.8657***
	(14.9137)	(23.4900)	(12.0411)	(17.7136)	(21.2990)	(6.0728)
N	1496	1097	1527	1189	1446	1380
adj. R^2	0.6115	0.4453	0.5123	0.4663	0.6320	0.5129

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.5 panel B Market return larger than |1%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0977***	0.0655***	0.0701***	0.0402***	0.0744***	0.0426***
	(5.3577)	(3.6420)	(4.3479)	(2.0226)	(2.1784)	(2.2828)
$\|R_{m,t}\|$	0.9651***	0.8936***	0.7361***	0.7123***	0.8868***	1.0149***
	(6.5428)	(3.6855)	(5.2190)	(4.1839)	(3.6577)	(7.5395)
$R_{m,t}^2$	-0.0378	-0.0033	0.0044	-0.0139	0.0105	-0.0311
	(-1.3953)	(-0.0596)	(0.1646)	(-0.4497)	(0.2672)	(-1.3410)
_cons	0.9950***	1.0694***	1.1410***	0.8514***	1.0541***	0.3921***
	(6.4046)	(4.5901)	(7.6136)	(4.6060)	(3.7299)	(2.6122)
N	371	732	470	268	930	516
adj. R^2	0.4841	0.3814	0.4629	0.3821	0.4684	0.6048

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0593***	0.0637***	0.0819***	0.0253*	0.0752***	-0.0061
	(2.0327)	(3.9742)	(2.2461)	(1.8322)	(3.9330)	(-0.0927)
$\|R_{m,t}\|$	0.6096***	0.8827***	0.6888***	0.4944***	0.0730	-0.0856
	(2.8314)	(6.8988)	(2.4410)	(6.4032)	(0.5049)	(-0.2361)
$R_{m,t}^2$	0.1138***	-0.0392	0.0551	-0.0014	0.1699***	0.1249*
	(2.5097)	(-1.6366)	(0.9575)	(-0.1316)	(6.3761)	(1.9266)
_cons	1.4592***	0.9275***	1.3991***	1.0795***	2.2286***	1.1895***
	(6.6194)	(6.8788)	(4.9110)	(10.6736)	(13.7186)	(3.1340)
N	682	408	738	536	699	586
adj. R^2	0.6248	0.4623	0.4905	0.3533	0.6719	0.5399

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.5 panel C Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1223***	0.0705***	0.0969***	0.0661***	0.0933***	0.0465*
	(3.9254)	(2.6838)	(4.2164)	(2.0900)	(1.9993)	(1.7587)
$\|R_{m,t}\|$	0.9802*	1.2720*	0.1309	0.0295	1.2521***	1.7806***
	(1.8229)	(1.6821)	(0.3150)	(0.0512)	(2.4414)	(5.9236)
$R_{m,t}^2$	-0.0394	-0.0605	0.0835	0.0770	-0.0222	-0.1166***
	(-0.5340)	(-0.4962)	(1.5837)	(0.9873)	(-0.3860)	(-3.7973)
_cons	1.0239	0.4960	2.2009***	2.0233***	0.2808	-1.0535*
	(1.1568)	(0.4402)	(2.9112)	(2.0745)	(0.2981)	(-1.8467)
N	73	182	109	45	273	143
adj. R^2	0.4299	0.3042	0.4316	0.4088	0.4349	0.4961

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0561	0.1012***	0.1223***	0.0101	0.0718***	-0.0185
	(1.2398)	(3.4608)	(2.3041)	(0.5768)	(2.7182)	(-0.1771)
$\|R_{m,t}\|$	0.4995	-0.0102	0.6585	0.5344***	-0.8624***	-0.7939
	(0.9029)	(-0.0163)	(0.8573)	(2.8987)	(-2.5130)	(-0.7550)
$R_{m,t}^2$	0.1278*	0.0947	0.0611	-0.0062	0.2701***	0.1859
	(1.7632)	(1.0498)	(0.5651)	(-0.3275)	(6.4948)	(1.5149)
_cons	1.6111*	2.3598***	1.4387	0.9962***	4.0100***	2.7108
	(1.6742)	(2.4336)	(1.1526)	(2.6902)	(6.5297)	(1.4570)
N	157	81	193	185	189	112
adj. R^2	0.6456	0.3522	0.4564	0.2814	0.7683	0.5552

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.5 panel D Market return larger than |3%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0831	0.0415	0.0785***	0.0746*	0.0797	0.0448
	(1.6688)	(0.6992)	(2.8404)	(2.2372)	(1.1601)	(1.1126)
$\|R_{m,t}\|$	3.5045*	3.9478	-1.0178	4.2952***	2.0543***	2.3672***
	(1.9724)	(1.5165)	(-1.0545)	(2.9944)	(2.1225)	(2.1268)
$R^2_{m,t}$	-0.3468*	-0.3951	0.1980*	-0.4117***	-0.0846	-0.1752*
	(-1.8156)	(-1.3321)	(1.9054)	(-2.5486)	(-1.0242)	(-1.7602)
_cons	-4.0309	-4.6664	4.8696***	-6.7545*	-1.9716	-2.3420
	(-1.0194)	(-0.8400)	(2.3101)	(-2.2816)	(-0.7947)	(-0.8365)
N	18	48	33	11	98	51
adj. R^2	0.4356	0.1485	0.5794	0.8368	0.3329	0.2480

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0364	0.0537	0.1192	0.0041	0.0402	-0.0549
	(0.4668)	(0.7390)	(1.3663)	(0.1888)	(1.0355)	(-0.3373)
$\|R_{m,t}\|$	0.4975	0.3472	0.1278	-0.0878	-1.3237	-1.7473
	(0.3354)	(0.1781)	(0.0561)	(-0.2332)	(-1.5321)	(-0.6071)
$R^2_{m,t}$	0.1314	0.0525	0.1108	0.0472	0.3097***	0.2601
	(0.9216)	(0.2462)	(0.4700)	(1.4970)	(3.8855)	(1.0153)
_cons	1.5123	1.4182	2.7238	2.5960***	5.1702***	5.2764
	(0.4384)	(0.3378)	(0.5225)	(2.6245)	(2.4821)	(0.7244)
N	52	17	69	76	57	36
adj. R^2	0.6009	0.4811	0.3508	0.1940	0.8137	0.5184

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.2.5 In the markets of Germany and France

Table 7.2.2.5 panel E Market return larger than |0.5%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0422***	0.0360	0.0727***	-0.0004	0.0097	0.0443***
	(2.9959)	(1.5249)	(2.9826)	(-0.0262)	(0.3728)	(2.4596)
$\|R_{m,t}\|$	0.7686***	0.3482***	0.7210***	0.6349***	0.5288***	0.7549***
	(9.6498)	(2.4465)	(6.1989)	(6.9062)	(4.1861)	(6.0903)
$R_{m,t}^2$	0.0018	0.1067***	0.1243***	0.0039	0.0359	0.0421
	(0.0840)	(3.0933)	(3.7056)	(0.1456)	(1.3086)	(1.1876)
_cons	1.4686***	1.8034***	1.2563***	0.9313***	1.2560***	1.3350***
	(26.5600)	(16.5525)	(16.2125)	(15.5180)	(12.2377)	(16.0252)
N	1263	1650	1322	1131	1842	1453
adj. R^2	0.4340	0.5002	0.5109	0.2912	0.4288	0.4647

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0390	0.0397***	0.0719***	0.0066	0.0779***	-0.0028
	(1.5388)	(1.9775)	(2.5546)	(0.2868)	(5.7309)	(-0.1193)
$\|R_{m,t}\|$	0.8281***	0.7992***	0.4370***	1.0595***	0.7945***	0.6397***
	(8.6488)	(7.2042)	(3.8232)	(10.5397)	(11.5741)	(3.3081)
$R_{m,t}^2$	0.0105	0.0103	0.1628***	0.0870***	-0.0244	0.0681
	(0.3938)	(0.3371)	(11.6551)	(3.5814)	(-1.6250)	(1.0916)
_cons	1.4162***	1.3908***	1.1406***	1.5295***	1.6952***	0.8182***
	(19.6176)	(18.4359)	(11.8462)	(19.0789)	(29.5642)	(6.8884)
N	1527	1440	1443	1540	1643	1396
adj. R^2	0.4340	0.4204	0.8827	0.6179	0.4111	0.4400

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.5 panel F Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0590***	0.0433*	0.0909***	0.0035	0.0115	0.0555***
	(3.5070)	(1.7526)	(3.1169)	(0.1539)	(0.4170)	(2.6800)
$\|R_{m,t}\|$	0.7653***	0.0663	0.9740***	0.9414***	0.5236***	0.8851***
	(4.8473)	(0.3055)	(3.9211)	(3.7475)	(2.6569)	(3.8835)
$R_{m,t}^2$	0.0031	0.1435***	0.0798	-0.0565	0.0364	0.0219
	(0.0960)	(3.4395)	(1.5609)	(-1.1107)	(1.0585)	(0.4400)
_cons	1.4820***	2.2089***	0.9736***	0.6110***	1.2665***	1.1764***
	(9.2771)	(9.4858)	(3.9193)	(2.5648)	(5.6881)	(5.2905)
N	483	925	544	378	1077	664
adj. R^2	0.4324	0.5205	0.5084	0.2976	0.4132	0.4575

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0528*	0.0502***	0.0823***	0.0080	0.0847***	0.0022
	(1.8980)	(2.1078)	(2.7306)	(0.2999)	(5.7236)	(0.0764)
$\|R_{m,t}\|$	1.0277***	1.1122***	0.5656***	1.3470***	0.6896***	0.9469***
	(8.0281)	(5.6902)	(2.5749)	(9.3208)	(5.8928)	(2.6381)
$R_{m,t}^2$	-0.0121	-0.0396	0.1496***	0.0548***	-0.0102	0.0202
	(-0.4756)	(-0.9771)	(6.3016)	(2.1535)	(-0.4926)	(0.2409)
_cons	1.1204***	1.0175***	0.9475***	1.1076***	1.8516***	0.4486
	(7.5551)	(5.2764)	(3.5941)	(6.6256)	(13.3483)	(1.3386)
N	753	634	653	742	875	549
adj. R^2	0.4476	0.4023	0.8915	0.6861	0.3626	0.4522

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.5 panel G Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0615***	0.0328	0.1657***	0.0305	0.0133	0.0632*
	(2.2986)	(1.0911)	(3.2001)	(0.4810)	(0.3645)	(1.9193)
$\lvert R_{m,t}\rvert$	0.4354	-1.6271***	1.2200	-0.4450	0.7061*	1.5981***
	(0.8801)	(-4.3658)	(1.2214)	(-0.2375)	(1.7314)	(2.0294)
$R_{m,t}^2$	0.0509	0.3272***	0.0493	0.1371	0.0188	-0.0686
	(0.7123)	(6.6446)	(0.3523)	(0.4730)	(0.3645)	(-0.6064)
_cons	1.9744***	5.4798***	0.6350	3.0070	0.9033	-0.0581
	(2.4975)	(8.6209)	(0.3951)	(1.0506)	(1.2679)	(-0.0461)
N	85	289	105	36	342	144
adj. R^2	0.4766	0.5727	0.4318	0.0791	0.3823	0.4373

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0827***	0.0853***	0.0932***	-0.0278	0.1033***	-0.0090
	(2.0888)	(2.1576)	(2.6150)	(-0.6897)	(5.5008)	(-0.1528)
$\lvert R_{m,t}\rvert$	1.6674***	1.7160***	1.9915***	1.5605***	0.8381***	1.8877*
	(4.2699)	(2.8529)	(3.5409)	(4.4529)	(2.9900)	(1.8388)
$R_{m,t}^2$	-0.0706***	-0.1161	0.0225	0.0382	-0.0262	-0.1056
	(-2.1499)	(-1.4196)	(0.4250)	(1.0990)	(-0.6994)	(-0.6985)
_cons	-0.2115	0.0308	-2.2847***	0.6152	1.5649***	-1.0172
	(-0.2643)	(0.0311)	(-2.1449)	(0.9123)	(3.2515)	(-0.6307)
N	192	140	160	169	293	83
adj. R^2	0.4411	0.2792	0.8797	0.7425	0.4037	0.3963

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.5 panel H Market return larger than |3%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0435	-0.0050	0.2081*	-0.0027	-0.0111	0.0650
	(1.1378)	(-0.1228)	(1.9345)	(-0.1635)	(-0.2150)	(1.0906)
$\|R_{m,t}\|$	-0.4302	-4.2908***	5.0510	14.4988***	0.3980	2.4477
	(-0.2018)	(-5.8567)	(1.0584)	(6.2667)	(0.4391)	(0.9573)
$R^2_{m,t}$	0.1429	0.5733***	-0.4101	-1.7838***	0.0425	-0.1713
	(0.5833)	(8.4372)	(-0.7158)	(-6.2239)	(0.4924)	(-0.5980)
_cons	3.9190	12.0058***	-7.0117	-25.6743***	1.7745	-1.6151
	(0.8814)	(6.5818)	(-0.7226)	(-5.5786)	(0.7926)	(-0.2964)
N	19	93	31	8	131	38
adj. R^2	0.5921	0.6905	0.4646	0.9499	0.2770	0.2374

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1660***	0.0825	0.0734*	-0.0603	0.0757***	-0.0717
	(2.6984)	(1.2985)	(1.7774)	(-0.9116)	(2.9352)	(-0.5677)
$\|R_{m,t}\|$	4.3611***	1.1523	4.1528***	1.5023	-0.1793	5.1613
	(3.3393)	(0.4625)	(3.6854)	(1.5985)	(-0.2723)	(1.4907)
$R^2_{m,t}$	-0.2828***	-0.0477	-0.1479	0.0455	0.0753	-0.4523
	(-2.9096)	(-0.1789)	(-1.5864)	(0.6387)	(1.0452)	(-1.2433)
_cons	-7.3338***	1.0156	-8.5208***	0.6851	3.8946***	-8.2843
	(-2.1657)	(0.1880)	(-2.8259)	(0.2789)	(2.6993)	(-1.0707)
N	48	30	83	48	109	21
adj. R^2	0.4909	0.2897	0.7932	0.7334	0.3244	0.3048

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.2.6 Larger market movements based on a proportion of the data

In the UK market

Table 7.2.2.6 panel A Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0611***	0.0606***	0.0504***	0.0014	0.0657***	0.0331***
	(4.1420)	(3.7377)	(3.6741)	(0.0892)	(2.0594)	(2.0306)
$\|R_{m,t}\|$	0.8796***	0.8065***	0.8422***	0.6924***	0.7670***	0.8126***
	(16.2179)	(6.2627)	(12.5967)	(11.2422)	(4.2452)	(10.3644)
$R_{m,t}^2$	-0.0276*	0.0119	-0.0154	-0.0103	0.0225	-0.0037
	(-1.8494)	(0.3223)	(-0.8898)	(-0.5262)	(0.6501)	(-0.1871)
_cons	1.0828***	1.1739***	1.0249***	0.8545***	1.2567***	0.6665***
	(33.5212)	(13.0542)	(24.4345)	(25.8560)	(7.5592)	(12.9207)
N	1435	1435	1435	1435	1435	1435
adj. R^2	0.5087	0.3974	0.5048	0.3876	0.4723	0.6266

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0583***	0.0356***	0.0726***	0.0151	0.0672***	0.0002
	(2.2591)	(2.6921)	(2.1966)	(1.2075)	(3.6228)	(0.0034)
$\|R_{m,t}\|$	0.7003***	0.7643***	0.7035***	0.6986***	0.4833***	0.1320
	(5.2605)	(15.8494)	(4.0860)	(13.2948)	(4.7619)	(0.6627)
$R_{m,t}^2$	0.1019***	-0.0239*	0.0531	-0.0293***	0.1178***	0.1033***
	(2.7873)	(-1.8901)	(1.2035)	(-2.5963)	(4.6978)	(2.0950)
_cons	1.3340***	1.0757***	1.3693***	0.7835***	1.6322***	0.8645***
	(14.2133)	(34.1785)	(11.0657)	(21.5581)	(21.3468)	(6.3859)
N	1435	1435	1435	1435	1435	1435
adj. R^2	0.6145	0.4518	0.5090	0.4795	0.6314	0.5110

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.6 panel B Largest 10% (10% of absolute value (above 5% and 5% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1000***	0.0612***	0.0888***	0.0390***	0.0933***	0.0438***
	(5.1343)	(2.7131)	(4.8915)	(1.9983)	(2.0274)	(2.0695)
$\|R_{m,t}\|$	1.0290***	1.1933***	0.6763***	0.7058***	1.2348***	1.3102***
	(5.9983)	(2.4201)	(3.4830)	(4.4482)	(2.4761)	(7.2673)
$R_{m,t}^2$	-0.0480	-0.0520	0.0154	-0.0130	-0.0207	-0.0660***
	(-1.6180)	(-0.5829)	(0.4653)	(-0.4376)	(-0.3669)	(-2.7612)
_cons	0.9150***	0.6507	1.2167***	0.8596***	0.3236	-0.1188
	(4.7015)	(1.0106)	(4.9664)	(5.1424)	(0.3585)	(-0.4580)
N	286	286	286	286	286	286
adj. R^2	0.4924	0.3415	0.4766	0.3872	0.4381	0.5838

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0469	0.0613***	0.1130***	0.0241	0.0752***	-0.0022
	(1.2508)	(3.4329)	(2.4220)	(1.5209)	(3.2501)	(-0.0282)
$\|R_{m,t}\|$	0.3267	0.9419***	0.6262	0.5156***	-0.5892***	-0.3171
	(0.9129)	(4.9014)	(1.0825)	(4.1263)	(-2.3520)	(-0.5625)
$R_{m,t}^2$	0.1464***	-0.0496	0.0640	-0.0037	0.2430***	0.1459*
	(2.5936)	(-1.4961)	(0.7149)	(-0.2584)	(7.1366)	(1.7644)
_cons	1.9479***	0.8535***	1.5044*	1.0385***	3.4307***	1.6269***
	(3.7490)	(3.7223)	(1.8011)	(4.9015)	(8.6871)	(2.1560)
N	286	286	286	286	286	286
adj. R^2	0.6218	0.4230	0.4639	0.3205	0.7450	0.5532

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.6 panel C Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1185***	0.0662***	0.0984***	0.0463***	0.0873	0.0465*
	(4.8785)	(2.3742)	(4.6063)	(1.9946)	(1.4927)	(1.7587)
$\|R_{m,t}\|$	1.0606***	1.8013***	0.4373	0.7646***	1.6620***	1.7806***
	(3.6863)	(2.0994)	(1.4474)	(3.4377)	(2.2051)	(5.9236)
$R_{m,t}^2$	-0.0505	-0.1301	0.0476	-0.0226	-0.0554	-0.1166***
	(-1.1491)	(-1.0049)	(1.1070)	(-0.6321)	(-0.7778)	(-3.7973)
_cons	0.8806***	-0.4617	1.6144***	0.7921***	-0.7978	-1.0535*
	(2.2129)	(-0.3374)	(3.2998)	(2.8023)	(-0.4676)	(-1.8467)
N	143	143	143	143	143	143
adj. R^2	0.4710	0.3062	0.4614	0.4082	0.3711	0.4961

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0494	0.0859***	0.1282***	0.0091	0.0673***	-0.0124
	(1.0540)	(3.8120)	(2.1438)	(0.4887)	(2.3431)	(-0.1284)
$\|R_{m,t}\|$	0.5777	0.7820***	0.3039	0.5809***	-0.8880***	-0.6073
	(0.9336)	(2.1287)	(0.3033)	(2.7247)	(-2.2004)	(-0.6824)
$R_{m,t}^2$	0.1208	-0.0190	0.0962	-0.0107	0.2728***	0.1705
	(1.5473)	(-0.3344)	(0.7344)	(-0.5044)	(5.9209)	(1.5543)
_cons	1.4247	1.0608***	2.2398	0.8883*	4.0506***	2.2719
	(1.2803)	(2.0737)	(1.2565)	(1.9398)	(5.2700)	(1.5469)
N	143	143	143	143	143	143
adj. R^2	0.6450	0.4096	0.4271	0.2702	0.7982	0.5611

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.2.6 panel D Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0388***	0.0366	0.0678***	-0.0022	0.0099	0.0445***
	(2.8042)	(1.5554)	(2.8063)	(-0.1306)	(0.3746)	(2.4646)
$\|R_{m,t}\|$	0.7161***	0.2531	0.6757***	0.6115***	0.5322***	0.7518***
	(9.9037)	(1.6110)	(6.1507)	(8.3155)	(3.4003)	(5.9997)
$R_{m,t}^2$	0.0119	0.1197***	0.1329***	0.0093	0.0355	0.0427
	(0.5788)	(3.3468)	(4.0432)	(0.3805)	(1.1646)	(1.1952)
_cons	1.5174***	1.9290***	1.2995***	0.9504***	1.2499***	1.3382***
	(31.7981)	(14.5230)	(18.5760)	(22.6216)	(8.3052)	(15.7939)
N	1435	1435	1435	1435	1435	1435
adj. R^2	0.4186	0.4996	0.5049	0.3023	0.4257	0.4650

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0396	0.0401***	0.0720***	0.0049	0.0791***	-0.0048
	(1.5568)	(1.9943)	(2.5580)	(0.2086)	(5.7378)	(-0.2066)
$\|R_{m,t}\|$	0.8398***	0.8027***	0.4395***	1.0558***	0.7869***	0.6284***
	(8.5100)	(7.2274)	(3.8270)	(9.9810)	(10.1647)	(3.3087)
$R_{m,t}^2$	0.0090	0.0097	0.1625***	0.0875***	-0.0233	0.0700
	(0.3388)	(0.3179)	(11.5962)	(3.5400)	(-1.4451)	(1.1304)
_cons	1.4012***	1.3871***	1.1373***	1.5339***	1.7049***	0.8297***
	(18.0357)	(18.3380)	(11.7218)	(17.3998)	(24.0670)	(7.2102)
N	1435	1435	1435	1435	1435	1435
adj. R^2	0.4338	0.4213	0.8829	0.6192	0.3977	0.4341

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.6 panel E Largest 10% (10% of absolute value (above 5% and 5% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0634***	0.0323	0.1111***	0.0217	0.0154	0.0593***
	(3.2739)	(1.0718)	(3.1307)	(0.8696)	(0.4013)	(2.3125)
$\|R_{m,t}\|$	0.7045***	-1.6322***	1.5097***	0.8603***	0.7824*	1.1111***
	(3.0719)	(-4.3469)	(3.6586)	(2.6262)	(1.7346)	(2.5963)
$R_{m,t}^2$	0.0128	0.3277***	-0.0040	-0.0382	0.0124	-0.0090
	(0.3110)	(6.6287)	(-0.0567)	(-0.5958)	(0.2259)	(-0.1214)
_cons	1.5659***	5.4907***	0.2387	0.6948***	0.7155	0.8267
	(5.7257)	(8.5347)	(0.4741)	(2.0995)	(0.8602)	(1.4890)
N	286	286	286	286	286	286
adj. R^2	0.4221	0.5727	0.5094	0.2745	0.3813	0.4738

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0671*	0.0595*	0.0932***	-0.0050	0.1024***	-0.0023
	(1.8697)	(1.9362)	(2.8204)	(-0.1430)	(5.4040)	(-0.0657)
$\|R_{m,t}\|$	1.3192***	1.3859***	1.0823***	1.3560***	0.8310***	1.4547***
	(5.0190)	(4.1161)	(2.8788)	(5.4245)	(2.8749)	(2.8762)
$R_{m,t}^2$	-0.0403	-0.0763	0.1014***	0.0544*	-0.0254	-0.0512
	(-1.4775)	(-1.3641)	(2.6994)	(1.7425)	(-0.6650)	(-0.5180)
_cons	0.5680	0.5987	-0.0967	1.0887***	1.5788***	-0.2760
	(1.1730)	(1.3542)	(-0.1640)	(2.6896)	(3.1424)	(-0.4781)
N	286	286	286	286	286	286
adj. R^2	0.4125	0.3305	0.8913	0.7233	0.3984	0.4901

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.2.6 panel F Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0680***	0.0169	0.1483***	0.0300	-0.0087	0.0634*
	(2.8074)	(0.4712)	(3.2239)	(0.8888)	(-0.1751)	(1.9230)
$\|R_{m,t}\|$	0.7668***	-3.4378***	1.0711	1.4507***	0.6726	1.6077***
	(2.1332)	(-6.3966)	(1.4300)	(2.4522)	(0.8275)	(2.0263)
$R_{m,t}^2$	0.0061	0.4976***	0.0668	-0.1402	0.0220	-0.0697
	(0.1076)	(8.7929)	(0.5907)	(-1.3220)	(0.2761)	(-0.6130)
_cons	1.4432***	9.8002***	0.8996	-0.0467	0.9533	-0.0763
	(2.8268)	(8.3029)	(0.8131)	(-0.0679)	(0.4914)	(-0.0600)
N	143	143	143	143	143	143
adj. R^2	0.4707	0.6274	0.4482	0.2765	0.3012	0.4358

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0931***	0.0861***	0.0920***	-0.0304	0.0931***	0.0067
	(2.1350)	(2.1958)	(2.5294)	(-0.7054)	(4.0256)	(0.1428)
$\|R_{m,t}\|$	1.9898***	1.7829***	2.2573***	1.5724***	0.1432	1.7933***
	(3.7946)	(3.0387)	(3.6280)	(3.9014)	(0.2785)	(2.4574)
$R_{m,t}^2$	-0.0980***	-0.1238	0.0004	0.0373	0.0442	-0.0926
	(-2.4011)	(-1.5403)	(0.0073)	(0.9891)	(0.7396)	(-0.7601)
_cons	-0.9593	-0.0969	-2.9823***	0.5863	3.1318***	-0.8651
	(-0.8352)	(-0.1014)	(-2.4135)	(0.7159)	(2.9985)	(-0.8687)
N	143	143	143	143	143	143
adj. R^2	0.4397	0.2892	0.8727	0.7353	0.3572	0.4637

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.3 The second Time period from 2011 to 2020

Regression results of sectors in the UK market using CCK model

Table 7.2.3.2 panel A regression results under CCK model in the UK market

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0458***	0.0345*	0.0354	0.0005	0.0848*	0.0196*
	(2.4384)	(1.7105)	(1.3485)	(0.0301)	(1.7039)	(1.7428)
$\lvert R_{m,t} \rvert$	0.6469***	0.7201***	0.6869***	0.5546***	1.1590***	0.6004***
	(17.6190)	(12.1025)	(15.3657)	(14.9651)	(7.5002)	(21.3824)
$R_{m,t}^2$	0.0248*	0.0563*	0.0203***	0.0074	0.0179	0.0208***
	(1.7920)	(1.8588)	(4.0741)	(0.4093)	(0.8580)	(2.0765)
_cons	1.0434***	0.9560***	1.0167***	0.7282***	1.0460***	0.6818***
	(81.9781)	(51.8125)	(58.4557)	(65.7851)	(9.7902)	(65.6184)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.5894	0.4829	0.6045	0.4171	0.7478	0.6697

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0703***	0.0367***	0.0906***	0.0114	0.0586***	-0.0136
	(3.0672)	(2.1179)	(4.2681)	(0.5072)	(2.4123)	(-0.8791)
$\lvert R_{m,t} \rvert$	0.8348***	0.6287***	0.8481***	0.6432***	1.1012***	0.3633***
	(9.0619)	(20.9452)	(14.4431)	(17.1064)	(26.6081)	(14.3889)
$R_{m,t}^2$	0.0950***	0.0120	-0.0093	-0.0068	-0.0384***	0.0074
	(2.2379)	(1.6133)	(-0.4367)	(-0.7905)	(-3.2669)	(0.9767)
_cons	1.0037***	0.9527***	1.3480***	0.7249***	0.9630***	0.5573***
	(33.6859)	(74.6243)	(50.4193)	(43.2856)	(56.2249)	(43.0490)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.5568	0.6067	0.4260	0.5307	0.5943	0.3313

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression results of sectors in Germany and France market using CCK model

Table 7.2.3.2 panel B regression results under CCK model in Germany and France market
$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0181	0.0147	0.0320	-0.0174	0.1052***	0.0453*
	(1.0663)	(0.3082)	(1.3663)	(-0.6652)	(3.0231)	(1.6675)
$\|R_{m,t}\|$	0.5452***	0.4630***	1.1207***	0.3378***	0.6387***	0.6804***
	(13.1752)	(7.4043)	(14.1608)	(3.6684)	(3.6753)	(16.6759)
$R_{m,t}^2$	0.0377***	0.1062***	0.0047	0.1554***	0.0828***	0.0870***
	(2.4643)	(4.8656)	(0.2007)	(2.5516)	(2.0484)	(15.7693)
_cons	1.5008***	1.3179***	1.2324***	0.8904***	1.4907***	1.2894***
	(78.4569)	(45.2858)	(35.6255)	(39.9680)	(14.5018)	(49.3405)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.3179	0.5974	0.5428	0.3515	0.5636	0.6539

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0962***	0.0206	-0.0033	0.0225	0.0683***	-0.0081
	(3.1261)	(0.7762)	(-0.0646)	(0.9157)	(2.3466)	(-0.5106)
$\|R_{m,t}\|$	0.6832***	0.7176***	0.5814***	1.5424***	0.7421***	0.6000***
	(6.0280)	(7.2887)	(3.3588)	(27.3517)	(8.5313)	(9.4699)
$R_{m,t}^2$	0.0960***	0.0632	0.1394***	0.0238***	0.0537*	0.0357
	(2.2842)	(1.5284)	(2.5774)	(4.2653)	(1.6612)	(1.1591)
_cons	1.1966***	1.4583***	1.0529***	0.8795***	1.5099***	0.7514***
	(27.2185)	(38.1967)	(15.2434)	(24.5362)	(42.2415)	(35.6234)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.5355	0.3807	0.6239	0.8957	0.4452	0.4377

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.3.3 Solution 1 Regression without constant value over the second time period

Table 7.2.3.3 Panel A regression results without constant in the UK market

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0663***	0.0184	0.0534	-0.0155	0.0828*	0.0093
	(2.2650)	(0.7551)	(1.3260)	(-0.7980)	(1.9403)	(0.5334)
$\|R_{m,t}\|$	2.3174***	2.3837***	1.8832***	1.8689***	1.7241***	1.6340***
	(30.5078)	(30.0469)	(28.9545)	(26.2061)	(24.2204)	(45.2712)
$R_{m,t}^2$	-0.2551***	-0.3711***	-0.0788***	-0.2921***	-0.0155	-0.1769***
	(-5.6332)	(-6.2965)	(-3.4145)	(-4.7185)	(-1.2209)	(-8.4299)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.7150	0.7702	0.7122	0.7402	0.8322	0.7925

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0322	0.0535***	0.0557***	-0.0002	0.0429	-0.0209
	(1.2033)	(2.0035)	(2.3364)	(-0.0087)	(1.5946)	(-1.3095)
$\|R_{m,t}\|$	2.3741***	1.8643***	2.5379***	1.4581***	2.4581***	1.0501***
	(39.2871)	(28.0315)	(24.9176)	(43.3858)	(35.6013)	(24.3435)
$R_{m,t}^2$	-0.2571***	-0.1401***	-0.3342***	-0.0965***	-0.2566***	-0.1058***
	(-6.3585)	(-4.3474)	(-6.1637)	(-8.0277)	(-6.5563)	(-4.5955)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.7931	0.7329	0.7674	0.7402	0.7921	0.7049

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.3 Panel B regression results without constant in Germany and France market

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	-0.0096	0.0938	0.0204	-0.0156	0.1103***	0.0643
	(-0.3370)	(1.5757)	(0.8473)	(-0.5194)	(3.1337)	(1.4471)
$\|R_{m,t}\|$	2.7930***	1.7871***	2.5388***	2.0991***	1.7036***	1.9554***
	(22.3893)	(34.5964)	(48.3019)	(27.4636)	(21.4447)	(39.9572)
$R_{m,t}^2$	-0.3938***	-0.0152	-0.2308***	-0.3970***	-0.0341	-0.0288
	(-4.3701)	(-0.5761)	(-10.6659)	(-5.6377)	(-1.2798)	(-1.4593)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.7068	0.7273	0.7846	0.7300	0.7731	0.7625

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1002***	0.0105	0.0169	0.0353***	0.0472	-0.0326*
	(2.7433)	(0.3082)	(0.4003)	(1.9722)	(1.4233)	(-1.7772)
$\|R_{m,t}\|$	2.0419***	2.6435***	1.7986***	2.2125***	2.5151***	1.6771***
	(33.9416)	(29.2848)	(29.4003)	(75.2912)	(40.9542)	(24.0678)
$R_{m,t}^2$	-0.1177***	-0.3297***	-0.0443	-0.0195***	-0.2497***	-0.1842***
	(-3.6409)	(-6.0527)	(-1.6271)	(-6.8024)	(-7.8761)	(-3.9148)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.7685	0.7505	0.7702	0.9095	0.7567	0.7552

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.3.4 Solution 2 Regression results in SCSAD over the second time period

Table 7.2.3.4 Panel A Regression results under SCSAD model in the UK market

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	1.9377***	1.9708***	1.6834***	1.5636***	1.6758***	1.3893***
	(46.3686)	(47.6005)	(35.3260)	(57.4028)	(43.9921)	(62.6066)
$R_{m,t}^2$	0.0127	-0.0012	0.0391	-0.0310	0.0073	-0.0079
	(0.4574)	(-0.0670)	(1.2924)	(-1.3077)	(1.1668)	(-0.8434)
$R_{m,t}^3$	-0.0226***	-0.0495***	-0.0012	-0.0378***	-0.0007	-0.0201***
	(-3.5477)	(-4.1387)	(-0.4887)	(-5.0559)	(-1.5866)	(-7.5659)
_cons	0.0614***	0.0416***	0.0343*	0.0266***	0.0426	0.0280***
	(3.5178)	(2.5134)	(1.6966)	(2.0946)	(1.3666)	(2.5195)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.6816	0.7473	0.6924	0.7120	0.8333	0.7691

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	2.0498***	1.5978***	2.0179***	1.2651***	2.0836***	0.8850***
	(69.4437)	(44.2784)	(39.2906)	(40.2393)	(51.4170)	(46.8482)
$R_{m,t}^2$	-0.0045	0.0089	0.0187	-0.0050	0.0148	-0.0156*
	(-0.2289)	(0.3862)	(1.2770)	(-0.3510)	(0.6891)	(-1.6749)
$R_{m,t}^3$	-0.0320***	-0.0089***	-0.0307***	-0.0070***	-0.0223***	-0.0098***
	(-5.3042)	(-2.4847)	(-3.5526)	(-4.2612)	(-4.1540)	(-4.3458)
_cons	0.0306	0.0779***	0.0077	0.0196	0.0297*	0.0046
	(1.5659)	(4.5313)	(0.3129)	(1.3581)	(1.6499)	(0.3974)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.7792	0.7048	0.7367	0.7193	0.7650	0.6841

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.4 Panel B Regression results under SCSAD model in Germany and France market

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	2.2882***	1.7168***	2.1542***	1.7135***	1.5804***	1.8564***
	(53.4591)	(48.7619)	(65.6293)	(57.2670)	(52.9475)	(52.6810)
$R_{m,t}^2$	-0.0376	0.0083	-0.0116	-0.0327	0.0327***	0.0116
	(-1.1038)	(0.2986)	(-1.2651)	(-1.1249)	(2.4214)	(1.3173)
$R_{m,t}^3$	-0.0410***	0.0005	-0.0227***	-0.0602***	-0.0005	-0.0003
	(-4.1571)	(0.2048)	(-8.6545)	(-4.8759)	(-0.2515)	(-0.3820)
_cons	0.0464*	0.0502	0.0607***	0.0275	-0.0196	0.0303
	(1.7654)	(1.6118)	(2.5122)	(1.6385)	(-0.4265)	(1.3893)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.6723	0.7259	0.7696	0.7079	0.7741	0.7596

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.8322***	2.1663***	1.7158***	2.1332***	2.1075***	1.4402***
	(65.7242)	(62.2402)	(39.9186)	(85.4183)	(64.1542)	(61.4058)
$R_{m,t}^2$	0.0425***	-0.0068	0.0115	0.0010	0.0173	-0.0502***
	(2.9258)	(-0.2468)	(0.6846)	(0.5467)	(1.1484)	(-3.3655)
$R_{m,t}^3$	-0.0079***	-0.0328***	-0.0036	-0.0008***	-0.0213***	-0.0218***
	(-3.0765)	(-4.7652)	(-1.0472)	(-4.7196)	(-6.3200)	(-5.2960)
_cons	0.0113	0.0518*	-0.0161	0.0417*	0.0232	0.0327***
	(0.4849)	(1.6588)	(-0.7136)	(1.9452)	(0.8627)	(2.1853)
N	2557	2557	2557	2557	2557	2557
adj. R^2	0.7618	0.7281	0.7691	0.9085	0.7374	0.7401

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.3.5 Solution 3 Regression considering large market returns

In the UK market

Table 7.2.3.5 panel A Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0593***	0.0325	0.0455	0.0081	0.0844*	0.0236*
	(2.9822)	(1.5000)	(1.6273)	(0.4808)	(1.7874)	(1.9586)
$\|R_{m,t}\|$	0.8313***	1.0015***	0.7963***	0.6785***	1.3586***	0.5845***
	(9.9021)	(9.1358)	(9.8481)	(7.6088)	(7.0325)	(9.7682)
$R_{m,t}^2$	-0.0001	-0.0058	0.0125	-0.0146	0.0066	0.0243*
	(-0.0033)	(-0.1849)	(1.5861)	(-0.5772)	(0.3040)	(1.6823)
_cons	0.8656***	0.7414***	0.8849***	0.6313***	0.6215***	0.6912***
	(14.1343)	(10.5040)	(14.8143)	(11.6405)	(2.9577)	(16.9142)
N	707	992	910	830	1622	933
adj. R^2	0.6947	0.4916	0.6712	0.3912	0.7604	0.6865

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0663***	0.0418***	0.0982***	0.0118	0.0705***	-0.0117
	(2.7611)	(2.3104)	(4.5270)	(0.5091)	(2.7787)	(-0.7316)
$\|R_{m,t}\|$	1.1264***	0.7532***	1.0117***	0.8233***	1.3756***	0.4321***
	(5.9813)	(13.4613)	(11.4153)	(12.6117)	(16.4420)	(9.3584)
$R_{m,t}^2$	0.0369	-0.0010	-0.0358*	-0.0247***	-0.0757***	-0.0023
	(0.6346)	(-0.1222)	(-1.7183)	(-3.1116)	(-6.6799)	(-0.3096)
_cons	0.7559***	0.8096***	1.1809***	0.5115***	0.6969***	0.4844***
	(6.5181)	(19.1124)	(17.0612)	(9.5064)	(10.8707)	(12.5442)
N	1154	927	1335	1087	974	1268
adj. R^2	0.5838	0.6980	0.4159	0.5693	0.6078	0.3329

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.5 panel B Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0793***	0.0435	0.0608	0.0205	0.0848*	0.0301***
	(3.0038)	(1.4716)	(1.6424)	(0.7677)	(1.8524)	(2.0100)
$\|R_{m,t}\|$	1.1114***	1.2927***	0.8317***	0.6916***	1.5926***	0.6496***
	(5.9588)	(6.0745)	(6.4604)	(2.9794)	(6.8918)	(5.5612)
$R_{m,t}^2$	-0.0327	-0.0594	0.0111	-0.0159	-0.0057	0.0155
	(-1.2957)	(-1.6392)	(1.0127)	(-0.3689)	(-0.2566)	(0.7496)
_cons	0.4927***	0.4547***	0.8271***	0.6327***	0.0093	0.6131***
	(2.3349)	(2.0630)	(5.0704)	(2.5632)	(0.0273)	(4.9288)
N	210	323	255	197	1023	316
adj. R^2	0.7098	0.4403	0.6694	0.3107	0.7659	0.6911

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0696***	0.0548***	0.1057***	0.0139	0.1031***	-0.0104
	(2.2804)	(2.3232)	(4.2271)	(0.4853)	(3.1314)	(-0.5494)
$\|R_{m,t}\|$	1.5584***	0.8546***	1.3796***	0.9745***	1.4177***	0.6010***
	(4.3694)	(7.8755)	(10.4866)	(7.8814)	(7.8619)	(6.2098)
$R_{m,t}^2$	-0.0343	-0.0099	-0.0871***	-0.0381***	-0.0778***	-0.0228***
	(-0.4234)	(-0.8788)	(-5.0937)	(-3.6822)	(-3.9087)	(-2.0160)
_cons	0.2558	0.6653***	0.6935***	0.2653	0.6466***	0.2483***
	(0.7715)	(4.9200)	(4.3947)	(1.6413)	(3.0935)	(2.1507)
N	435	287	617	383	323	523
adj. R^2	0.5605	0.6803	0.4078	0.5409	0.5313	0.3499

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.5 panel C Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1243***	0.1110*	0.0995*	0.0553	0.0812*	0.0490***
	(2.5143)	(1.8563)	(1.7866)	(0.9312)	(1.7425)	(2.1794)
$\|R_{m,t}\|$	2.0667***	1.8311*	0.5465***	0.6542	2.1934***	1.0604***
	(2.9806)	(1.9245)	(2.6013)	(0.5013)	(7.3425)	(2.5723)
$R_{m,t}^2$	-0.1253	-0.1282	0.0315***	-0.0091	-0.0343	-0.0249
	(-1.6513)	(-1.0432)	(2.4099)	(-0.0560)	(-1.5346)	(-0.4760)
_cons	-1.3861	-0.3345	1.5915***	0.7811	-2.0246***	-0.2860
	(-1.0764)	(-0.2124)	(2.9598)	(0.3509)	(-2.9632)	(-0.4215)
N	40	47	51	22	415	59
adj. R^2	0.5796	0.3454	0.7635	0.4346	0.7736	0.8137

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0741	0.0901***	0.1081***	0.0216	0.1627***	0.0004
	(1.2826)	(2.3371)	(2.5522)	(0.4465)	(2.5942)	(0.0102)
$\|R_{m,t}\|$	1.1667	1.0552***	1.6581***	1.0347***	1.2054*	0.8861***
	(0.7696)	(3.5679)	(3.5683)	(2.3669)	(1.8773)	(2.7266)
$R_{m,t}^2$	0.0106	-0.0224	-0.1218***	-0.0423	-0.0510	-0.0518
	(0.0475)	(-0.9329)	(-2.5299)	(-1.3245)	(-0.8212)	(-1.5695)
_cons	1.0279	0.1902	0.2543	0.1422	1.0898	-0.2676
	(0.4397)	(0.3148)	(0.3033)	(0.1433)	(0.8853)	(-0.4417)
N	85	59	143	85	58	95
adj. R^2	0.3550	0.6724	0.2174	0.3584	0.3552	0.2397

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.5 panel D Market return larger than |3%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0535	0.0903	0.1304	1.6002	0.0936*	0.0587
	(0.5999)	(0.9518)	(1.6943)	(0.2290)	(1.8539)	(1.2985)
$\|R_{m,t}\|$	2.5292	2.2973	-0.0839	0.0000	2.9111***	2.0605
	(1.1810)	(0.5473)	(-0.2064)	(.)	(7.7654)	(1.5150)
$R_{m,t}^2$	-0.1768	-0.1880	0.0691***	0.2317	-0.0642***	-0.1218
	(-0.9211)	(-0.4151)	(3.4301)	(0.2978)	(-2.8920)	(-0.8877)
_cons	-2.5111	-1.2246	3.7051***	5.3670	-5.1942***	-2.6966
	(-0.4694)	(-0.1310)	(2.5537)	(0.3789)	(-4.3313)	(-0.8254)
N	15	14	24	5	194	21
adj. R^2	0.2767	0.1655	0.8098	0.4787	0.7629	0.6465

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1735	0.0986	0.1349	0.0194	0.1417	-0.0268
	(1.2980)	(1.5880)	(1.6136)	(0.3167)	(1.4140)	(-0.4678)
$\|R_{m,t}\|$	3.1598	0.7377	1.8171	1.8492*	1.3152	0.3185
	(0.3892)	(0.9976)	(1.3104)	(1.9330)	(1.0522)	(0.4417)
$R_{m,t}^2$	-0.1634	0.0009	-0.1346	-0.0964	-0.0688	-0.0058
	(-0.1752)	(0.0165)	(-1.0947)	(-1.4704)	(-0.6070)	(-0.0922)
_cons	-4.1123	1.1375	-0.0945	-2.4307	1.1127	1.1582
	(-0.2422)	(0.5472)	(-0.0269)	(-0.9071)	(0.3629)	(0.6427)
N	18	24	34	35	18	29
adj. R^2	0.3732	0.5371	0.1133	0.3519	0.1858	0.1230

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.3.5 panel E Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0233	0.0132	0.0293	-0.0163	0.1056***	0.0486*
	(1.3013)	(0.2663)	(1.2749)	(-0.5727)	(3.0363)	(1.7444)
$\|R_{m,t}\|$	0.6958***	0.4246***	1.6256***	0.4456*	0.7156***	0.7542***
	(9.7393)	(3.9001)	(16.6938)	(1.9165)	(2.8928)	(9.7028)
$R_{m,t}^2$	0.0161	0.1097***	-0.0706***	0.1311	0.0752	0.0809***
	(0.9531)	(4.5190)	(-3.8945)	(1.3955)	(1.5851)	(13.7382)
_cons	1.3475***	1.3559***	0.6839***	0.8028***	1.3626***	1.1948***
	(26.6334)	(15.4199)	(9.0793)	(6.6017)	(6.1369)	(15.9914)
N	1043	1332	1320	968	1817	1319
adj. R^2	0.4373	0.6496	0.5881	0.3695	0.5715	0.7199

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1014***	0.0195	0.0025	0.0281	0.0660***	-0.0080
	(3.2047)	(0.7053)	(0.0469)	(1.3741)	(2.2318)	(-0.4767)
$\|R_{m,t}\|$	0.8710***	0.9975***	0.8541***	1.7733***	0.9891***	0.7290***
	(4.4082)	(6.6106)	(2.6639)	(25.4993)	(7.4462)	(7.0570)
$R_{m,t}^2$	0.0699	0.0153	0.1018	0.0093*	0.0166	0.0141
	(1.3460)	(0.3375)	(1.4310)	(1.8137)	(0.4779)	(0.4339)
_cons	0.9897***	1.1763***	0.7563***	0.5178***	1.2440***	0.6302***
	(7.1378)	(11.8122)	(3.2333)	(7.2480)	(13.3032)	(9.4171)
N	1387	1347	1325	1362	1428	1152
adj. R^2	0.5407	0.4191	0.6444	0.9225	0.4585	0.4591

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.5 panel F Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0421*	0.0211	0.0222	-0.0283	0.1046***	0.0597*
	(1.7484)	(0.3562)	(0.8588)	(-0.7009)	(2.9173)	(1.8772)
$\lvert R_{m,t}\rvert$	0.9215***	0.5191***	2.1109***	1.4552***	0.8688***	0.7735***
	(6.9709)	(2.7464)	(15.1368)	(2.9325)	(2.6242)	(4.9477)
$R_{m,t}^2$	-0.0123	0.1023***	-0.1341***	-0.0772	0.0610	0.0794***
	(-0.5985)	(3.7277)	(-7.1359)	(-0.5870)	(1.1284)	(8.2459)
_cons	1.0745***	1.2134***	0.0081	-0.1973	1.0730***	1.1711***
	(7.3247)	(5.3574)	(0.0492)	(-0.4673)	(2.7303)	(5.5526)
N	338	601	611	270	1218	580
adj. R^2	0.4794	0.7137	0.5431	0.4042	0.5795	0.7780

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1251***	0.0192	0.0083	0.0296	0.0794***	-0.0158
	(3.4779)	(0.5762)	(0.1422)	(1.5791)	(2.3902)	(-0.7229)
$\lvert R_{m,t}\rvert$	1.1270***	1.3911***	1.4962***	2.0175***	1.5096***	1.0245***
	(3.4479)	(6.3112)	(2.6895)	(24.3752)	(8.3670)	(6.9048)
$R_{m,t}^2$	0.0387	-0.0452	0.0227	-0.0050	-0.0510	-0.0283
	(0.5997)	(-0.9717)	(0.2422)	(-0.9736)	(-1.6092)	(-1.0433)
_cons	0.6398*	0.7058***	-0.1442	-0.0086	0.5364***	0.2665*
	(1.9205)	(3.0885)	(-0.2408)	(-0.0724)	(2.7243)	(1.6667)
N	673	610	591	666	663	439
adj. R^2	0.5374	0.3902	0.6444	0.9463	0.4558	0.4700

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.5 panel G Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0246	0.0067	0.0346	-0.1130	0.1147***	0.1013***
	(0.5591)	(0.0603)	(0.9940)	(-1.2038)	(2.6731)	(2.0175)
$\|R_{m,t}\|$	1.0770***	0.2432	1.8603***	8.2766***	1.1167***	0.4791
	(2.4341)	(0.3679)	(4.9660)	(2.1288)	(1.9747)	(1.0659)
$R_{m,t}^2$	-0.0252	0.1216***	-0.1101***	-1.1350*	0.0413	0.0996***
	(-0.5501)	(2.3416)	(-2.8654)	(-1.8833)	(0.5861)	(3.5184)
_cons	0.5942	1.7874	0.5792	-10.4351*	0.4866	1.9197***
	(0.7529)	(1.3288)	(0.7661)	(-1.8329)	(0.4875)	(2.0462)
N	46	102	169	29	514	112
adj. R^2	0.6937	0.7811	0.3178	0.4582	0.5567	0.8416

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1847***	0.0538	-0.0017	0.0379*	0.1271***	-0.0603
	(3.1549)	(0.8683)	(-0.0253)	(1.7769)	(2.5149)	(-1.5099)
$\|R_{m,t}\|$	1.1553	1.9145***	4.1507***	2.3198***	2.2437***	1.7633***
	(1.2411)	(2.4688)	(3.7663)	(17.0865)	(4.1558)	(2.5758)
$R_{m,t}^2$	0.0343	-0.1076	-0.2527*	-0.0208***	-0.1283***	-0.1116
	(0.2919)	(-1.2581)	(-1.9210)	(-2.6160)	(-2.3254)	(-1.6414)
_cons	0.6937	-0.1474	-5.4212***	-0.9961***	-0.8074	-1.1453
	(0.4303)	(-0.1018)	(-2.8564)	(-2.8978)	(-0.8020)	(-0.8907)
N	138	111	135	173	149	56
adj. R^2	0.4964	0.2674	0.6277	0.9594	0.3887	0.5086

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.5 panel H Market return larger than |3%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	-0.0317	-0.0439	0.0416	-0.5299	0.1436***	0.0991
	(-0.2589)	(-0.2218)	(0.9235)	(-2.4744)	(2.5857)	(1.3566)
$\|R_{m,t}\|$	0.8008	0.0736	1.0381	-83.7077	1.5560*	0.5254
	(0.3506)	(0.0442)	(1.0453)	(-2.6922)	(1.6644)	(0.5007)
$R_{m,t}^2$	-0.0099	0.1331	-0.0416	10.6758	0.0131	0.0969
	(-0.0477)	(1.2504)	(-0.4663)	(2.6206)	(0.1428)	(1.5396)
_cons	1.3620	2.2436	2.8257	165.6828	-0.9145	1.7560
	(0.2588)	(0.4994)	(1.1409)	(2.8453)	(-0.4109)	(0.5842)
N	9	27	57	6	221	28
adj. R^2	0.6545	0.7950	0.2269	0.7225	0.5605	0.8712

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.2703***	0.0729	-0.0038	0.0345	0.1756*	-0.1299*
	(3.3754)	(0.6090)	(-0.0494)	(1.4445)	(1.8889)	(-1.8451)
$\|R_{m,t}\|$	3.9930*	4.4761	9.9772***	2.5076***	4.3587***	6.0601***
	(1.7245)	(1.2348)	(5.8078)	(12.5871)	(2.1801)	(2.4336)
$R_{m,t}^2$	-0.2215	-0.3567	-0.7598***	-0.0294***	-0.3138*	-0.5061***
	(-1.0111)	(-1.0130)	(-5.0174)	(-2.7312)	(-1.7767)	(-2.2979)
_cons	-6.0977	-5.9607	-20.7717***	-1.8284***	-6.0846	-11.5822*
	(-1.1277)	(-0.7207)	(-4.7792)	(-2.5029)	(-1.2097)	(-1.9584)
N	43	29	50	81	39	15
adj. R^2	0.5967	0.2804	0.6068	0.9600	0.4302	0.7043

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.3.6 Larger market movements based on a proportion of the data condition

In the UK market

Table 8.6.3.6 panel A Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0530***	0.0326	0.0402	0.0040	0.0850*	0.0229***
	(2.8065)	(1.5635)	(1.5011)	(0.2560)	(1.8337)	(1.9827)
$\lvert R_{m,t}\rvert$	0.7091***	0.9321***	0.7470***	0.6252***	1.4703***	0.5918***
	(12.2777)	(10.0104)	(10.8507)	(9.5571)	(6.8922)	(12.3768)
$R_{m,t}^2$	0.0165	0.0084	0.0159***	-0.0056	0.0006	0.0231*
	(1.1230)	(0.2738)	(2.3278)	(-0.2544)	(0.0276)	(1.7904)
_cons	0.9880***	0.8009***	0.9509***	0.6760***	0.3445	0.6845***
	(32.4884)	(15.5870)	(22.1565)	(21.3482)	(1.2514)	(25.0606)
N	1279	1279	1279	1279	1279	1279
adj. R^2	0.6800	0.4993	0.6586	0.4119	0.7625	0.6930

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0671***	0.0405***	0.0994***	0.0121	0.0654***	-0.0118
	(2.8281)	(2.3096)	(4.5620)	(0.5322)	(2.6534)	(-0.7414)
$\lvert R_{m,t}\rvert$	1.0847***	0.6847***	1.0372***	0.7771***	1.2753***	0.4296***
	(6.1809)	(14.3704)	(11.6050)	(13.0107)	(18.6214)	(9.3599)
$R_{m,t}^2$	0.0447	0.0063	-0.0396*	-0.0203***	-0.0627***	-0.0020
	(0.7941)	(0.7996)	(-1.9561)	(-2.5039)	(-5.8742)	(-0.2644)
_cons	0.7964***	0.8906***	1.1515***	0.5724***	0.8039***	0.4874***
	(7.7167)	(28.7773)	(15.9553)	(12.7037)	(17.5398)	(12.7630)
N	1279	1279	1279	1279	1279	1279
adj. R^2	0.5675	0.6712	0.4175	0.5597	0.6029	0.3322

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.6 panel B Largest 10% (10% of absolute value (above 5% and 5% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0731***	0.0534*	0.0608	0.0258	0.0853*	0.0331***
	(2.9374)	(1.6660)	(1.6424)	(1.0784)	(1.7336)	(2.0849)
$\lvert R_{m,t} \rvert$	1.0451***	1.3281***	0.8317***	0.7699***	2.5482***	0.5564***
	(6.4081)	(5.3258)	(6.4604)	(4.2575)	(7.2491)	(3.7691)
$R_{m,t}^2$	-0.0258	-0.0634	0.0111	-0.0261	-0.0495***	0.0283
	(-1.1362)	(-1.5967)	(1.0127)	(-0.7053)	(-2.1687)	(1.1403)
_cons	0.5945***	0.4060	0.8271***	0.5312***	-3.5053***	0.7471***
	(3.4210)	(1.4554)	(5.0704)	(3.1033)	(-3.5078)	(4.3267)
N	255	255	255	255	255	255
adj. R^2	0.7032	0.4283	0.6694	0.3530	0.7580	0.6696

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0785***	0.0551***	0.1074***	0.0146	0.1131***	-0.0122
	(2.1419)	(2.2554)	(3.2313)	(0.4476)	(3.2256)	(-0.5146)
$\lvert R_{m,t} \rvert$	1.8171***	0.8709***	1.6457***	0.9752***	1.4721***	0.8359***
	(3.4910)	(7.4185)	(5.5297)	(5.9693)	(7.1302)	(4.8733)
$R_{m,t}^2$	-0.0712	-0.0113	-0.1207***	-0.0381***	-0.0826***	-0.0479***
	(-0.7012)	(-0.9532)	(-3.7275)	(-2.9616)	(-3.6745)	(-2.4342)
_cons	-0.1100	0.6357***	0.2838	0.2635	0.5540***	-0.1645
	(-0.1886)	(4.1475)	(0.6062)	(1.0514)	(2.1827)	(-0.6660)
N	255	255	255	255	255	255
adj. R^2	0.5206	0.6782	0.3051	0.4976	0.5362	0.3600

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.6 panel C Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0874***	0.0826***	0.0737	0.0170	0.0895*	0.0428***
	(2.8771)	(2.0987)	(1.5936)	(0.5755)	(1.6782)	(2.2147)
$\lvert R_{m,t}\rvert$	1.3476***	1.7826***	0.7359***	0.8460***	3.5078***	0.4638
	(5.2048)	(4.1608)	(4.2972)	(2.9148)	(8.0988)	(1.5637)
$R_{m,t}^2$	-0.0579*	-0.1244***	0.0183	-0.0380	-0.0873***	0.0418
	(-1.7474)	(-2.0848)	(1.5063)	(-0.7631)	(-3.9659)	(0.9923)
_cons	0.0898	-0.2822	1.0514***	0.4305	-8.2334***	0.8778***
	(0.2649)	(-0.4929)	(3.2248)	(1.2864)	(-4.9338)	(2.0085)
N	127	127	127	127	127	127
adj. R^2	0.6974	0.4609	0.6380	0.3687	0.7448	0.6787

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0717	0.0627***	0.1107***	0.0213	0.1449***	-0.0039
	(1.4285)	(2.0583)	(2.4944)	(0.5222)	(3.2534)	(-0.1241)
$\lvert R_{m,t}\rvert$	1.8901*	0.8797***	1.8444***	1.1091***	1.4480***	0.9763***
	(1.8550)	(4.8359)	(3.6603)	(3.9967)	(4.3923)	(3.6153)
$R_{m,t}^2$	-0.0818	-0.0114	-0.1403***	-0.0477***	-0.0760***	-0.0605***
	(-0.5041)	(-0.7094)	(-2.6773)	(-2.2948)	(-2.2613)	(-2.0749)
_cons	-0.2254	0.6250***	-0.1463	-0.0621	0.5741	-0.4681
	(-0.1567)	(2.0426)	(-0.1579)	(-0.1147)	(1.1515)	(-1.0177)
N	127	127	127	127	127	127
adj. R^2	0.4169	0.6515	0.2262	0.4551	0.4683	0.3076

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.3.6 panel D Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0230	0.0116	0.0301	-0.0181	0.1043***	0.0489*
	(1.3139)	(0.2315)	(1.3057)	(-0.6677)	(2.9226)	(1.7481)
$\|R_{m,t}\|$	0.6207***	0.4287***	1.6371***	0.3813***	0.8331***	0.7606***
	(9.2916)	(3.8376)	(16.5044)	(2.0375)	(2.5882)	(9.5079)
$R_{m,t}^2$	0.0275	0.1094***	-0.0721***	0.1467*	0.0641	0.0803***
	(1.5744)	(4.5023)	(-3.9687)	(1.7296)	(1.1991)	(13.4955)
_cons	1.4220***	1.3499***	0.6695***	0.8518***	1.1462***	1.1859***
	(32.4783)	(14.5898)	(8.5282)	(10.2122)	(3.0873)	(15.1702)
N	1279	1279	1279	1279	1279	1279
adj. R^2	0.3920	0.6548	0.5848	0.3753	0.5784	0.7220

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1028***	0.0220	0.0030	0.0278	0.0671***	-0.0071
	(3.2203)	(0.7890)	(0.0576)	(1.3770)	(2.2407)	(-0.4340)
$\|R_{m,t}\|$	0.9169***	1.0237***	0.8943***	1.7953***	1.0470***	0.7199***
	(4.3756)	(6.6231)	(2.7276)	(25.3351)	(7.5171)	(7.4749)
$R_{m,t}^2$	0.0639	0.0113	0.0966	0.0080	0.0085	0.0156
	(1.2034)	(0.2488)	(1.3461)	(1.5629)	(0.2457)	(0.4892)
_cons	0.9335***	1.1473***	0.7075***	0.4768***	1.1747***	0.6392***
	(6.0274)	(10.8422)	(2.8951)	(6.2897)	(11.1714)	(10.9859)
N	1279	1279	1279	1279	1279	1279
adj. R^2	0.5440	0.4174	0.6478	0.9238	0.4596	0.4657

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.6 panel E Largest 10% (10% of absolute value (above 5% and 5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0470*	0.0198	0.0252	-0.0313	0.1323***	0.0799***
	(1.7597)	(0.2530)	(0.7871)	(-0.7577)	(2.4805)	(2.0665)
$\|R_{m,t}\|$	0.7951***	0.3790	2.0901***	1.4678***	1.2786	0.7210***
	(4.9301)	(1.0989)	(7.7716)	(2.8387)	(1.4577)	(2.5676)
$R_{m,t}^2$	0.0039	0.1122***	-0.1334***	-0.0797	0.0307	0.0834***
	(0.1677)	(3.1831)	(-4.5168)	(-0.5938)	(0.3417)	(4.7739)
_cons	1.2575***	1.4948***	0.0909	-0.2113	-0.0064	1.2857***
	(6.3908)	(2.7056)	(0.1889)	(-0.4699)	(-0.0032)	(2.6691)
N	255	255	255	255	255	255
adj. R^2	0.4531	0.7452	0.3808	0.3953	0.5501	0.8174

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1527***	0.0384	0.0019	0.0346*	0.0888***	-0.0163
	(3.2212)	(0.8708)	(0.0292)	(1.7223)	(2.0492)	(-0.6033)
$\|R_{m,t}\|$	1.4773***	1.7868***	2.6758***	2.1972***	1.9698***	1.0648***
	(2.5343)	(5.2184)	(3.1132)	(19.2252)	(5.1759)	(5.0107)
$R_{m,t}^2$	0.0018	-0.0954*	-0.1065	-0.0147***	-0.1026***	-0.0334
	(0.0210)	(-1.8996)	(-0.9055)	(-2.1857)	(-2.3595)	(-1.1034)
_cons	0.0143	0.1113	-2.2525*	-0.5442***	-0.2561	0.2085
	(0.0173)	(0.2248)	(-1.8335)	(-2.2156)	(-0.4066)	(0.7504)
N	255	255	255	255	255	255
adj. R^2	0.5294	0.3590	0.6321	0.9560	0.3786	0.4367

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.3.6 panel F Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0448	0.0076	0.0433	-0.0446	0.1790***	0.0986***
	(1.3014)	(0.0744)	(1.1772)	(-0.8103)	(2.7040)	(2.0343)
$\|R_{m,t}\|$	0.7318***	0.2506	2.2124***	1.7812***	3.2363***	0.5319
	(3.0910)	(0.4510)	(4.7139)	(2.0017)	(3.0409)	(1.2502)
$R_{m,t}^2$	0.0111	0.1211***	-0.1423***	-0.1361	-0.0882	0.0962***
	(0.3614)	(2.6441)	(-3.1455)	(-0.7332)	(-0.9622)	(3.5887)
_cons	1.3577***	1.7697	-0.2350	-0.5927	-6.8360***	1.7684***
	(3.8599)	(1.6480)	(-0.2293)	(-0.6150)	(-2.2905)	(2.0421)
N	127	127	127	127	127	127
adj. R^2	0.4802	0.7757	0.3292	0.3315	0.6273	0.8394

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1976***	0.0680	-0.0074	0.0371*	0.1362***	-0.0357
	(3.3027)	(1.1690)	(-0.1075)	(1.6635)	(2.5459)	(-1.0116)
$\|R_{m,t}\|$	1.0519	1.6742***	4.3070***	2.4289***	2.4252***	1.2214***
	(1.0571)	(2.6259)	(3.7925)	(15.6587)	(4.0106)	(3.5099)
$R_{m,t}^2$	0.0447	-0.0803	-0.2675***	-0.0260***	-0.1450***	-0.0544
	(0.3627)	(-1.0951)	(-1.9969)	(-2.8774)	(-2.3964)	(-1.3877)
_cons	0.9165	0.3258	-5.7835***	-1.4493***	-1.2196	-0.0353
	(0.5208)	(0.2849)	(-2.9030)	(-3.2950)	(-1.0402)	(-0.0639)
N	127	127	127	127	127	127
adj. R^2	0.4986	0.2741	0.6219	0.9626	0.3930	0.4295

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.4 Further investigation time period 2006 to 2010

7.2.4.2 Normal regression model

Table 7.2.4.2 panel A regression results under CCK model in the UK market

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0557***	0.0441*	0.0295*	-0.0016	0.0611***	0.0264
	(2.9085)	(1.7929)	(1.7821)	(-0.0966)	(2.0179)	(1.3674)
$\|R_{m,t}\|$	0.8264***	0.8271***	0.8206***	0.6204***	0.6305***	0.7265***
	(16.2821)	(11.7693)	(15.6824)	(14.4781)	(8.5844)	(11.6750)
$R_{m,t}^2$	-0.0134	0.0054	-0.0142	-0.0052	0.0078	0.0071
	(-0.7955)	(0.2642)	(-0.9753)	(-0.3621)	(0.4949)	(0.3838)
_cons	1.1051***	1.1204***	1.0995***	0.8585***	1.3638***	0.7685***
	(46.1302)	(33.3399)	(40.5605)	(46.2676)	(28.0467)	(25.7353)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.5170	0.3740	0.5314	0.4117	0.4276	0.6226

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0567	0.0364***	0.0358*	0.0182	0.0536***	-0.0077
	(1.6133)	(2.1928)	(1.8588)	(1.3533)	(2.2260)	(-0.1063)
$\|R_{m,t}\|$	0.7879***	0.8074***	0.7406***	0.5258***	0.9311***	0.1927
	(6.6184)	(19.3844)	(14.5174)	(13.9810)	(10.4428)	(1.3679)
$R_{m,t}^2$	0.0771	-0.0376***	0.0025	-0.0060	0.0285	0.0690
	(1.6379)	(-2.9465)	(0.2396)	(-0.8485)	(0.6896)	(1.4829)
_cons	1.2887***	1.0436***	1.4199***	1.0343***	1.1432***	0.6679***
	(27.0050)	(48.3928)	(40.8223)	(35.1831)	(35.9802)	(12.5001)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.5287	0.5045	0.4723	0.4073	0.5001	0.4861

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.2 panel B regression results under CCK model in the markets of Germany and France

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0476***	0.0391	0.0730***	0.0165	0.0129	0.0628***
	(2.7069)	(1.3516)	(2.2606)	(0.6933)	(0.4248)	(3.1901)
$\|R_{m,t}\|$	0.6749***	0.6648***	0.7097***	0.5168***	0.4363***	0.8194***
	(12.3621)	(8.5498)	(8.9479)	(9.8759)	(5.3300)	(13.7462)
$R_{m,t}^2$	0.0195	0.0193	0.1153***	0.0291	0.0309	0.0035
	(1.1218)	(0.7910)	(3.9535)	(1.2233)	(1.4779)	(0.2040)
_cons	1.4980***	1.3908***	1.3905***	0.9577***	1.2196***	1.3462***
	(52.7096)	(34.6563)	(36.9847)	(45.8869)	(24.6523)	(39.6728)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.4269	0.3325	0.4866	0.3507	0.4506	0.4628

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0260	0.0434	0.0269*	-0.0021	0.0580***	-0.0024
	(0.6265)	(1.5292)	(1.7446)	(-0.0677)	(3.3155)	(-0.1190)
$\|R_{m,t}\|$	0.6540***	0.7412***	0.5990***	0.9825***	0.6000***	0.5639***
	(9.2346)	(9.2950)	(11.6307)	(13.2023)	(12.4009)	(12.2544)
$R_{m,t}^2$	0.0278	0.0162	0.0172	0.0856***	-0.0076	0.0159
	(1.2024)	(0.6305)	(1.2011)	(4.2659)	(-0.8096)	(1.0401)
_cons	1.4573***	1.5309***	1.0848***	1.9066***	1.6266***	0.8671***
	(37.4809)	(38.3881)	(38.1474)	(37.7950)	(53.7037)	(37.1933)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.4258	0.4241	0.4718	0.6134	0.3412	0.3790

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.4.3 Solution 1 Regression without constant value

Table 7.2.4.3 panel A regression without constant under CCK model in the UK market

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0590***	0.0544*	0.0143	-0.0020	0.0650***	0.0351*
	(2.4730)	(1.7267)	(0.6435)	(-0.0584)	(2.0680)	(1.7412)
$\|R_{m,t}\|$	2.4991***	2.5353***	2.2074***	2.0349***	1.7732***	1.5827***
	(29.9570)	(35.6886)	(25.1759)	(21.1893)	(27.6175)	(49.0580)
$R_{m,t}^2$	-0.4050***	-0.4285***	-0.2905***	-0.3452***	-0.1322***	-0.1329***
	(-8.2651)	(-10.6805)	(-6.8590)	(-5.3494)	(-6.6095)	(-11.1613)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7808	0.7602	0.7859	0.7438	0.7469	0.8086

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1395***	0.0172	0.0539	0.0119	0.0608	0.0294
	(3.0493)	(0.8552)	(1.3330)	(0.5961)	(1.1933)	(0.3948)
$\|R_{m,t}\|$	2.2881***	2.3728***	2.1866***	1.5548***	2.7371***	0.8718***
	(15.3121)	(28.0006)	(27.3631)	(15.1739)	(25.0858)	(10.3647)
$R_{m,t}^2$	-0.1590***	-0.4227***	-0.2225***	-0.1757***	-0.4041***	-0.0112
	(-1.9874)	(-8.2686)	(-6.9688)	(-4.4907)	(-5.2837)	(-0.2861)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7612	0.7913	0.7735	0.7568	0.7809	0.6578

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.3 panel B regression without constant under CCK model in the markets of Germany and France
$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1102***	0.0797*	0.0549	-0.0151	0.0402	0.0652***
	(2.0787)	(1.9469)	(1.4583)	(-0.5450)	(1.2135)	(2.3442)
$\|R_{m,t}\|$	2.8643***	2.3588***	2.6928***	2.2189***	1.4127***	2.5254***
	(27.7898)	(31.7053)	(32.7809)	(26.9103)	(27.7677)	(30.5988)
$R_{m,t}^2$	-0.4536***	-0.2862***	-0.3535***	-0.4608***	-0.0870***	-0.3455***
	(-6.9685)	(-7.4184)	(-7.7690)	(-7.3917)	(-4.8322)	(-8.3682)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7556	0.7266	0.7737	0.7515	0.7442	0.7822

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0951***	0.0614	0.0388	0.0458	0.1421***	-0.0113
	(2.1274)	(1.4691)	(1.6166)	(0.8341)	(2.8854)	(-0.4082)
$\|R_{m,t}\|$	2.1558***	2.6058***	2.0208***	2.7615***	2.5090***	1.7647***
	(34.9595)	(28.8711)	(39.5627)	(22.3399)	(27.1828)	(23.2540)
$R_{m,t}^2$	-0.1650***	-0.3429***	-0.2763***	-0.1528***	-0.3215***	-0.2273***
	(-6.2267)	(-7.5011)	(-10.9185)	(-2.8715)	(-7.0405)	(-4.9409)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7262	0.7602	0.7832	0.7956	0.7356	0.7484

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.4.4 Solution 2 Regression results in SCSAD

Table 7.2.4.4 Panel A Regression results under SCSAD model in the UK market

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	1.9759***	2.0341***	1.7643***	1.6116***	1.4529***	1.3480***
	(41.9677)	(45.1109)	(38.4704)	(38.1909)	(35.3493)	(56.5696)
$R_{m,t}^2$	-0.0011	0.0137	-0.0150	-0.0187	0.0082	0.0006
	(-0.0757)	(0.7033)	(-1.4468)	(-0.7541)	(0.8181)	(0.0772)
$R_{m,t}^3$	-0.0552***	-0.0668***	-0.0345***	-0.0449***	-0.0088***	-0.0132***
	(-5.9245)	(-7.6344)	(-5.4570)	(-4.5575)	(-4.1885)	(-8.4870)
_cons	0.0958***	0.0542*	0.0586***	0.0482***	0.0519	0.0686***
	(3.5353)	(1.7213)	(2.0676)	(2.0837)	(1.3615)	(3.2102)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7499	0.7382	0.7579	0.7082	0.7239	0.7961

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	2.0337***	1.8505***	1.7711***	1.1967***	2.2524***	0.8186***
	(41.7778)	(39.5687)	(47.1931)	(25.5219)	(45.7001)	(16.9990)
$R_{m,t}^2$	0.0800***	-0.0209	0.0236	-0.0104	0.0443	0.0026
	(3.2590)	(-1.4489)	(1.5992)	(-1.1869)	(1.4981)	(0.0888)
$R_{m,t}^3$	-0.0170***	-0.0636***	-0.0198***	-0.0149***	-0.0506***	0.0003
	(-2.6098)	(-5.9587)	(-5.8252)	(-3.2477)	(-4.4286)	(0.0768)
_cons	-0.0428	0.0732***	0.0619	0.0533*	0.0317	0.0072
	(-1.2006)	(2.7945)	(1.6041)	(1.7776)	(1.0273)	(0.2114)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7504	0.7586	0.7479	0.7244	0.7568	0.6563

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.4 Panel B Regression results under SCSAD model in Germany and France market

$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	2.2701***	1.9366***	2.2119***	1.7504***	1.1954***	2.0120***
	(49.1255)	(46.8369)	(46.3515)	(43.6839)	(44.0765)	(42.9444)
$R_{m,t}^2$	0.0405	0.0234	0.0178	-0.0447*	0.0043	0.0079
	(1.3388)	(1.1442)	(0.8185)	(-1.9357)	(0.3977)	(0.5331)
$R_{m,t}^3$	-0.0554***	-0.0312***	-0.0459***	-0.0809***	-0.0059***	-0.0406***
	(-6.1465)	(-6.5287)	(-5.3483)	(-6.7046)	(-3.8383)	(-5.9839)
_cons	0.0852***	0.0582	0.0564	0.0465***	0.0924***	0.0743***
	(2.3431)	(1.5733)	(1.5291)	(2.0018)	(2.5096)	(2.1257)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7192	0.7025	0.7552	0.7202	0.7294	0.7554

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.8680***	2.0763***	1.6318***	2.4126***	1.9916***	1.4607***
	(49.6490)	(45.2487)	(51.9864)	(56.2283)	(42.2525)	(45.0102)
$R_{m,t}^2$	0.0422***	0.0154	0.0055	0.0000	0.0410*	-0.0160
	(3.2809)	(0.6654)	(0.4171)	(0.0008)	(1.8511)	(-1.0474)
$R_{m,t}^3$	-0.0138***	-0.0374***	-0.0355***	-0.0080***	-0.0318***	-0.0254***
	(-10.7924)	(-5.7000)	(-8.1038)	(-2.4633)	(-6.2979)	(-4.9572)
_cons	0.0016	0.0543	0.0681***	0.0357	0.1220***	0.0052
	(0.0468)	(1.3265)	(2.4786)	(0.6791)	(3.0800)	(0.2292)
N	1305	1305	1305	1305	1305	1305
adj. R^2	0.7097	0.7319	0.7579	0.7828	0.6967	0.7248

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.4.5 Solution 3 Regression considering large market returns

In the UK market

Table 7.2.4.5 panel A Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0686***	0.0526***	0.0323*	-0.0017	0.0624***	0.0279
	(3.4860)	(2.0626)	(1.9011)	(-0.0985)	(2.0565)	(1.4726)
$\|R_{m,t}\|$	0.9741***	1.0289***	0.7878***	0.6083***	0.7477***	0.8908***
	(10.6378)	(7.6187)	(8.7052)	(6.9413)	(7.7088)	(9.7124)
$R_{m,t}^2$	-0.0403***	-0.0395	-0.0078	-0.0007	-0.0054	-0.0175
	(-1.9716)	(-1.3104)	(-0.3885)	(-0.0333)	(-0.3431)	(-0.8776)
_cons	0.9647***	0.9555***	1.1284***	0.8554***	1.1978***	0.5875***
	(13.3769)	(9.6382)	(15.6076)	(13.4608)	(12.6164)	(8.1149)
N	549	659	656	494	841	691
adj. R^2	0.5347	0.3416	0.4978	0.4287	0.4346	0.6585

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0603*	0.0448***	0.0358*	0.0203	0.0573***	-0.0091
	(1.7262)	(2.6261)	(1.8141)	(1.4832)	(2.3394)	(-0.1249)
$\|R_{m,t}\|$	0.7511***	0.7907***	0.7542***	0.5522***	0.7655***	0.1208
	(3.8754)	(10.4157)	(9.5101)	(10.1932)	(4.1175)	(0.4926)
$R_{m,t}^2$	0.0821	-0.0311*	0.0013	-0.0091	0.0649	0.0772
	(1.4621)	(-1.8782)	(0.0993)	(-1.0225)	(1.1200)	(1.3336)
_cons	1.3292***	1.0471***	1.3917***	0.9917***	1.2722***	0.7450***
	(10.1137)	(16.7740)	(18.4529)	(18.6326)	(10.5141)	(4.2530)
N	665	604	770	804	562	684
adj. R^2	0.5711	0.4497	0.4613	0.4140	0.4682	0.4996

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.5 panel B Market return larger than |1%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0959***	0.0631***	0.0461***	0.0264	0.0718***	0.0346*
	(4.3767)	(2.1681)	(2.4766)	(1.3252)	(2.2610)	(1.7024)
$\|R_{m,t}\|$	1.1602***	1.0799***	0.6883***	0.5451***	0.9205***	1.1037***
	(6.6945)	(3.4354)	(4.3542)	(2.9821)	(7.2532)	(8.1744)
$R_{m,t}^2$	-0.0679***	-0.0456	0.0088	0.0116	-0.0230	-0.0450***
	(-2.2803)	(-0.7767)	(0.3147)	(0.3442)	(-1.5800)	(-2.1053)
_cons	0.7416***	0.8785***	1.2537***	0.9309***	0.9043***	0.2813*
	(3.8513)	(2.6290)	(6.8206)	(4.6143)	(5.1147)	(1.7481)
N	244	301	321	183	505	330
adj. R^2	0.5245	0.2821	0.4594	0.4310	0.4250	0.6482

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0624	0.0694***	0.0427***	0.0229	0.0821***	-0.0196
	(1.5893)	(3.6491)	(1.9911)	(1.5837)	(2.8704)	(-0.2381)
$\|R_{m,t}\|$	0.6290***	0.8951***	0.8193***	0.4607***	0.2972	0.0029
	(1.9854)	(5.7683)	(6.2750)	(5.6018)	(0.7329)	(0.0071)
$R_{m,t}^2$	0.0964	-0.0437	-0.0070	0.0024	0.1489*	0.0890
	(1.4428)	(-1.5491)	(-0.3975)	(0.2340)	(1.6806)	(1.2176)
_cons	1.5030***	0.9033***	1.3058***	1.1404***	1.8123***	0.9301***
	(4.4861)	(5.3080)	(7.5304)	(9.9994)	(4.4890)	(2.1911)
N	290	271	424	462	214	326
adj. R^2	0.5867	0.4630	0.4345	0.3463	0.4849	0.4909

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.5 panel C Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1157***	0.0790*	0.0733***	0.0432	0.0895***	0.0371
	(3.4285)	(1.7983)	(3.0087)	(1.4306)	(2.2856)	(1.3904)
$\|R_{m,t}\|$	0.9763	0.1691	0.1664	0.1940	1.4174***	1.7105***
	(1.5637)	(0.1382)	(0.3774)	(0.3381)	(5.4666)	(5.6241)
$R_{m,t}^2$	-0.0423	0.0757	0.0743	0.0551	-0.0656***	-0.1114***
	(-0.5000)	(0.4206)	(1.3507)	(0.7140)	(-3.2625)	(-3.6602)
_cons	1.0833	2.4980	2.2194***	1.6015	-0.2329	-0.8870
	(1.0443)	(1.2741)	(2.7348)	(1.6041)	(-0.4297)	(-1.4736)
N	61	62	92	33	175	105
adj. R^2	0.4030	0.2116	0.4253	0.4958	0.4110	0.5448

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0366	0.0950***	0.0779***	0.0071	0.0504	-0.0313
	(0.5742)	(2.9677)	(2.9682)	(0.3998)	(0.9894)	(-0.2452)
$\|R_{m,t}\|$	-0.4085	0.1029	0.8857***	0.6194***	-3.6375*	-0.4398
	(-0.5082)	(0.1500)	(3.0931)	(3.4060)	(-1.7806)	(-0.4303)
$R_{m,t}^2$	0.1994***	0.0723	-0.0121	-0.0147	0.7111***	0.1269
	(2.1660)	(0.7371)	(-0.3988)	(-0.7587)	(2.2831)	(1.0136)
_cons	3.5676***	2.1849***	1.1816***	0.8089***	7.9384***	1.9325
	(2.3732)	(2.0367)	(2.1122)	(2.2762)	(2.6181)	(1.0889)
N	64	63	145	175	39	78
adj. R^2	0.6606	0.3241	0.4318	0.3083	0.6278	0.4488

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.5 panel D Market return larger than |3%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0762	0.0672	0.0693***	0.0546*	0.0807	0.0226
	(1.3711)	(1.8000)	(2.2503)	(2.3732)	(1.5943)	(0.6473)
$\|R_{m,t}\|$	4.0363***	2.7560	-0.7610	3.3709***	1.6221***	2.8014***
	(2.2732)	(0.6237)	(-0.7369)	(3.2520)	(2.9974)	(3.1596)
$R^2_{m,t}$	-0.4091*	-0.2638	0.1682	-0.3097***	-0.0824***	-0.2141***
	(-2.1571)	(-0.4770)	(1.5026)	(-2.6374)	(-2.1816)	(-2.7373)
_cons	-5.0964	-2.3133	4.3675*	-4.8720*	-0.7581	-3.5180
	(-1.2774)	(-0.2669)	(1.9552)	(-2.2506)	(-0.4891)	(-1.5963)
N	15	13	30	10	73	41
adj. R^2	0.4678	0.4774	0.5768	0.8810	0.2504	0.3824

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	-0.2463*	0.0574	0.0645*	0.0033	-0.1609	-0.0571
	(-1.9101)	(0.7491)	(1.9457)	(0.1498)	(-2.1632)	(-0.2687)
$\|R_{m,t}\|$	-5.9104*	-0.9511	0.6434	-0.0953	-33.4601	0.2545
	(-1.8627)	(-0.5359)	(0.8361)	(-0.2525)	(-2.1021)	(0.1109)
$R^2_{m,t}$	0.7149***	0.2062	0.0103	0.0476	4.2963*	0.0796
	(2.5515)	(1.0905)	(0.1545)	(1.5087)	(2.3709)	(0.3792)
_cons	16.2236***	3.9863	1.7544	2.6220***	68.1779	-0.3526
	(2.1613)	(1.0183)	(0.8793)	(2.6359)	(1.9818)	(-0.0608)
N	20	14	52	75	7	28
adj. R^2	0.7643	0.4675	0.3892	0.1921	0.9158	0.4137

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.4.5 panel E Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0526***	0.0472	0.0816***	0.0207	0.0123	0.0629***
	(2.9117)	(1.5756)	(2.4625)	(0.8183)	(0.4005)	(3.1286)
$\|R_{m,t}\|$	0.6793***	0.8480***	0.8444***	0.5432***	0.3965***	0.9351***
	(6.8667)	(5.9062)	(5.9324)	(4.4746)	(3.1263)	(9.4873)
$R_{m,t}^2$	0.0220	-0.0094	0.0909***	0.0248	0.0357	-0.0173
	(0.9120)	(-0.2869)	(2.4016)	(0.7491)	(1.3872)	(-0.8232)
_cons	1.4714***	1.1978***	1.2501***	0.9305***	1.2695***	1.2300***
	(20.0283)	(10.8913)	(11.9894)	(11.1222)	(11.2332)	(14.6592)
N	603	705	683	552	894	704
adj. R^2	0.4978	0.3587	0.5054	0.3188	0.4397	0.4574

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0327	0.0500*	0.0300*	-0.0011	0.0582***	-0.0001
	(0.7969)	(1.7263)	(1.8911)	(-0.0351)	(3.1590)	(-0.0042)
$\|R_{m,t}\|$	0.8193***	0.8529***	0.7234***	0.9316***	0.5834***	0.5525***
	(7.5942)	(6.0469)	(8.2461)	(7.9245)	(7.6181)	(6.3537)
$R_{m,t}^2$	0.0086	-0.0019	-0.0051	0.0931***	-0.0041	0.0195
	(0.3816)	(-0.0545)	(-0.2601)	(3.7561)	(-0.3331)	(0.9448)
_cons	1.2578***	1.4090***	0.9603***	1.9493***	1.6309***	0.8660***
	(13.1128)	(13.4681)	(14.3768)	(18.1011)	(24.6346)	(13.0710)
N	702	720	717	786	699	652
adj. R^2	0.4763	0.4321	0.5123	0.6521	0.3353	0.3680

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.5 panel F Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0678***	0.0529	0.0928***	0.0254	0.0116	0.0723***
	(3.2626)	(1.5476)	(2.4771)	(0.8111)	(0.3613)	(3.3214)
$\|R_{m,t}\|$	0.8060***	0.9777***	0.9327***	1.0359***	0.4538***	1.0918***
	(4.5195)	(3.7694)	(3.2846)	(3.4411)	(2.5230)	(6.8991)
$R_{m,t}^2$	0.0015	-0.0279	0.0761	-0.0701	0.0298	-0.0417
	(0.0419)	(-0.6053)	(1.3713)	(-1.2164)	(0.9765)	(-1.5775)
_cons	1.3341***	1.0341***	1.1501***	0.4016	1.1684***	1.0375***
	(7.2301)	(3.8057)	(3.7993)	(1.3663)	(5.5562)	(5.6531)
N	240	340	333	207	576	363
adj. R^2	0.5622	0.3457	0.4822	0.3649	0.4487	0.4520

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0625	0.0572*	0.0433***	-0.0004	0.0661***	0.0186
	(1.3888)	(1.7484)	(2.5137)	(-0.0118)	(3.1511)	(0.7156)
$\|R_{m,t}\|$	1.0843***	1.2480***	0.7085***	1.1185***	0.4977***	0.7573***
	(6.0257)	(5.3094)	(4.2622)	(6.4145)	(3.5896)	(4.9702)
$R_{m,t}^2$	-0.0194	-0.0614	-0.0025	0.0736***	0.0069	-0.0111
	(-0.8518)	(-1.3681)	(-0.0820)	(2.6436)	(0.3730)	(-0.4565)
_cons	0.8631***	0.9053***	0.9882***	1.6415***	1.7633***	0.6229***
	(3.6879)	(3.7222)	(5.5222)	(7.4799)	(10.0677)	(3.4433)
N	340	359	346	431	323	247
adj. R^2	0.5115	0.4198	0.4822	0.7081	0.3131	0.4062

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.5 panel G Market return larger than |2%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0751***	0.0644	0.1734***	0.0394	0.0093	0.0835***
	(2.7297)	(1.0999)	(2.9033)	(0.4565)	(0.2251)	(2.8092)
$\|R_{m,t}\|$	0.8844	0.7548	1.0160	-1.2045	0.6553***	1.4305***
	(1.5633)	(0.8520)	(0.9242)	(-0.5630)	(2.0599)	(2.5974)
$R_{m,t}^2$	-0.0021	-0.0054	0.0821	0.2475	0.0114	-0.0842
	(-0.0268)	(-0.0480)	(0.5462)	(0.7719)	(0.2838)	(-1.2510)
_cons	1.0800	1.5357	0.8948	4.1529	0.7199	0.4586
	(1.1386)	(1.0286)	(0.4977)	(1.2318)	(1.2689)	(0.4679)
N	49	73	77	27	202	96
adj. R^2	0.6724	0.2484	0.4756	0.0577	0.4086	0.3922

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1300***	0.1023***	0.0807***	-0.0269	0.0807***	0.0273
	(2.0943)	(2.2171)	(3.6069)	(-0.5869)	(2.8952)	(0.6069)
$\|R_{m,t}\|$	2.2419***	1.5279***	0.7800*	1.3561***	0.8606***	1.2909***
	(3.8235)	(2.1420)	(1.7484)	(3.5821)	(3.0286)	(2.4358)
$R_{m,t}^2$	-0.1219***	-0.0933	-0.0113	0.0547	-0.0313	-0.0788
	(-2.6251)	(-1.0129)	(-0.1793)	(1.4596)	(-1.0073)	(-1.2605)
_cons	-1.5895	0.4087	0.9061	1.0914	1.0336*	-0.2316
	(-1.3259)	(0.3378)	(1.2435)	(1.4866)	(1.8747)	(-0.2420)
N	80	104	82	134	74	41
adj. R^2	0.5609	0.2835	0.5345	0.7527	0.4921	0.4883

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.5 panel H Market return larger than |3%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0586	-0.0220	0.2067	-14.1264***	-0.0105	0.0797
	(1.6908)	(-0.2410)	(1.5639)	(-5.5042)	(-0.1918)	(1.6124)
$\|R_{m,t}\|$	-2.7606	0.6295	5.0340	0.0000	0.7523	3.7432*
	(-0.9979)	(0.2889)	(0.8166)	(.)	(1.3019)	(1.8117)
$R_{m,t}^2$	0.4062	0.0149	-0.4094	-1.7357***	0.0047	-0.3284
	(1.2961)	(0.0646)	(-0.5549)	(-5.4092)	(0.0893)	(-1.4943)
_cons	8.8260	1.4970	-6.9121	-24.9723***	0.3764	-4.7167
	(1.5347)	(0.3189)	(-0.5528)	(-4.9357)	(0.2462)	(-1.0358)
N	15	19	24	6	90	26
adj. R^2	0.6527	0.3328	0.4237	0.9410	0.3172	0.3533

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1878***	0.0741	0.0481*	-0.0600	0.0554***	-0.0750
	(2.1762)	(1.0464)	(1.8609)	(-0.8723)	(2.1837)	(-1.3660)
$\|R_{m,t}\|$	4.8627***	1.4625	1.2910	1.4307	0.4892	1.7536
	(3.1996)	(0.5009)	(0.7778)	(1.5124)	(0.6195)	(1.2011)
$R_{m,t}^2$	-0.3225***	-0.0814	-0.0651	0.0519	0.0084	-0.1349
	(-2.8085)	(-0.2623)	(-0.3307)	(0.7193)	(0.1197)	(-0.9440)
_cons	-8.7582***	0.3637	-0.3201	0.8044	1.7465	-1.1938
	(-2.2002)	(0.0571)	(-0.0937)	(0.3265)	(0.8518)	(-0.3604)
N	26	25	29	46	25	12
adj. R^2	0.5837	0.2733	0.6227	0.7388	0.5681	0.4447

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.4.6 Larger market movements based on a proportion of the data condition

In the UK market

Table 7.2.4.6 panel A Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0663***	0.0520***	0.0327*	-0.0011	0.0698***	0.0292
	(3.4297)	(2.0383)	(1.9248)	(-0.0635)	(2.2696)	(1.5448)
$\lvert R_{m,t}\rvert$	0.9280***	1.0176***	0.7920***	0.5894***	0.8569***	0.9220***
	(11.5450)	(7.4384)	(8.7149)	(7.8970)	(8.0482)	(10.0286)
$R_{m,t}^2$	-0.0317	-0.0372	-0.0084	0.0032	-0.0167	-0.0217
	(-1.6099)	(-1.2211)	(-0.4190)	(0.1575)	(-1.1682)	(-1.1163)
_cons	1.0090***	0.9661***	1.1237***	0.8710***	1.0195***	0.5477***
	(17.9189)	(9.5518)	(15.4760)	(18.2201)	(8.1243)	(7.3483)
N	653	653	653	653	653	653
adj. R^2	0.5432	0.3384	0.4990	0.4147	0.4438	0.6685

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0589*	0.0428***	0.0366*	0.0221	0.0542***	-0.0085
	(1.6845)	(2.5213)	(1.8306)	(1.5933)	(2.2437)	(-0.1166)
$\lvert R_{m,t}\rvert$	0.7451***	0.7968***	0.7866***	0.5461***	0.8145***	0.1312
	(3.8058)	(11.2349)	(8.7172)	(8.2892)	(5.0320)	(0.5185)
$R_{m,t}^2$	0.0830	-0.0328***	-0.0029	-0.0081	0.0548	0.0761
	(1.4730)	(-2.0512)	(-0.2047)	(-0.8144)	(1.0064)	(1.2979)
_cons	1.3360***	1.0420***	1.3462***	0.9998***	1.2282***	0.7309***
	(9.9459)	(18.6139)	(14.3019)	(13.3405)	(13.0137)	(3.9301)
N	653	653	653	653	653	653
adj. R^2	0.5709	0.4561	0.4618	0.3891	0.4857	0.5018

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.6 panel B Largest 10% (10% of absolute value (above 5% and 5% below 0))

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1105***	0.0578	0.0740***	0.0306	0.0843*	0.0368
	(4.2973)	(1.6236)	(3.3473)	(1.4750)	(1.9773)	(1.4842)
$\|R_{m,t}\|$	1.3755***	1.5986***	0.5825***	0.5586***	1.6168***	1.6164***
	(5.3386)	(2.8574)	(2.0269)	(2.7593)	(4.9283)	(6.6921)
$R^2_{m,t}$	-0.0977***	-0.1390	0.0260	0.0102	-0.0813***	-0.1018***
	(-2.4821)	(-1.4854)	(0.6181)	(0.2842)	(-3.2420)	(-3.9730)
_cons	0.4276	0.2591	1.4125***	0.9075***	-0.7728	-0.6873
	(1.2617)	(0.3555)	(3.1717)	(3.8525)	(-1.0254)	(-1.5629)
N	130	130	130	130	130	130
adj. R^2	0.5293	0.2844	0.4890	0.4943	0.3783	0.5784

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0409	0.0819***	0.0742***	0.0109	0.0946***	-0.0159
	(0.8178)	(3.5150)	(2.7141)	(0.5636)	(3.1040)	(-0.1488)
$\|R_{m,t}\|$	0.1305	0.6996***	0.6941***	0.4417*	-0.0705	-0.0423
	(0.2570)	(2.0178)	(2.1118)	(1.9679)	(-0.1216)	(-0.0590)
$R^2_{m,t}$	0.1488*	-0.0114	0.0067	0.0018	0.2090*	0.0934
	(1.9366)	(-0.2106)	(0.1941)	(0.0865)	(1.8310)	(0.9328)
_cons	2.4106***	1.1797***	1.6088***	1.2347***	2.2960***	1.0049
	(3.1515)	(2.5202)	(2.4062)	(2.4566)	(3.5703)	(0.9500)
N	130	130	130	130	130	130
adj. R^2	0.5937	0.3999	0.4001	0.2382	0.5572	0.4853

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.6 panel C Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1128***	0.0695	0.0860***	0.0282	0.0947*	0.0452
	(3.4289)	(1.5850)	(3.1786)	(1.1315)	(1.8083)	(1.4978)
$\|R_{m,t}\|$	1.2295***	0.5565	-0.1622	0.6009*	1.4035***	2.4528***
	(2.1643)	(0.4737)	(-0.2600)	(1.9286)	(2.2648)	(4.7180)
$R_{m,t}^2$	-0.0756	0.0197	0.1129	0.0037	-0.0670	-0.1806***
	(-0.9879)	(0.1133)	(1.5501)	(0.0774)	(-1.5890)	(-3.7362)
_cons	0.6369	1.8541	2.8785***	0.8471*	-0.0467	-2.6696***
	(0.6796)	(0.9918)	(2.3318)	(1.8866)	(-0.0250)	(-2.2864)
N	65	65	65	65	65	65
adj. R^2	0.4147	0.2139	0.4724	0.5118	0.2184	0.5407

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0352	0.0971***	0.0798***	0.0110	0.1022***	-0.0398
	(0.5537)	(3.1010)	(2.6341)	(0.4727)	(2.5292)	(-0.2917)
$\|R_{m,t}\|$	-0.3718	0.0125	0.7742	0.4113	-0.6333	-0.4281
	(-0.4687)	(0.0193)	(1.4549)	(0.9465)	(-0.5381)	(-0.3797)
$R_{m,t}^2$	0.1962***	0.0851	-0.0006	0.0078	0.2937	0.1266
	(2.1427)	(0.9148)	(-0.0125)	(0.2218)	(1.4866)	(0.9530)
_cons	3.4819***	2.3363***	1.4195	1.1843	3.1238***	1.8709
	(2.3602)	(2.3105)	(1.1070)	(0.9978)	(2.0049)	(0.9066)
N	65	65	65	65	65	65
adj. R^2	0.6613	0.3200	0.4331	0.2593	0.6026	0.4467

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.4.6 panel D Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0504***	0.0472	0.0837***	0.0199	0.0114	0.0632***
	(2.8094)	(1.5596)	(2.5116)	(0.8071)	(0.3615)	(3.1252)
$\|R_{m,t}\|$	0.6559***	0.8616***	0.8224***	0.5504***	0.4376***	0.9926***
	(6.9715)	(5.5139)	(5.4464)	(5.4862)	(2.6732)	(9.7214)
$R_{m,t}^2$	0.0260	-0.0115	0.0955***	0.0231	0.0315	-0.0271
	(1.1110)	(-0.3352)	(2.4416)	(0.7687)	(1.0802)	(-1.2943)
_cons	1.4946***	1.1822***	1.2714***	0.9245***	1.1973***	1.1662***
	(21.9850)	(9.3508)	(11.0625)	(14.7834)	(6.7069)	(12.8660)
N	653	653	653	653	653	653
adj. R^2	0.4832	0.3505	0.4975	0.3334	0.4494	0.4660

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0338	0.0508*	0.0313*	-0.0017	0.0574***	0.0001
	(0.8186)	(1.7317)	(1.9560)	(-0.0543)	(3.0772)	(0.0026)
$\|R_{m,t}\|$	0.8394***	0.8957***	0.6857***	0.9262***	0.5889***	0.5546***
	(7.3994)	(5.8527)	(7.0319)	(6.8457)	(7.2566)	(6.3961)
$R_{m,t}^2$	0.0064	-0.0087	0.0016	0.0938***	-0.0049	0.0192
	(0.2835)	(-0.2445)	(0.0750)	(3.5704)	(-0.3806)	(0.9308)
_cons	1.2310***	1.3591***	1.0004***	1.9562***	1.6242***	0.8639***
	(11.6435)	(11.2708)	(12.6882)	(14.2360)	(22.2873)	(13.0835)
N	653	653	653	653	653	653
adj. R^2	0.4797	0.4303	0.4973	0.6651	0.3342	0.3686

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.6 panel E Largest 10% (10% of absolute value (above 5% and 5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0812***	0.0568	0.1368***	0.0434	-0.0009	0.0854***
	(3.4803)	(1.1259)	(2.7307)	(1.1699)	(-0.0179)	(3.1469)
$\|R_{m,t}\|$	0.6910***	1.0143	0.5183	1.2276***	0.4461	1.2457***
	(2.6290)	(1.6118)	(0.7714)	(2.6137)	(0.9423)	(3.2331)
$R_{m,t}^2$	0.0184	-0.0344	0.1416	-0.1005	0.0277	-0.0614
	(0.4164)	(-0.4000)	(1.3783)	(-1.1897)	(0.5548)	(-1.2327)
_cons	1.5140***	1.0181	1.8047*	0.1566	1.2997	0.7954
	(4.4655)	(1.0774)	(1.8554)	(0.3054)	(1.2176)	(1.2575)
N	130	130	130	130	130	130
adj. R^2	0.5512	0.2576	0.4354	0.3344	0.3250	0.4029

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0906	0.0736*	0.0697***	-0.0264	0.0795***	0.0215
	(1.6239)	(1.6868)	(3.4995)	(-0.5686)	(3.3011)	(0.7069)
$\|R_{m,t}\|$	1.6600***	1.0601*	1.1187***	1.3977***	0.5689***	0.9714***
	(4.4339)	(1.6806)	(3.7661)	(3.5959)	(2.6483)	(3.8473)
$R_{m,t}^2$	-0.0723***	-0.0399	-0.0543	0.0513	-0.0008	-0.0399
	(-2.3049)	(-0.4695)	(-1.1963)	(1.3526)	(-0.0324)	(-1.1766)
_cons	-0.2637	1.2834	0.2780	0.9916	1.6367***	0.3100
	(-0.3915)	(1.2407)	(0.6594)	(1.2973)	(4.7660)	(0.8560)
N	130	130	130	130	130	130
adj. R^2	0.5436	0.2320	0.6012	0.7515	0.4261	0.4497

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.4.6 panel F Largest 5% (5% of absolute value (above 2.5% and 2.5% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.1019***	0.0604	0.1662***	0.0601	-0.0156	0.1206***
	(3.9046)	(0.9951)	(2.5272)	(1.0990)	(-0.2475)	(3.5508)
$\|R_{m,t}\|$	0.2659	1.3501	-0.0026	1.8839***	0.3532	1.7638***
	(0.5819)	(1.4895)	(-0.0016)	(2.0559)	(0.3263)	(2.1670)
$R_{m,t}^2$	0.0748	-0.0709	0.2157	-0.2020	0.0328	-0.1177
	(1.1676)	(-0.6286)	(1.0060)	(-1.2965)	(0.3993)	(-1.2220)
_cons	2.2500***	0.3275	2.7144	-0.7820	1.6767	-0.2376
	(3.0662)	(0.2123)	(0.9921)	(-0.6792)	(0.5034)	(-0.1546)
N	65	65	65	65	65	65
adj. R^2	0.5980	0.3000	0.4169	0.3014	0.2382	0.4687

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1425***	0.0764	0.0884***	-0.0405	0.0754***	0.0324
	(2.1465)	(1.4666)	(3.6447)	(-0.6659)	(2.7381)	(0.8580)
$\|R_{m,t}\|$	2.5687***	1.3450	0.5405	1.1131	0.6949***	1.5152***
	(3.5546)	(1.1707)	(0.8240)	(1.5706)	(2.2225)	(4.0299)
$R_{m,t}^2$	-0.1485***	-0.0723	0.0181	0.0737	-0.0145	-0.1034***
	(-2.6179)	(-0.5285)	(0.2085)	(1.2530)	(-0.4427)	(-2.0893)
_cons	-2.3937	0.7226	1.3715	1.7613	1.3908***	-0.6789
	(-1.5287)	(0.3310)	(1.1613)	(1.0479)	(2.1471)	(-1.1516)
N	65	65	65	65	65	65
adj. R^2	0.5510	0.2485	0.5013	0.7371	0.4660	0.5815

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.5 Investigate herding behaviour in 2020

7.2.5.2 Normal regression model

Table 7.2.5.2 panel A UK 2020 regression results under CCK model

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0494	0.0129	0.0401	0.0993***	0.1660***	0.0186
	(1.0525)	(0.2452)	(0.6333)	(2.1062)	(3.6851)	(0.6798)
$\|R_{m,t}\|$	0.9135***	1.1694***	0.8086***	0.9154***	0.8819***	0.8502***
	(8.1111)	(8.9192)	(7.1121)	(7.9030)	(9.7865)	(10.7802)
$R_{m,t}^2$	-0.0238	-0.0581***	0.0093	-0.0456	0.0001	-0.0243
	(-1.2250)	(-1.9885)	(0.7788)	(-1.4994)	(0.0086)	(-1.5662)
_cons	1.2643***	0.9141***	1.4187***	0.7750***	2.2899***	0.6941***
	(19.5200)	(13.1949)	(19.2484)	(17.5683)	(16.7817)	(17.3391)
N	210	210	210	210	210	210
adj. R^2	0.7069	0.6405	0.6931	0.5732	0.7424	0.8109

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1332***	0.0274	0.0913	-0.0045	0.1219***	0.0323
	(2.0836)	(0.6670)	(1.5913)	(-0.0893)	(4.1287)	(0.7067)
$\|R_{m,t}\|$	1.0306***	0.7999***	1.0266***	0.8326***	0.8293***	0.4958***
	(6.1054)	(9.2458)	(7.0983)	(7.9823)	(11.0766)	(5.4866)
$R_{m,t}^2$	-0.0138	-0.0144	-0.0502***	-0.0241	-0.0107	-0.0064
	(-0.2952)	(-1.2621)	(-2.1467)	(-1.3686)	(-0.8887)	(-0.5024)
_cons	1.0736***	1.2665***	1.6086***	1.0007***	1.1661***	0.6855***
	(11.1284)	(20.2112)	(16.3185)	(11.6886)	(22.6280)	(8.2421)
N	210	210	210	210	210	210
adj. R^2	0.5929	0.7347	0.4950	0.5839	0.7703	0.3843

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.5.2 panel B Germany and France 2020 regression results under CCK model

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0885*	0.0483	0.1250***	0.0152	0.1692***	0.0418
	(1.7163)	(0.8042)	(2.5051)	(0.1894)	(2.1693)	(0.8824)
$\lvert R_{m,t}\rvert$	0.7287***	0.8026***	0.7787***	0.6807***	1.0323***	1.3934***
	(6.0041)	(6.4242)	(4.9096)	(3.0730)	(5.9467)	(10.5804)
$R_{m,t}^2$	0.0081	-0.0358*	0.0124	0.0546	0.0070	-0.0756***
	(0.3857)	(-1.8977)	(0.5150)	(0.7394)	(0.2872)	(-3.9093)
_cons	1.9471***	1.5803***	2.2562***	1.0705***	1.6621***	1.2195***
	(20.4994)	(16.4061)	(14.8772)	(12.8291)	(10.4706)	(11.1320)
N	210	210	210	210	210	210
adj. R^2	0.4383	0.3147	0.4954	0.4423	0.5894	0.6123

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0878	0.0651	-0.0010	0.0700	0.0968	-0.0415
	(1.5027)	(1.0442)	(-0.0096)	(1.1486)	(0.9359)	(-0.6611)
$\lvert R_{m,t}\rvert$	0.9935***	0.9904***	1.8091***	1.1336***	1.3494***	0.7717***
	(7.5715)	(6.2957)	(4.7511)	(9.1513)	(5.8732)	(5.5062)
$R_{m,t}^2$	-0.0394***	-0.0359	-0.0513	-0.0264	-0.0608*	-0.0207
	(-1.9817)	(-1.4055)	(-0.7026)	(-1.0476)	(-1.6860)	(-0.8787)
_cons	1.2744***	1.9094***	0.7002***	1.0526***	1.6849***	0.8756***
	(14.5419)	(16.6204)	(3.1409)	(13.5466)	(11.7872)	(12.1176)
N	210	210	210	210	210	210
adj. R^2	0.5117	0.4065	0.6960	0.5485	0.4703	0.4913

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.5.3 Solution 1 Regression without constant value

Table 7.2.5.3 panel A UK 2020 Regression without constant value

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0080	0.0066	0.0146	0.0752	0.1685***	-0.0148
	(0.1457)	(0.1204)	(0.1835)	(1.2465)	(3.1668)	(-0.4497)
$\|R_{m,t}\|$	2.1015***	2.3354***	1.6885***	1.9233***	1.6685***	1.5868***
	(18.9728)	(20.1769)	(14.4733)	(20.0860)	(22.1901)	(22.6764)
$R_{m,t}^2$	-0.1874***	-0.2842***	-0.0537***	-0.2183***	-0.0345***	-0.1403***
	(-6.0529)	(-6.6959)	(-3.0176)	(-6.3832)	(-7.1204)	(-8.2732)
N	210	210	210	210	210	210
adj. R^2	0.7993	0.8480	0.7846	0.8066	0.8222	0.8779

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0853	-0.0109	0.0683	-0.0332	0.0813	0.0194
	(1.2353)	(-0.2112)	(1.0772)	(-0.6363)	(1.5908)	(0.4265)
$\|R_{m,t}\|$	2.2860***	1.7247***	2.4633***	1.5326***	1.9683***	1.0185***
	(22.4307)	(17.2198)	(19.0317)	(20.7970)	(18.7528)	(16.0752)
$R_{m,t}^2$	-0.2496***	-0.1100***	-0.2503***	-0.0991***	-0.1586***	-0.0706***
	(-6.5613)	(-4.5374)	(-6.9250)	(-6.2534)	(-5.9153)	(-4.6873)
N	210	210	210	210	210	210
adj. R^2	0.8228	0.8207	0.7920	0.8136	0.8343	0.7223

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.5.3 panel B Germany and France 2020 Regression without constant value

$CSAD_t = \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	-0.0755	0.0348	0.0510	-0.0870	0.1478*	-0.0170
	(-0.8886)	(0.4117)	(0.8656)	(-1.1139)	(1.9040)	(-0.3511)
$\|R_{m,t}\|$	2.9777***	2.3801***	2.6572***	2.4586***	1.9229***	2.5292***
	(23.1972)	(18.4398)	(24.0368)	(14.8811)	(18.4033)	(30.5476)
$R_{m,t}^2$	-0.3262***	-0.2388***	-0.2208***	-0.4033***	-0.0679***	-0.2343***
	(-8.1708)	(-5.5285)	(-9.0057)	(-4.4860)	(-4.7796)	(-11.6792)
N	210	210	210	210	210	210
adj. R^2	0.7332	0.7402	0.7657	0.7667	0.7908	0.8660

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0251	-0.0011	-0.0064	0.0369	0.0071	-0.1042
	(0.4216)	(-0.0138)	(-0.0683)	(0.5767)	(0.0698)	(-1.4674)
$\|R_{m,t}\|$	2.2176***	2.8330***	2.3387***	2.6071***	2.8652***	1.7404***
	(21.0429)	(20.2426)	(11.5646)	(29.2984)	(19.4488)	(16.1759)
$R_{m,t}^2$	-0.1992***	-0.3048***	-0.1167***	-0.3297***	-0.2551***	-0.1606***
	(-6.4224)	(-7.1340)	(-2.4694)	(-8.9299)	(-8.4289)	(-5.4090)
N	210	210	210	210	210	210
adj. R^2	0.8046	0.7559	0.8511	0.8257	0.7898	0.7681

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.5.4 Solution 2 Regression results in SCSAD

Table 7.2.5.4 panel A UK 2020 regression results under SCSAD model
$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	1.7149***	1.9142***	1.4824***	1.6184***	1.4431***	1.3274***
	(21.7751)	(21.8848)	(16.3985)	(19.8650)	(22.6474)	(25.1809)
$R_{m,t}^2$	-0.0025	-0.0020	0.0230	0.0165	0.0101***	-0.0058
	(-0.1021)	(-0.0912)	(0.8229)	(0.3785)	(4.4712)	(-0.6902)
$R_{m,t}^3$	-0.0174***	-0.0371***	-0.0009	-0.0261***	-0.0009***	-0.0153***
	(-3.5473)	(-4.6924)	(-0.4189)	(-2.8336)	(-6.3395)	(-6.9922)
_cons	0.0148	0.0226	-0.0299	0.0233	0.0899	-0.0013
	(0.1768)	(0.3598)	(-0.2882)	(0.4322)	(0.5635)	(-0.0294)
N	210	210	210	210	210	210
adj. R^2	0.7754	0.8280	0.7706	0.7817	0.8084	0.8613

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.9031***	1.4179***	1.9512***	1.3109***	1.6021***	0.8572***
	(24.4474)	(20.1636)	(21.3700)	(17.9582)	(19.3808)	(18.8034)
$R_{m,t}^2$	0.0151	0.0085	-0.0039	-0.0189	0.0087	0.0116
	(0.4564)	(0.3601)	(-0.1630)	(-1.0199)	(0.5446)	(0.5842)
$R_{m,t}^3$	-0.0309***	-0.0062***	-0.0234***	-0.0091***	-0.0129***	-0.0047*
	(-3.9855)	(-2.0936)	(-5.0376)	(-4.1589)	(-3.8235)	(-1.8214)
_cons	0.0635	-0.0428	0.1261	0.0637	0.1101	-0.0560
	(0.7733)	(-0.5034)	(1.1760)	(0.8039)	(1.5915)	(-0.8089)
N	210	210	210	210	210	210
adj. R^2	0.8088	0.7950	0.7628	0.7993	0.8010	0.7123

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.5.4 panel B Germany and France 2020 regression results under SCSAD model

$$SCSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 + \gamma_3 R_{m,t}^3 + \mu_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	2.4642***	1.9410***	2.1689***	2.0648***	1.6642***	2.1494***
	(20.4841)	(19.6006)	(23.0699)	(18.6033)	(20.6690)	(30.5571)
$R_{m,t}^2$	-0.0203	0.0225	0.0062	-0.1183***	0.0264***	-0.0200
	(-0.2882)	(0.3321)	(0.3446)	(-3.1146)	(2.0919)	(-0.9659)
$R_{m,t}^3$	-0.0358***	-0.0191***	-0.0185***	-0.0860***	-0.0025***	-0.0267***
	(-3.0858)	(-1.9996)	(-6.1598)	(-4.9985)	(-2.3054)	(-7.5764)
_cons	-0.0651	0.0909	0.0317	0.1596***	0.0123	0.0290
	(-0.5283)	(0.7840)	(0.2272)	(2.5174)	(0.0855)	(0.3243)
N	210	210	210	210	210	210
adj. R^2	0.7046	0.7066	0.7418	0.7557	0.7864	0.8526

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	1.8711***	2.3385***	2.1322***	2.2229***	2.3812***	1.4821***
	(22.0606)	(20.7568)	(17.5695)	(31.8132)	(18.2419)	(15.4610)
$R_{m,t}^2$	-0.0249	-0.0718***	0.0092	0.0937	0.0116	-0.0513
	(-0.8649)	(-2.0858)	(0.5822)	(1.3076)	(0.4268)	(-1.2599)
$R_{m,t}^3$	-0.0211***	-0.0395***	-0.0126***	-0.0311***	-0.0233***	-0.0202***
	(-5.0143)	(-6.2826)	(-3.8435)	(-2.0294)	(-5.5390)	(-3.1739)
_cons	0.1546*	0.3058***	-0.1137	-0.0438	-0.1032	0.0197
	(1.7943)	(2.4568)	(-1.1305)	(-0.5269)	(-0.8752)	(0.3052)
N	210	210	210	210	210	210
adj. R^2	0.7830	0.7360	0.8559	0.8119	0.7749	0.7490

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.5.5 Solution 3 Regression considering large market returns

In the UK market

Table 7.2.5.5 panel A Market return larger than |0.5%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0493	0.0111	0.0405	0.1043***	0.1653***	0.0183
	(1.0133)	(0.2048)	(0.6278)	(2.0944)	(3.6409)	(0.6480)
$\|R_{m,t}\|$	1.0214***	1.2564***	0.8139***	0.9876***	0.8686***	0.8148***
	(4.9658)	(5.7452)	(5.7206)	(4.7859)	(8.0411)	(6.1898)
$R_{m,t}^2$	-0.0371	-0.0745*	0.0088	-0.0562	0.0006	-0.0191
	(-1.2645)	(-1.9384)	(0.6667)	(-1.2633)	(0.0915)	(-0.8737)
_cons	1.1225***	0.8375***	1.4174***	0.7072***	2.3333***	0.7309***
	(5.4675)	(4.6562)	(9.4008)	(4.5631)	(11.2587)	(6.0004)
N	97	113	127	97	156	111
adj. R^2	0.6940	0.5964	0.6766	0.4676	0.7403	0.7675

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1190*	0.0295	0.0931	-0.0100	0.1225***	0.0340
	(1.7865)	(0.6916)	(1.5988)	(-0.1897)	(4.0463)	(0.7407)
$\|R_{m,t}\|$	1.2734***	0.8187***	1.2316***	0.8848***	0.7614***	0.6075***
	(4.9943)	(6.3715)	(5.5828)	(5.6712)	(7.0080)	(4.5087)
$R_{m,t}^2$	-0.0563	-0.0157	-0.0765***	-0.0295	-0.0023	-0.0191
	(-0.9870)	(-1.0917)	(-2.7122)	(-1.4855)	(-0.1469)	(-1.2530)
_cons	0.8268***	1.2246***	1.3436***	0.9112***	1.2425***	0.5245***
	(4.2304)	(9.0367)	(5.9005)	(5.0065)	(11.6307)	(3.1626)
N	119	117	129	142	118	139
adj. R^2	0.6322	0.7278	0.4515	0.5360	0.7693	0.3799

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.5.5 panel B Market return larger than |1%|

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0582	0.0154	0.0341	0.1080*	0.1672***	0.0232
	(1.1305)	(0.2480)	(0.4969)	(1.7348)	(3.6494)	(0.7678)
$\|R_{m,t}\|$	1.3026***	1.2169***	0.6989***	0.6318	0.8342***	0.7889***
	(3.9001)	(2.8503)	(3.6085)	(1.2797)	(6.1434)	(3.7911)
$R_{m,t}^2$	-0.0670	-0.0703	0.0155	-0.0071	0.0020	-0.0154
	(-1.5401)	(-1.1462)	(1.0997)	(-0.0880)	(0.2715)	(-0.5275)
_cons	0.6462	0.9291*	1.6895***	1.1837*	2.4586***	0.7722***
	(1.5336)	(1.7028)	(4.3828)	(1.8452)	(7.2263)	(2.7356)
N	55	53	70	41	119	54
adj. R^2	0.6814	0.4833	0.6376	0.3231	0.7210	0.7372

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1224	0.0354	0.0659	-0.0110	0.1332***	0.0375
	(1.5820)	(0.7884)	(1.0801)	(-0.1927)	(4.2310)	(0.7810)
$\|R_{m,t}\|$	1.3244***	0.7287***	1.3285***	0.9518***	0.6643***	0.8220***
	(2.4618)	(3.7245)	(3.9031)	(4.0178)	(4.0147)	(4.1137)
$R_{m,t}^2$	-0.0656	-0.0075	-0.0912***	-0.0357	0.0095	-0.0404***
	(-0.7000)	(-0.4050)	(-2.3541)	(-1.4905)	(0.4420)	(-2.0173)
_cons	0.7868	1.4073***	1.2070***	0.7804***	1.3924***	0.1313
	(1.2586)	(4.7990)	(2.5648)	(2.1341)	(6.2803)	(0.4508)
N	66	76	74	95	58	95
adj. R^2	0.5283	0.6575	0.3789	0.4836	0.7938	0.4125

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.5.5 panel C Market return larger than |0.5%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0891*	0.0461	0.1146***	-0.0219	0.1644***	0.0247
	(1.8055)	(0.7646)	(2.3566)	(-0.2568)	(2.1250)	(0.5246)
$\|R_{m,t}\|$	1.1275***	0.7724***	1.1471***	1.3057***	1.2434***	1.7006***
	(6.3729)	(4.3558)	(6.0485)	(2.7234)	(6.1558)	(9.9500)
$R_{m,t}^2$	-0.0423*	-0.0316	-0.0301	-0.0913	-0.0099	-0.1174***
	(-1.8202)	(-1.3660)	(-1.1975)	(-0.6919)	(-0.4185)	(-5.1521)
_cons	1.4781***	1.5944***	1.7306***	0.5900***	1.2211***	0.8644***
	(9.0365)	(9.4107)	(8.7648)	(2.0485)	(4.9286)	(4.9593)
N	107	133	138	95	155	154
adj. R^2	0.6777	0.3040	0.6562	0.4773	0.6018	0.6029

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0775	0.0628	-0.0061	0.0693	0.0731	-0.0524
	(1.3162)	(0.9817)	(-0.0653)	(1.1142)	(0.6922)	(-0.7940)
$\|R_{m,t}\|$	1.1908***	1.0766***	2.4655***	1.4328***	1.8106***	0.8708***
	(5.9493)	(4.5188)	(4.7955)	(5.6466)	(5.0467)	(3.9146)
$R_{m,t}^2$	-0.0641***	-0.0469	-0.1282	-0.0803*	-0.1168***	-0.0354
	(-2.4216)	(-1.3952)	(-1.5818)	(-1.9653)	(-2.4521)	(-1.0880)
_cons	1.0421***	1.7922***	-0.2917	0.7805***	1.0925***	0.7847***
	(5.2964)	(7.2455)	(-0.5983)	(3.7287)	(3.4756)	(4.6600)
N	132	120	142	113	140	114
adj. R^2	0.4867	0.3835	0.6754	0.5789	0.4702	0.5143

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7.2.5.5 panel D Market return larger than |1%|

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0773	0.0251	0.1174***	-0.0657	0.1608***	0.0175
	(1.3232)	(0.3671)	(2.3448)	(-0.6309)	(2.0591)	(0.3447)
$\|R_{m,t}\|$	1.2974***	0.9164***	1.3898***	1.2676	1.5043***	2.0310***
	(4.3862)	(3.3394)	(5.1739)	(1.4032)	(5.8550)	(7.0442)
$R_{m,t}^2$	-0.0656*	-0.0506	-0.0556*	-0.0965	-0.0290	-0.1575***
	(-1.8884)	(-1.6363)	(-1.7612)	(-0.4921)	(-1.2196)	(-4.4871)
_cons	1.2899***	1.3909***	1.3265***	0.7028	0.5873	0.3859
	(3.6800)	(3.6888)	(3.7734)	(0.7787)	(1.2476)	(0.9604)
N	52	71	87	37	106	87
adj. R^2	0.6800	0.3006	0.6693	0.2961	0.5772	0.5681

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0891	0.0230	-0.0302	0.0913	0.0774	-0.0504
	(1.4367)	(0.3428)	(-0.3425)	(1.1363)	(0.6842)	(-0.6462)
$\|R_{m,t}\|$	1.4807***	1.2309***	3.4509***	2.2273***	2.0224***	0.9256***
	(5.4674)	(2.9705)	(4.8910)	(4.0057)	(3.5808)	(2.8325)
$R_{m,t}^2$	-0.0942***	-0.0705	-0.2337***	-0.2061***	-0.1402***	-0.0423
	(-2.8470)	(-1.3883)	(-2.5366)	(-2.4412)	(-2.1242)	(-0.9764)
_cons	0.5948*	1.5823***	-2.1006***	-0.1101	0.7786	0.7328***
	(1.7972)	(2.7293)	(-2.2110)	(-0.1865)	(1.1238)	(2.0410)
N	73	74	95	47	84	54
adj. R^2	0.5283	0.3385	0.6397	0.6428	0.3870	0.4725

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2.5.6 Larger market movements based on a proportion of the data condition

In the UK market

Table 7.2.5.6 panel A Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0499	0.0162	0.0430	0.1028***	0.1691***	0.0215
	(1.0350)	(0.2971)	(0.6598)	(2.0941)	(3.6870)	(0.7662)
$\|R_{m,t}\|$	1.0330***	1.2272***	0.7743***	1.0014***	0.8388***	0.8733***
	(5.4805)	(5.3522)	(5.0727)	(5.1948)	(5.5388)	(7.2143)
$R_{m,t}^2$	-0.0384	-0.0689*	0.0115	-0.0585	0.0019	-0.0264
	(-1.3888)	(-1.7360)	(0.8590)	(-1.3733)	(0.2366)	(-1.2819)
_cons	1.1046***	0.8697***	1.5013***	0.6922***	2.4416***	0.6462***
	(6.3003)	(4.4689)	(7.6172)	(5.1628)	(5.8209)	(6.7028)
N	105	105	105	105	105	105
adj. R^2	0.7099	0.5903	0.6631	0.4851	0.7193	0.8157

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.1190*	0.0304	0.0939	-0.0132	0.1247***	0.0326
	(1.7564)	(0.7054)	(1.5832)	(-0.2373)	(4.0764)	(0.6895)
$\|R_{m,t}\|$	1.3801***	0.8057***	1.2902***	0.9116***	0.7258***	0.6704***
	(5.1014)	(5.6830)	(4.7764)	(4.2148)	(6.0681)	(3.4508)
$R_{m,t}^2$	-0.0732	-0.0145	-0.0833***	-0.0324	0.0019	-0.0259
	(-1.2535)	(-0.9513)	(-2.5412)	(-1.4118)	(0.1148)	(-1.3180)
_cons	0.6966***	1.2487***	1.2536***	0.8668***	1.2943***	0.4183
	(3.2055)	(7.5394)	(3.8395)	(2.7187)	(10.1069)	(1.4549)
N	105	105	105	105	105	105
adj. R^2	0.6380	0.7099	0.4154	0.4841	0.7613	0.3515

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the markets of Germany and France

Table 7.2.5.6 panel B Largest 50% of returns (50% of absolute value (above 25% and 25% below 0))

$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$

	All	Communications	Consumer Discretionary	Consumer Staples	Energy	Financials
$R_{m,t}$	0.0909*	0.0453	0.1186***	-0.0244	0.1605***	0.0167
	(1.8376)	(0.7249)	(2.4190)	(-0.2924)	(2.0520)	(0.3391)
$\|R_{m,t}\|$	1.1100***	0.8586***	1.3032***	1.3296***	1.4946***	1.9719***
	(6.1217)	(4.2337)	(5.4865)	(3.0294)	(5.7485)	(8.0416)
$R_{m,t}^2$	-0.0398*	-0.0414	-0.0465	-0.0967	-0.0284	-0.1507***
	(-1.6686)	(-1.6292)	(-1.6057)	(-0.7784)	(-1.1816)	(-4.8884)
_cons	1.4983***	1.4740***	1.4750***	0.5694***	0.6130	0.4783
	(8.8307)	(6.7182)	(5.0969)	(2.3096)	(1.2743)	(1.5257)
N	105	105	105	105	105	105
adj. R^2	0.6736	0.3186	0.6654	0.5015	0.5734	0.5849

	Health Care	Industrials	Materials	Real Estate	Technology	Utilities
$R_{m,t}$	0.0736	0.0539	-0.0158	0.0731	0.0683	-0.0540
	(1.2549)	(0.8320)	(-0.1770)	(1.1718)	(0.6308)	(-0.8076)
$\|R_{m,t}\|$	1.3968***	1.1085***	3.0829***	1.5329***	2.0714***	0.9181***
	(6.5490)	(3.9941)	(4.6727)	(5.6344)	(4.6309)	(3.8903)
$R_{m,t}^2$	-0.0871***	-0.0521	-0.1951***	-0.0970***	-0.1464***	-0.0413
	(-3.1355)	(-1.3998)	(-2.1596)	(-2.1935)	(-2.6678)	(-1.2151)
_cons	0.7431***	1.7537***	-1.3971*	0.6833***	0.7107	0.7249***
	(3.4450)	(5.4562)	(-1.6907)	(2.9659)	(1.5126)	(3.8567)
N	105	105	105	105	105	105
adj. R^2	0.5595	0.3634	0.6426	0.5895	0.4426	0.5186

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$