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Studies of liquidity in the London Stock Exchange

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Abstract

The thesis studies liquidity related issues in the London Stock Exchange from 2001 to 2013 from different viewpoints. The first chapter introduces and motivates the study. The second chapter fully discusses the liquidity and liquidity measures from multiple dimensions and examines liquidity using five liquidity measures: relative spread, the Amihud ratio, the Rtotr ratio, zero trading volume days and zero return days. The time-series study shows that liquidity changes over time and largely depends on the financial environment. The analysis compares liquidity measures and finds that Rtotr may not be a reliable liquidity measure during a financial crisis due to the turnover anomaly. Moreover, the empirical results support the prior findings in the literature that relative spread is positively related to volatility, and negatively related to price and trading volume. The Amihud ratio, zero trading days and zero return days are better measures of explaining relative spread. All these findings give a better understanding of liquidity measures and enlighten the following deeper research.

The third chapter continues to study liquidity and market characteristics from a panel viewpoint and the chapter extends the fixed effects model to solve the problem that some of the variables are not stationary. The panel results give more powerful explanations of liquidity. In particular, less liquid stocks are associated with higher volatility, lower price and lower

trading volume. Market value has differing relationships with the various liquidity measures.

The fourth chapter expands the liquidity research field and contains both theoretical and empirical work indicating that more liquid stocks have higher kurtosis and first lag autocorrelation due to higher transaction costs. In addition, the empirical results show skewness is also negatively related to liquidity. The final chapter presents the conclusions of the research.

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List of Abbreviations

No.	Abbreviation	Stands For
1	ADF	Augmented Dickey-Fuller
2	ADR	American Depositary Receipt
3	AIM	Formerly the Alternative Investment Market
4	Amihud	Return to Trading Volume
5	AMSE	America Stock Exchange
6	AR	Autoregressive Model
7	BBO	Best Bid and Offer
8	FTSE	Financial Time Stock Exchange
9	GLS	Generalised Least Square
10	LSE	London Stock Exchange.
11	LTCM	Long-Term Capital Management
12	MV	Market Value
13	NA	Not Available
14	NASDAQ	National Association of Securities Dealers Automated Quotations
15	NMS	Normal Market Size
16	NYSE	New York Stock Exchange
17	OLS	Ordinary Least Square
18	P	Price
19	PDF	Probability Density Function
20	PP	Phillips-Perron Test
21	R	Daily Return

22	RI	Return Index
23	RS	Relative Spread
24	Rtotr	Return to Turnover
25	SEAQ	Stock Exchange Automated Quotation system
26	STD	Standard Deviation
27	TR	Turnover Ratio
28	VOL	Trading Volume

Chapter 1 Introduction

1.1 Introduction

Liquidity is always a crucial issue in the financial field. In the stock market, liquidity is defined as the degree to which it is possible to trade a security close to its intrinsic value within a short period. If the security price deviates from its intrinsic value because of trading, this can be seen as illiquidity. The financial crisis in 2007 and 2008 caused world-wide market recessions, and one of the important related discussions is about liquidity. Market participants care about liquidity which is reflected in the return of stocks. Liquidity does affect market price and changes over time as shown by both theoretical and empirical works. Fully understanding and measuring liquidity is important for both investors and market makers.

The first chapter of the thesis focuses on liquidity and liquidity measures from an empirical perspective. The liquidity is affected by exogenous trading expenses, inventory risk and private information (Amihud et al, 2005). Usually, actual transaction costs involve brokerage fees. Inventory risk occurs when market makers have the risk of holding stock and price is changing quickly. As for private information, all market participants are worried about it and their willingness to trade depends on the counter party's private information. Liquidity issues are triggered when those situations exist. Measuring liquidity is a vital component when studying liquidity. Chapter 2 and chapter 3 study the comparison of liquidity measures and the relationship between liquidity measures and market characteristics from cross-sectional and panel viewpoints. The thesis shows the performance of liquidity measures in different situations. After fully discussing the liquidity related issues, we extend the liquidity research field by building a theoretical model to identity the links between liquidity and skewness, kurtosis and autocorrelation in chapter 4. Chapter 5 gives a conclusion to the thesis and discusses future research.

1.2 Motivation

Though many studies have discussed liquidity and liquidity measures in the last few decades, most of them concentrate on the US markets. The London Stock Exchange, as one of the oldest and largest stock markets, is in need of further research. In this thesis, the data is focused on UK domestic stock using daily data from 2001 to 2013. The long sample length and daily data ensure the power of the results for the study of time-series liquidity issues.

There is no consensus about measuring liquidity. Amihud and Mendelson (1986b) use relative spread which is defined as bid-ask spread divided by mid-quoted price to capture liquidity when studying the market liquidity. This directly measures the tightness of liquidity. Amihud (2002) propose the Amihud ratio to measure price impact using trading volume and daily return. Florackis et al (2011) develop the Amihud ratio to construct the Rtotr ratio using turnover rate and daily return to eliminate size bias. Both the Amihud ratio and the Rtotr ratio capture price impact which is a proxy for market depth. Lesmond et al (1999) and Kang and Zhang (2014) use zero return days and zero trading volume days respectively to capture liquidity. Based on these two measures, we directly calculate the number of non-return or non-trading days to measure illiquidity more intuitively in this thesis. The principle of zero return days is based on the notion that traders will not trade if the transaction costs are higher than the potential profit. In other words, marginal traders will trade only when the return is higher than the associated transaction costs. Zero trading days is a more direct measure than zero return days. All these five liquidity measures examine liquidity from different perspectives and thus the comparisons between them are interesting.

In Chapter 3, we examine the relationship between liquidity measures and market characteristics (volatility, price, trading volume and market value) from a panel viewpoint. In many prior papers and our results, the cross-sectional results are insignificant under certain circumstances, especially when liquidity changes over time. However, only using with cross-sectional data will not take account of any time-series effects. In contrast to cross-sectional data, panel data also contains time-series information. Panel data takes individual firm effects into consideration and unobservable effects can be eliminated. Thus the results from panel data are more powerful and efficient. Analysing panel data, however, is complex. In order to deal with non-stationarity problems in the variables, we extend the fixed effects model to compare the relationship between liquidity measures and market proxies by decomposing the intercepts of the fixed effects model. We then focus on the relationship between liquidity measures and price, and market value which are both non-stationary.

Chapter 4 firstly tests the relationship of liquidity with skewness, kurtosis and autocorrelation using a new model. Transaction costs or trading expenses are one of the main reasons for stock illiquidity and we focus on these in this chapter. In theory, stock price movements follow a random walk and a price movement is not related to the previous movement. In practice, price movements do not follow a random walk. Ng et al (2008) find that transaction costs affect the time-series properties of returns. If the market is not liquid, stock prices will deviate from their intrinsic value because of transaction costs. Under this situation, prices will not follow a random walk and autocorrelation will exist. Based on the previous findings and assumptions, we develop a new model to test this aspect of price movements. The model also indicates that less liquid stock with higher transaction costs have higher kurtosis.

1.3 Contribution

The thesis aims to contribute to a deeper understanding of liquidity issues in the UK market and uses a long sample period to support and develop the academic research of liquidity. This thesis covers the stock liquidity field in the London Stock Exchange where there is a lack of prior studies. The five liquidity measures cover different dimensions of liquidity attributes, such as tightness and market depth. The varieties of liquidity measures provide a more comprehensive understanding of liquidity characteristics. Relative spread captures trading costs; the Amihud ratio and the Rtotr ratio capture price impact; zero trading days and zero return days are more intuitive liquidity measures based on direct observations of trading and returns. The time-series studies of liquidity measures show that liquidity changes over time, and support the finding of Amihud and Mendelson (1987). The financial crisis undoubtedly affected market liquidity and market return is negatively related with market liquidity. The FTSE All-Share Index movements tend to have opposite movement trends compared to those of the relative spread and zero trading days measures from 2001 to 2013. The study shows that trading costs are negatively related to stock market conditions. Therefore, liquidity largely depends on the economic environment.

Simple cross-sectional correlation analysis and portfolio analysis show that the liquidity measures are highly positively related to one another. Less liquid stocks seem to have lower trading volume, market value and turnover rate.

In order to fully study the time series results, we divide the whole period into three sub-periods and results show that turnover rate may not be a reliable liquidity measure during the financial crisis. Using time-series correlation analysis, the results show that turnover ratio is positively related to liquidity measures, such as relative spread, during the financial crisis. It can be seen as higher transaction costs are associated with higher turnover ratio. Investors would ignore higher transaction costs during crisis. The Rtotr ratio involves the turnover ratio for capturing trading frequency. Summer's (2000) research shows that turnover is likely to goes up during liquidity crunches, as occurred during the Tequila Crisis, the Asian Crisis and the Brazilian Crisis. The result shows that the turnover rate cannot measure market liquidity during a financial crisis. Thus the Rtotr ratio may not be a reliable liquidity measure when financial crises or abnormal events happens. Moreover, the correlation coefficient between trading volume and turnover rate is 0.086 during financial crisis, which is much lower than any other period. All these interesting findings deserve more investigation in different markets in the future.

Based on the Stoll (2000) and Lesmond (2005) cross-sectional models, we support the findings that relative spread is positively correlated with volatility and negatively related to price and trading volume. Higher volatility stocks have higher transaction costs because the market makers want to have more compensation for volatility risk. Low price and trading volume stocks are less liquid and riskier so the transaction costs are higher. The relative spread is significantly negatively related to market value which is a different result to Stoll (2000) and Lesmond (2005). Larger market value stocks have less inventory risk so the transaction costs are lower. Also, the Amihud ratio, zero trading days and zero return days are better liquidity measures explaining transaction costs with higher R square value when added into regression models.

One of the main contributions of this thesis is the panel model of dealing with the five liquidity measures and market proxies. To our knowledge, it is the first study using a panel regression model to study liquidity. The results firstly show the relationship between liquidity and volatility, price, trading volume and market value using both panel and cross-sectional data. In addition, the extension of the fixed effects model solves the non-stationary problems for price and market value.

The highlight of the panel regression is that in contrast to the cross-sectional results, all the panel regression results are significant. Most coefficients of the cross-sectional regression, such as price, trading volume, are insignificant due to averaging values over a long period when liquidity changes over time. The panel regression approach clearly solves the problem and makes the results more efficient and powerful. The panel results show that relative spread, the Amihud ratio and the Rtotr ratio are positively related with volatility and negatively related with price and trading volume. Zero trading volume days and zero return days are negatively related with those market variables. Overall, the less liquid stocks tend to have higher volatility and low price, trading volume. More specifically, market makers who are afraid of volatility risk want more compensation. Relative spread is larger when market makers are uncertain about future returns. Higher volatile stocks are also related to low market depth as shown by higher Amihud ratio and Rtotr ratio. The negative connection between volatility and 0 trading days and 0 return days indicates that highly volatile stocks are more frequently traded in the stock market. More non-trading days cause low volatility. Lower price and trading volume stocks are less liquid. While, market value is inconsistent with different liquidity measures, it supports the findings of Stoll (2000) and Lesmond (2005).

Chapter 4 investigates the relationship between liquidity and return autocorrelation. Based on the approach in Ng et al (2008), we create a model to show the links between transaction costs and autocorrelation (lag 1). The model shows that larger transaction costs have a larger price movement bound. More specifically, the higher current trading expenses would lead to higher upper bound price or lower bound price. We also find that a positive price movement may lead to a positive price movement in the next period. Similarly, if the previous price movement is negative, the next period price movement would be negative. Thus, the autocorrelation is larger than zero. Continuations of trends in price movement depend on the transaction costs. When the transaction costs are higher, the stocks are less liquid and market participants may not react quickly to new information so that the price of a stock may not reflect its intrinsic value. So the autocorrelation is higher when the market is less liquid. The empirical results from the regression model support the assumption that less liquid stocks are associated with higher autocorrelation.

What is more, higher transaction costs can affect return distributions, as measured by factors such as skewness and kurtosis. The theoretical work has shown that higher trading expenses lead to leptokurtism. We also run simulations of return distribution and the results support the theoretical findings. In addition, the regression models, on the actual market data, show that less liquid stocks exhibit higher kurtosis. The relationship between transaction costs and skewness is more interesting. There is no obvious direct links, but the decile portfolios results show that stocks with negative skewness are less liquid. The empirical regression models also give the result that less liquid stocks are negatively related to skewness. This chapter expands the liquidity research field and explains the relationship between liquidity and stock returns in different ways creating possibilities for future research.

Chapter 2 Liquidity and liquidity measures comparison

2.1 Introduction

This chapter gives an integrated discussion about liquidity related factors and liquidity measures in the stock market. Liquidity in the stock market can be described as the ease of trading a security. If the stock can be traded quickly with low trading costs, the stock can be seen as a liquid stock. In general, there are three liquidity characteristics: tightness, depth and resiliency. All the liquidity measures are built to capture one or more characteristics. Although there are a number of studies on the London Stock Exchange, which is one of the largest stock markets, there is a lack of research about liquidity. The trading systems have improved in the last thirty years in this market and helped to increase market liquidity as discussed below.

Since Amihud and Mendelson (1986a) first linked stock market liquidity and spread, a number of liquidity measures have been created. From single-dimension measures (like trading volume, turnover rate) to multi-dimension measures (like the Amihud ratio and RtoTR ratio), every liquidity measure has its own properties. In this study, we not only use intuitive ways to measure liquidity, but also evolve complex approaches to capture liquidity. In this thesis, there are five liquidity measures: relative spread, the Amihud ratio, the RtoTR ratio, zero trading volume days and zero return days. Relative spread is one of the most traditional measures. The Amihud ratio and the RtoTR ratio capture the price impact and have been proved to perform well in developed countries. Zero trading volume days and zero return days are the most direct liquidity measures. One of the major contributions of this chapter tests the Lesmond (2005) model and gives a comparison of five different liquidity measures in the London Stock Exchange

This chapter contributes to the knowledge of stock liquidity in the London Stock Exchange by proposing an elaborate exercise studying liquidity both from time-series and cross-sectional viewpoints with five different liquidity measures. Liquidity changes over time and it fluctuated heavily during the financial crisis (Amihud et al, 1990). In this study, time-series liquidity measures based graphs illustrate trends in liquidity from 2001 to 2013. The FTSE All-Share Index is used to represent the market movement in the London Stock Exchange. The results show that liquidity do change over time and different time periods have different liquidity conditions. The liquidity proxies have a close relationship with the market price movement (FTSE All-Share Index).

Stoll (2000) studied friction and found links between spread and market characteristics, such as price and volume. Lesmond (2005) based on Stoll’s (2000) research, compared liquidity measures using a cross-sectional regression model. In this study, we follow the model and compare five liquidity measures, testing the relationship between them and market proxies.

Based on various methods, we show that the turnover ratio may not be a trustable liquidity proxy (Lesmond, 2005, Bekaert et al., 2007). Both time-series and cross-sectional results show that RtoTR, which includes the turnover ratio, performs worst when measuring liquidity compared with the other four liquidity measures. Though RtoTR does not have a size bias issue, it is poor at measuring liquidity when a financial crisis occurs.

Based on the models of Stoll (2000) and Lesmond (2005), the cross-sectional regression results show that the Amihud ratio, zero trading days and zero return days have increased explanatory power over other market characteristics and liquidity proxies. It supports Lesmond (2005) that the Amihud ratio and zero return days outperform other liquidity measures of explaining transaction costs. The relationships between relative spread and volatility, price and trading volume support Lesmond’s (2005) findings: positive for volatility, negative for price and trading volume. The results are also consistent with those of Stoll (2000).

There are three major contribution of Chapter 1. First, we use five different liquidity measures to test multiple liquidity aspects and show liquidity changes over time n the London Stock Exchange. Extending existing empirical work in the London Stock Exchange is quite promising. The economic situation has significant effect on liquidity condition. The findings also support some previous literatures that turnover ratio is not a reliable liquidity measure during the financial crisis. It can be explained by the ignorance of trading costs during the crisis. We test Stoll (2000) and Lesmond (2005)’s model in the London Stock Exchange, and find that Amihud ratio, zero trading days and zero return days are better liquidity measures at capturing relative spread (transaction costs). In addition, liquid stocks tend to have lower volatility, higher price, trading volume and market capitalization.

The chapter is designed as follows. The first section presents the literature review on the basic knowledge relating to liquidity, liquidity factors and liquidity measurements, and also an introduction to the trading mechanism and market structure. The history of trading system changes in the London Stock Exchange is also included in this section. The second section presents the liquidity measures which we choose to use and data details. The third section gives some basic descriptive data information including graphical analysis, correlation analysis and portfolio analysis. The last section presents the results and a discussion of liquidity measures comparisons in the London Stock Exchange using the model of Lesmond (2005).

2.2 Literature Review

2.2.1. Trading mechanism and market structure

2.2.1.1 Introduction

Securities markets are mechanisms for grouping buyers and sellers together and letting them trade (Foucault et al., 2013). There are three reasons for trading securities: hedging risk, speculation and arbitrage. Trading rules change over time and market organizers try to maximize the efficiency of markets by realizing trading gains and discovering asset values.

Foucault et al (2013) state that a trading mechanism defines the “rules of the game” that market participants must follow: it determines the action they can take (e.g., the kinds of orders they can place), their information about other market participants’ actions (e.g., whether they see quotes or orders), and the agreement to match buy and sell orders (e.g., whether orders are executed at a common price or not). There are two main types of trading mechanisms: the limit order market (or auction market) and dealer market. In a limit order market, which is also called an order-driven market, the final trades are based on price priority principles, so the higher bids and cheaper offers are more likely to be executed. By contrast, investors can only trade stocks with prices that are settled by specialized intermediaries, called “market makers” or “dealers” in a dealer market (quote-driven system).

In a limit order or auction market, investors’ orders are matched directly by trading platforms, normally electronic platforms like BATS in the United States or Chi-X in Europe. In a dealer market, all trades are mediated by professional intermediaries who set ask prices, at which the potential investors can buy securities from them, and bid prices, at which the potential investors can sell to them. So the buyers and seller are not directly connected with each other. Actually, many stock markets are hybrid, combining features of these two original mechanisms (Marshall, 2006, Foucault et al, 2013).

2.2.1.2 Trading system in the London Stock Exchange

The LSE is one of the largest and oldest stock exchanges in the world. In order to maximize liquidity for all participants and become more readily competitive with other world-class exchanges (such as the New York stock exchange), the LSE has undertaken a series of changes since the ‘Big Bang’ in 1986, which was one of the most important milestones in the history of the LSE. The trading system was a major change resulting from this.

Clemons and Weber (1990) state that before the Big Bang the LSE was lagging behind other world-class exchanges because of its relatively low trading volume. The Big Bang represented the deregulation of the securities market. In 1986, the LSE became one of the first exchanges to trade stock via computer and telephone instead of performing trading face to face on a market floor. This was realized by adopting a computerized system known as SEAQ, which is a quote-driven system that continuously displays up-to-date stock prices quoted by market makers and trading reports for stocks. This system is supported by dealers who quote firm bid and offer prices, and a maximum transaction size for the securities in which they are registered. Prices for larger transactions are subject to negotiation. Dealers are obliged to display this information to the market throughout the trading day. SEAQ is a competitive dealership market. Brokers wishing to respond to a bid or offer must contact the displaying firm by telephone and arrange the transaction.

Michie (1999) believes that the most important feature of the SEAQ system is the existence of market makers. Market makers provide bid and offer prices with the suggested normal market size (NMS)[1] for those prices, effectively competing with other market makers to display the best prices for stocks.

The introduction of the SEAQ system greatly increased liquidity as well as trading volumes in the LSE. To tackle the increasing volumes of business, the LSE launched a new electronic system in 1997, SETS, which replaced the SEAQ system used by the top 100 stocks.

SETS is a fully automated, screen-based system for all the securities in the FTSE 100 Index and many of the securities in the FTSE 250 Index. The order book is based on an order matching system in which member firms display their bid (buying) and offer (selling) orders to the market. Public investors can also display their orders through member firms' systems. Orders entered into the system are displayed anonymously and automatically executed during continuous trading when the price details match one another.

The introduction of SETS means trading by telephone happened less and less, as buyers and sellers are matched automatically and orders are displayed on a computer screen which can show the whole picture of what is happening on the stock market and improve the transparency of stock trading. The biggest difference between the SETS system and SEAQ lies in the market makers. In the SETS system, there are no market makers; this also means that the bid–offer spread is narrower. However, people can still trade through market makers in the LSE.

There are now three major trading systems in the domestic market in the LSE: SETS, SETSqx and SEAQ. SETSqx (Stock Exchange Electronic Trading Service – quotes and crosses) is a trading service for securities that are less liquid than those traded on SETS. SETSqx replaced SEAQ for all Main Market securities in October 2007.

[1] NMS is used to set the minimum quoted size that market maker are required to trade. The normal market size is normally set at 2.5% of the total volume of shares for a given company. This stops very large trades from affecting the share price as market makers are not obliged to provide quotes for transactions which fall outside of the normal market size.

SEAQ is the LSE's non-electronically executable quotation service, which currently allows market makers to quote prices in AIM (formerly the Alternative Investment Market) securities (those not traded on SETS or SETSqx), as well as a number of fixed interest securities.

Consistent with earlier studies (Stoll, 2000; Cai et al, 2004) suggest that the total cost of trading is lower on order-driven systems. It is clearly seen that for liquid securities the real cost of trading is lower owing to increased order flow and competition from public investors (through limit order placement) for the provision of liquidity. However, Cai et al. (2004) also indicate that informational asymmetry is significantly higher in order-driven systems, which could possibly be due to the anonymity of market participants (and counterparties to transactions) or stealth trading by informed investors. Significantly, order size has a major impact upon the level of informational and real frictions, and medium trades have very high informational costs compared to small and large ones.

Muscarella and Piwowar (2001), Kalay et al (2002) and Jain (2005) find that improvement of trading system make the market more liquid. The development of trading systems in London Stock Exchange has improved market liquidity. In one World Federation of Exchanges report, the turnover ratio changed from 40.5% in 1995 to 152.7% in 2008 in the LSE (Florackis et al., 2011). Naik and Yadav (2004) state that when FTSE 100 stocks are traded on an electronic limit-order trading system, liquidity is significantly increased. The reduction of trading commissions has also contributed to the growth of alternative, automated trading systems (Chakravarty et al., 2005).

2.2.2 Basic concept of liquidity

2.2.2.1 Liquidity and liquidity risk

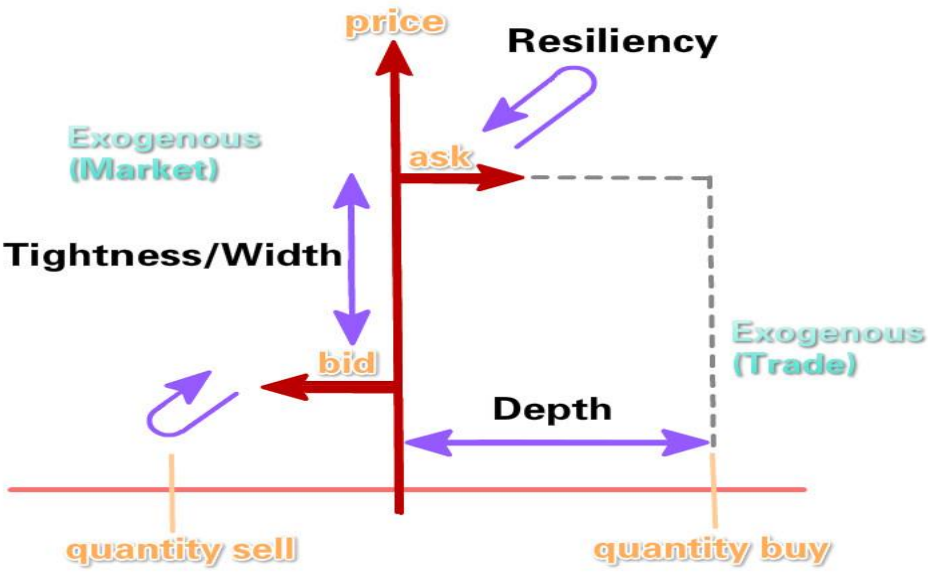
Liquidity is a complicated concept and it can be explained in different ways in different fields, such as macroeconomics, corporate finance and financial economics. In the financial market field, there is no consensus regarding a precise explanation of liquidity. Kyle (1985) state that liquidity is an elusive concept. Amihud (2002) proposes that liquidity cannot be captured in a single way and should be measured in different dimensions. However, liquidity, usually defined as market liquidity, can be considered to be the ease of trading a financial instrument or the degree to which an asset or security can be bought or sold in the market without affecting the asset's price (Galariotis and Giouvris, 2009, Chiang and Zheng, 2015). Assets that can be bought or sold easily are known as liquid assets (e.g. Government bonds, large company stocks, treasury bills, etc.). Illiquid assets, such as residency mortgage-related assets, which figured prominently in the recent financial crisis, are those that cannot be sold quickly and sold fairly (e.g. small company stocks, property, etc.).

There are two kinds of liquidity risk: funding liquidity risk and market liquidity risk (Brunnermeier and Pedersen, 2008). Funding liquidity risk is associated with cash flow. Funding liquidity is the ability to settle obligations with immediacy. Therefore, an institution is illiquid (meaning that it is experiencing a funding liquidity risk) if it is unable to meet its liabilities and obligations (for example, pay its bills) as they become due without suffering unacceptable losses. Current ratios (the ratio of current assets to current liabilities) and the quick ratio (the ratio of current assets less inventories to current liabilities) are the classic indicators of funding liquidity risk.

Market liquidity risk is associated with the ease of exiting a position. It can be seen as the risk which occurs when a position cannot be offset quickly without heavily affecting market price. For example, real estate may suffer market liquidity risk because, in most cases, it cannot be sold immediately unless a low price is offered. Compared to funding liquidity risk, market liquidity risk is more relevant in the stock market. Market liquidity has been a critical role since the LTCM (Liang and Wei, 2012), and it is more focused after financial crisis from 2007. Consequently, this thesis focuses on the market liquidity risk.

There are at least three angles used to measure market liquidity risk: tightness, depth and resiliency (Kyle, 1985). Firstly, tightness, also called bid–ask spread, measures market liquidity in the price dimension. It measures the divergence between actual transaction prices and quoted midmarket prices. High liquidity assets will have a tight bid–ask spread. The gap between actual transaction price and quoted price is small. Secondly, highly liquid assets are also characterized by good depth, which is a measure of the volume of trades possible without affecting prices too much. This measures liquidity in the quantity dimension. For large quantity transactions, market liquidity can be measured by market impact (also called endogenous liquidity), which illustrates how the price changes with the transaction quantity. For example, if there is a large buying order for a highly liquid stock, the order would have less impact of driving the price higher. Such a large volume order for an illiquid stock results in a higher price for that stock. Thirdly, market liquidity is assessed in the time dimension by resiliency. Resiliency means the market's ability to rebound from temporarily incorrect prices. For example, when a large amount of stock is sold in a liquid market, prices may fall temporarily but should rebound quickly. Therefore, for liquid assets, large volumes of transactions do not influence prices much.

Figure 2.1: Liquidity characteristics



Moreover, many authors explain the liquidity attributes in different ways. Sarr and Lybek (2002) propose that there are five attributes of stock liquidity, with two more attributes that add on Kyle's measures (1985). One is immediacy, which captures the speed at which preset orders can be executed. More specifically, a dealer market and pure auction market have different trading mechanisms in different stock exchanges.

Thus immediacy may vary in different stock markets. The other is breadth, which is defined as a situation where orders can be both numerous and huge in volume, with little impact on prices.

2.2.2.2 Factors affecting liquidity

There are several factors affecting the illiquidity of securities. First, demand pressure and inventory risk could trigger illiquidity in an asset (Amihud et al, 2005). Demand pressure or inventory risk occurs when buyers or sellers want to buy or sell an asset immediately but market participants cannot meet their urgent request. As a result, market makers have to meet the agent's request and expose themselves to the risk of price changes while they have the asset in inventory. In order to compensate for this risk, a compensation cost will transfer to the market maker. And this compensation cost can be seen as illiquidity, which costs the agent more money. At the same time, large buying or selling orders could trigger a price impact that leads to a higher price for buying or a lower price for selling. This is quite similar to the market depth discussed previously. The price impact can be several percentage points associated with the transaction costs. The size of the price impact determines the liquidity of the stock with high price impact indicating less liquidity.

Second, private information is another factor (Bagehot, 1971, Kyle, 1985, Easley and O'Hara, 1987, Glosten and Harris, 1988, Brennan and Subrahamanyam, 1996, Gârleanu and Pedersen, 2004). Amihud et al. (2005) state that certain investors or corporate insiders could gain superior information (or information processing ability) about the basic value of a stock. This could lead to an adverse selection problem: informed traders in possession of bad news are likely to sell, and informed traders with good news have an incentive to buy (Akerlof, 1970). For instance, an informed trader could have a better return due to private information. Market participants with private information have an incentive to take into strategic account the price effect of their trades, and market makers strategically protect themselves against informed traders (Amihud et al., 2005). Bagehot (1971) states that market makers obtain money by trading with uninformed liquidity traders and lose it to informed traders. Kyle (1985) maintains that a market where an informed and an uninformed "noise" trader each submit a market order for an asset would mean the market maker setting the price depending on the aggregate order flow such that he or she emerges with zero gain. This is because the market maker cannot distinguish which order flow is proposed by an informed trader or uninformed trader. An agent having private information can sell the stock at a higher price and buy the stock at a lower price. Under this situation, market makers have to set higher bid-ask spreads to compensate thus making assets less liquid. Diamond and Verrecchia (1991) state that information asymmetry has negative effect on market liquidity.

Third, exogenous transaction costs, such as brokerage fees and order processing charges, occur when a security is traded. Lo et al. (2004) have found that the trading expenses can be large when the market participants have high-frequency trading needs. For example, when there are large numbers of orders for buying one stock, the stock's demand pressure increases dramatically and it costs market participants more in compensation to buy the stock. (different trading system charges or faxes)

2.2.3 Liquidity measurement

2.2.3.1 Spread

Spread can capture the costs of trading stocks and trading frictions in a stock market. Besides trading fees and trading taxes in the stock exchange, investors also have to pay the bid–ask spread, which is a cost for the instant command of a trade.

2.2.3.1.1 Relative spread

The most intuitive measure of the cost of a small round-trip transaction is the gap between the best ask quote and best bid quote, known as the bid–ask spread. If we want to normalize it by the midprice (average price of bid price and ask price), it will become the relative spread, where:

$$Relative\,spread = \left|\frac{ask\ price - bid\ price}{mid\ price}\right|$$

In the United States, the quoted spread is known as the Best Bid and Offer (BBO), because they can be entirely filled at the best quotes. The quoted ask (offer) price contains a premium for immediate purchase, and the bid price similarly reflects a concession required for immediate sale. Foucault et al (2013) mention that the relative spread for small orders is the most widely reported measure of illiquidity. Aitken and Forde (2003) also state that this is an effective and accurate way of calculating the liquidity of stocks for small investors.

Especially for larger stock orders, orders are usually gauged by conducting a weighted average bid–ask spread. For example, for the buy and sell limit orders requested at a given point in time, assume that the average execution price for a bid market order of size t is $b(t)$ and the average execution price for an ask market order size t is $a(t)$. The weighted-average bid–ask spread for an order size t is $S(t) = b(t) - a(t)$, so the relative weighted average bid–ask spread is:

$$S(t) = \frac{b(t) - a(t)}{mid\ price}$$

Consequently, when t is so small that the entire offer can be filled at the BBO, this reduces to the spread s. In this situation, $S(t)$ rises when the trade size t increases. The depth of market can affect the spread with a larger trade size *t*.

There are several drawbacks to this method. Petersen and Fialkowski (1994) conclude that actual transaction costs cannot be measured through the quoted spread. The relationship between actual transaction costs and the posted bid–ask spread is quite weak. Records of daily bid–ask spreads may provide little useful information since they are noisy data and usually from end-of-day transactions. Market makers may also manipulate closing price bid–ask spreads, which will generate useless information. Acharya and Pederson (2005) state that bid–ask spread does not measure the costs of trading many shares very well. For instance, if an investor wants to buy 1000 shares of stock, and there are only 100 shares available at the moment, then the investor must increase the price to get another 900 shares of stock. Market impact and the opportunity cost of trading are not considered when it comes to large trades using relative spread.

2.2.3.1.2 Effective spread

Effective spread is another spread measurement. Although in many papers, the definitions of effective spread are slightly different usually it is defined as the absolute value between the trade price and the corresponding quote midpoint price. For example, a bid order for 1000 shares arrives and executes at an average price of 50.50, when the current midquote price is 50.45. The effective spread of this order is 50.50-50.45=0.05, which is also called the percentage of the midquote 0.05/50.45=0.099%.

Chordia et al. (2000) propose two definitions: one is the effective spread, which is defined as the difference between the execution price and the mid-point of the prevailing bid–ask price; the other is the proportional effective spread, which is defined as the effective spread divided by the mid-point of the prevailing bid–ask price.

Cao and Petrasek (2014) define effective spread as 2× (|P-M|)/M in their research, where P is the closing price and M is the quoted midpoint price. They state that the quoted midpoint price reflects the fundamental value of the stock and the effective spread can be set as the difference between the transaction price and the fundamental value of the stock. In theory, the quoted spread does not take orders into consideration. The orders are executed at prices better than the original set spread.

The effective spread can be seen as a measure of price impact, because it measures the deviation of the actual execution price from the midprice prevailing just before the trade (Foucault et al, 2013). For larger orders, the effective spread increases as trades occur at less favorable prices.

However, this measurement is hard to calculate. The classification of buy or sell data is complex. Error noise cannot be eliminated. In addition, the basic theory of effective spread is based on comparison of the average price and prevailing price and reconstructing these orders is hard to execute.

2.2.3.1.3 Amortized spread

Chalmers and Kadlec (1998) have examined the effect of amortized spread in AMSE

(America stock exchange) and NYSE (New York stock exchange) in the US market. This measure captures both the magnitude of the spread and the length of investors' holding periods (Chalmers and Kadlec, 1998). It is defined as the product of the effective spread and the number of shares traded aggregated over all trades for each day and expressed as an annualized fraction of equity value. In other words, amortized spread can be seen as effective spread multiplied by share turnover.

$$Amortized\ spread \approx \frac{|P-M|}{P} \times \frac{V}{Shares\ out}$$

where P is the transaction price and M is the midpoint of the prevailing bid–ask quote, V is the number of shares traded. Marshall and Young (2003) also choose amortized spread to measure liquidity in the Australian stock market.

But amortized spread only reflects transaction costs which are related to the bid–ask spread. Brokerage fees or commissions are not tested. And more importantly, the bid–ask spread on the required return is determined by expecting holding periods, while the amortized spread captures the realized holding return. The limitation is significant if the stock's amortized spread is significantly driven by unanticipated shocks to turnover (Marshall, 2006).

2.2.3.2 One-dimensional volume based liquidity measures

In the early work on testing liquidity, many researchers used alternative measures based on daily data on volume, shares outstanding and prices. These data are available for most markets. These data are generally much easier to obtain compared to spread data.

Brennan et al. (1998) use the stock's dollar trading volume as a factor testing liquidity.

Datar et al. (1998) use stock turnover (the ratio of stock trading volume to the number of shares outstanding) as a measure of liquidity. Rouwenhorst (1999), Ang and Levine and Schmukler (2003) also use the turnover to measure stock liquidity. The higher the turnover of a stock, the more liquid it is, because the demand is high compared to the number of shares outstanding.

2.2.3.3 Multi-dimensional volume based liquidity measures

By contrast with the former simple proxies of liquidity, researchers have tried to capture more aspects of the characteristics of liquidity. Combining a one-dimensional liquidity measure with multi-dimensional liquidity measures is popular[2].

The first well-known multi-dimensional liquidity measure is the Amivest liquidity ratio. Khan and Baker (1993), Amihud et al. (1997) and Berkman and Eleswarapu (1998) test the Amivest liquidity ratio in their research. The Amivest liquidity ratio is:

$$Amivest_{it} = \frac{1}{D}\sum_{d=1}^{D_{it}} \frac{|Volume|}{|R_{itd}|}$$

where R_{itd} is the daily return (daily percentage of price change), D_{it} is the number of trading days in year *t* and volume is the trading volume of day *i*. The ratio tests the price impact of a stock and implies a one percent change in share price. So, if the stock has a higher Amivest ratio, one share of stock needs to be traded frequently to move the stock price. A lower ratio means that the stock is less liquid.

The most impressive aspect of the Amivest ratio is that it combines the trading volume and absolute price change in one single dimension. The ratio shows that a stock can take trading volume without changing price. A higher ratio suggests that a large trading volume has little consequence on price. In other words, a higher ratio represents better liquidity of a stock.

There are several drawbacks to this measure. The first one is that it does not take spread into consideration. Secondly, it does not include non-trading days, which often happen in emerging markets and for small stocks.

Amihud (2002) creates a model testing the effect of illiquidity:

$$Amihud\ ratio = \frac{1}{D_{it}}\sum_{d=1}^{D_{it}} \frac{|R_{iyd}|}{VOLD_{iyd}}$$

[2] Also, some researches divide liquidity measures into: trading based measures and order based measures (Chollet et al, 2006; Goyenko et al, 2009)

R_{iyd} is the return (daily price change) on stock i on day *d* of year y, and $VOLD_{iyd}$ is the respective daily volume in dollars (Amihud, 2002). In my research, VOLD=price $\times$ turnover by volume.

This ratio gives the absolute percentage price change per dollar of daily trading volume, or the daily price impact of the order flow. The Amihud ratio is also quite close to the theoretically well-based concept of Kyle's (1985) λ (price impact proxy) and Silber (1975)'s measure of thinness (the ratio of absolute price change to absolute excess demand for trading). More specifically, large buy or sell orders of illiquid equities result in widening short-term stock price movements because of adverse selection and inventory costs. Brennan et al. (1998) and Chordia et al. (2001) have already shown that liquidity is highly correlated to trading volume. This ratio is used to find the effect of trading volume on stock price movement (Acharya and Pedersen, 2005). The ratio directly measures the impact of a (monetary) unit of trading volume on stock return and means that the larger the response of returns, the more illiquid the equity is considered to be (Florackis et al. (2011). Amihud (2002) state the Amihud ratio can be seen as a disagreement between traders about new information. If there is a stock price change without trading, it indicates an agreement of the implication of news. While if there is a disagreement of new, the trading volume would increase. So the Amihud ratio can be interpreted as a measure of consensus belief among investors about new information.

Amihud's (2002) ratio has its shortcomings. Firstly, there is a significant bias within the ratio from a cross-sectional perspective. It cannot compare stocks with different market capitalization. Size effect has been existence for a long time (Banz, 1981, Ye and Turner, 2014). Cochrane (2005) states that the Amihud ratio is expected to be much higher for small stocks and it could lead to the inaccurate conclusion that stocks with a small market value are more illiquid than stocks with a large market value. Secondly, investors' stock holding horizons are not considered in the ratio. Although this ratio is intended to calculate the transaction cost in an intuitive way, trading frequency is not fully incorporated in the ratio. As discussed above, trading frequency is quite important, for both cross-section and time-series variation. And zero volume days also occur leading this estimator to be undefined.

Florackis et al. (2011) propose a new price impact ratio, which is based on the return-to-turnover ratio. They use data from stocks traded on the LSE:

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}}$$

where TR_{itd} is the turnover ratio of stock i at day d and D_{it} and R_{itd} are as previously defined. In contrast with Amihud's ratio, Florackis et al. (2011) have developed the Amihud ratio by changing trading volume to turnover ratio in the denominator of Amihud's ratio. There is no size effect bias in the RtoTR ratio because turnover does not necessarily exhibit an inherent size-related pattern. Moreover, turnover rates can also incorporate the effects of trading frequency on asset prices. Lesmond (2005) states that turnover is a ubiquitous liquidity proxy. It captures trading frequency.

However, Lesmond (2005) proposes that turnover cannot account for the cost per trade, which changes significantly in assets. Moreover, turnover is likely unable to capture liquidity conditions during a financial crisis.

2.2.3.4 Non-trading measures

Lesmond et al. (1999) propose a new measure, which is called LOT.

$$ZR_{i,t} = N_{i,t} / T_t$$

where T_t is the number of trading days in month t and $N_{i,t}$ is the number of zero-return days of stock i in month t . One potential caveat of ZR is that it may produce the same level of illiquidity for multiple stocks for multiple periods. Informed traders will trade only if the value of information exceeds the marginal costs of trading (Garman and Ohlson, 1980, Lo et al, 2004). Zero return days happen more frequently because new information must aggregate more before informed trades affecting price. So possible informed trades and commission costs are expressed in this equation.

Liu (2006) proposes a turnover-adjusted zero-return measure,

$$LMx_{i,t} = \left[N_Z + \frac{\frac{1}{TV_\chi}}{DF} \right] \times \frac{21\chi}{N_\chi}$$

where N_Z is the number of zero-volume days in the previous *x* months; TV_χ is turnover over the previous *x* months, which is computed as the sum of the daily trading volume divided by the number of shares outstanding; N_χ is the total number of trading days over the previous χ months; and DF is a deflator that constrains the ratio. Lam and Tam (2011) and Kim and Lee (2014) also use this zero-volume days to measure liquidity in Hong Kong stock market and US market.

This equation captures multiple dimensions of liquidity (Liu, 2006). The number of zero daily trading volume captures the continuity of trading and the potential delay or difficulty in executing orders. And the turnover adjustment captures the dimension of trading quantity.

Bekaert et al. (2007) continue Lesmond (2005) study with zero return days to measure liquidity and find no-trade days similarly to no-return days suggest low liquidity.

Based on former study of Zhang (2010), Kang and Zhang (2014) state that the proportion of zero-volume days can measure the occurrence of the no-trade phenomenon more directly than the zero-return measure. The zero-based measure known as Zero Vol, is defined as follows:

$$ZeroVol = \frac{Number\ of\ days\ with\ zero\ volumes\ in\ a\ month}{Total\ number\ of\ trading\ days\ in\ a\ month}$$

In many emerging markets, the frequency of non-trading days is quite high. In such markets, there are days or even weeks when no transactions are recorded and the exchange simply reports the “stale price” of the last actual trade. Also, when an emergency arises, such as a financial crisis, non-trading measures are better proxies for illiquidity.

2.2.3.5 Other measures

Roll (1984) proposes a new estimator of the effective spread from the serial covariance of the change in price. Roll's measure needs a negative autocovariance return. If the sample serial covariance is positive, the Roll measure is undefined and set to be equal to zero. The version of the Roll's measure estimator is: P_{t-1}

$$\text{Roll} = \begin{cases} 2\sqrt{-Cov(\Delta\text{Pt} - \Delta\text{Pt} - 1)} \\ 0 \end{cases}$$

If when $Cov(\Delta\text{Pt} - \Delta\text{Pt} - 1) < 0$, the Roll value is $2\sqrt{-Cov(\Delta\text{Pt} - \Delta\text{Pt} - 1)}$, while if $Cov(\Delta\text{Pt} - \Delta\text{Pt} - 1) \geq 0$, the Roll value is zero.

Hasbrouck (2004) examines a Gibbs sampler estimation of the Roll model. The assumption is that the public information shock in the Roll model is normally distributed.

Easley et al. (2002) use a probability of informed (PIN) trading model to test informed trading, where PIN focuses on the fraction of informed-based orders. It is straightforward to show that the probability that the opening trade is information-based, PIN , is

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b}$$

where $\alpha\mu + \varepsilon_s + \varepsilon_b$ is the arrival rate for all orders and $\alpha\mu$ is the arrival rate for information-based orders; ε_s is rate of orders from uninformed sellers; ε_b is the rate of orders from uninformed buyers. The ratio is thus the fraction of orders that arise from informed traders or the probability that the opening trade is information-based. The result shows that PIN is negatively correlated with size and positively correlated with the bid–ask spread.

2.2.4 Comparison of liquidity measures

Due to the increasing importance of liquidity in finance, especially asset pricing, there is much work in the literature classifying different types of liquidity measures and comparing the results from using different measures.

Aitken and Forde (2003) state that liquidity measures can be divided into two broad types: trade-based measures (trading volume) and order-based measures (bid–ask spread). The choice of measure is of importance since this study highlights that there is little correlation between these two types of measures, which means different measures may produce significantly different results. Other evidence indicates that measuring liquidity using an order-based measure results in a better proxy for liquidity.

Lesmond (2005) compares Roll's measure (Roll, 1984), the Amivest measure (Amihud et al., 1997), the Amihud ratio (Amihud, 2002), LOT measure (Lesmond et al., 1999) and turnover among 31 emerging markets. This shows that each measure has its own strengths and weaknesses when used to compare cross-country or within-country liquidity. With factor analysis and the Vuong (1989) model, the results show that the LOT measure (zero return days) provides stronger explanations of market characteristics.

The study by Goyenko et al. (2009) gives valuable summary information by conducting a comprehensive investigation of all liquidity measures which are widely used in the literature: effective spread, realized spread, Roll's (1984) measure, the LOT measure, Amihud ratio and so on. The methodology is to conduct annual and monthly estimates of each proxy against liquidity benchmarks in order to decide which measure is the best. Their findings suggest that the new effective and realized spread outperforms the others most of the time, while Amihud's measure (2002) does better when measuring price impact.

Florackis et al. (2011) test the Amihud ratio and RtoTR ratio using stocks in the London Stock Exchange. Their findings show that the Amihud ratio may have a size bias and that the RtoTR ratio captures both trading frequency and trading costs.

Another analysis from Kang and Zhang (2014) indicates that the original Amihud ratio performs better than other measures in an actively-traded stock market, while the non-trading frequency measure (Zero Volume) outperforms other measures in less liquid markets with a large number of non-trading days. Then they develop AdjILLIQ, an adjusted version of the Amihud illiquidity measure, by combining the merits of the original Amihud ratio and Zero volume. Their findings also show that AdjILLIQ outperforms other measures significantly in less actively traded markets and for small-size stocks.

Ho and Chang (2015) investigate the ability of four market liquidity measures, including Amihud (2002), Pástor and Stambaugh's measure (2003), the bid–ask spread and finally the turnover ratios, by using data from the China Stock Market and Comparing the performance of these four measures. Their results show that, in terms of identifying the liquidity risk premium, the Amihud measure and Pástor–Stambaugh's measure perform better than the others.

2.2.5 Liquidity studies in LSE

Compared to a number of liquidity studies of the US market, there is a lack of research in the LSE. In addition, the discussions of liquidity measures are limited. Gemmill (1996) state that block trades may lead to liquidity issues in the London Stock Exchange. Abhyankar et al (1997) use bid-ask spread and trading volume to test intra-day liquidity in the London Stock Exchange and find stocks are less liquid at the market opening time. Hansch et al (1998) discuss that the inventory may cause liquidity problems in a dealership market using evidence from the London Stock Exchange. Huang and Masulis (2003) compare using trading frequency and trading size in the LSE, and find both methods have advantages. Florackis et al (2011) propose a new liquidity measure: Rtotr ratio. Both Amihud ratio and Rtotr ratio are tested in the LSE, where the Amihud ratio may exhibits size bias.

The previous section has discussed about the trading system in the LSE. There are two major trading mechanisms: Order driven and quote driven systems. Amihud and Mendelson (1987) state that each trading series is affect by different mechanisms. Lauterbach (2011) find that liquidity conditions in continuous and call auctions in Tel-Aviv Exchange vary. Cai et al (2004) find that differences in market environment (UK and US market) could affect trading volume and differences in trading system could affect bid-ask spread patterns. The bid-ask spread exhibits Reverse J-shape in the LSE (SETS) while exhibits U-shape in the US market (NYSE and NASDAQ). In the SEAQ trading platform of the LSE, the dealers have such obligations which are called "designated market makers" (Foucault et al, 2013). The dealers have to execute incoming up to the threshold size at the price quoted. All these findings show that liquidity may vary in different markets. This does not happen in US market. So the importance of liquidity in the LSE is crucial when studying liquidity world-widely.

2.2.6 Conclusion

This section has made clear that there is no single unambiguous definition of liquidity and that there are several characteristics of liquidity, such as tightness, depth and resiliency. As discussed before, there are a number of studies in the literature focusing on measuring liquidity. Since Amihud and Mendelson (1986b) firstly proposed the relationship between liquidity and relative spread, research has been undertaken to test the multiple dimensions of liquidity rather than the single dimension of liquidity. However, liquidity changes over time, especially in different economic periods or different regions. For example, the Amihud ratio is not a suitable liquidity measure in emerging markets or during a financial crisis. The above analysis has shown that it is hard to be certain which liquidity measure is the best. A one-dimensional liquidity measure is clearer and less complicated, while the multi-dimensional liquidity measure can capture more liquidity characteristics. Therefore, we use five different measures to test liquidity in the London Stock Exchange.

2.3. Data and Research Design

2.3.1 Liquidity measurements

Based on the previous literature and data available, we choose five reliable measures to test illiquidity.

Relative spread: dollar spread divided by the average of the bid and ask price (Amihud and Mendelson, 1986b):

$$\mathrm{RS} = \frac{ask - bid}{(ask + bid)/2}$$

Relative spread is the most intuitive indicator of liquidity (Lesmond, 2005). In contrast to effective spread, relative spread is much easier to calculate. In addition, it directly captures the trading costs and proxies for tightness of liquidity. And in the London Stock Exchange, data on bid and ask prices are available for most years.

Amihud ratio (ILLIQ): R_{iyd} is the return (daily price change) on stock i on day *d* of year y, and $VOLD_{iyd}$ is the respective daily volume in dollars (Amihud, 2002). In my research, VOLD=price $\times$ turnover by volume.

$$Amihud\ ratio = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{iyd}|}{VOLD_{iyd}}$$

The Amihud ratio is the most popular proxy for illiquidity and has many advantageous features (Martinez et al, 2005). It takes the price impact into consideration and captures the order flows. The denominator uses the absolute daily return which is calculated by $((R_t - R_{t-1})/R_{t-1})$to test the price impact. The numerator uses the trading volume, which has been used to measure liquidity for a long time.

The Florackis ratio (RtoTR): TR_{itd} is the turnover ratio (ratio of trading volume in number to the number of shares outstanding) of stock i at day d and R_{iyd} is the return on stock i on day d of year y (Florackis et al., 2011). In my research, TR=turnover by volume/common shares outstanding.

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}}$$

Florackis et al. (2011) state that RtoTR has no size bias. The turnover rate performs better at capturing the trading frequency than trading volume. What is the more, Rtotr ratio captures price impact.

Non-trading volume days: zero daily trading volume days (refers to turnover by volume of numbers in Datastream).

Non-return days: zero daily return $((R_t - R_{t-1})/R_{t-1})$ days (no return **changes**), where the daily return is calculated; R_t is the return index of day t and R_{t-1} is the return index of day $t-1$.

Both non-trading volume days and non-return days are intuitive ways to test illiquidity. Based on Lesmond et al. (1999), the informed trader will only trade when the value of information exceeds the trading costs. So non-trade days are proxies for illiquidity. Moreover, non-trading days work better when emergencies arise, such as a financial crisis. During a financial crisis, most of the liquidity proxies' data are abnormal and all stocks are traded less.

2.3.2 Data selection and filters

All the data: the bid–ask price, closing price, trading volume in number, return index and common shares outstanding, are collected from the Datastream database. The initial sample consists of all common UK domestic stocks (denominated in pounds) listed on the London Stock Exchange for the period from 23/05/2001 to 30/12/2013 (3185 days excluding Bank Holidays). All the stocks are listed from 2001 to 2013 and if the stock is delisted during this period, it is excluded. This approach is in line with the approach of the prior literature in this area such as Stoll (2000) and Lesmond (2005). One possibility is that liquidity is a very short term attribute so that survivor bias probably will not heavily affect liquidity-related studies.

Because of data restrictions of the London Stock Exchange, trading volume data are only available for most stocks from 23/05/2001. Also, stocks which lack trading volume data, unit trusts, investment trusts and ADRs are excluded. Thus there are 585 stocks at the outset.

There are many missing data values from the Datastream database. Firstly, the daily trading volume data (turnover by volume from Datastream) lacks a number of data. After checking the validation of trading volume data with the Datastream authority, they suggest that we should replace the Not Available (NA) data as zero value data. Secondly, according to Amihud (2002), we set the daily Amihud ratio as missing if that day is a non-trading day.

Based on the methods of Ince and Porter (2006) and Lee (2011), we reduce the influence of data errors in Datastream (Table 2.1). As the return index (RI) in Datastream includes stock splits and dividends, the stock returns computed from the RI measure could round very small returns to zero value. We exclude stocks whose RI is less than 0.01. Also, we set stocks whose daily share trading volume is larger than the total shares outstanding as missing if this is for less than 100 days and delete the stock if it is more than 100 days. We set the daily return to be missing if any daily return above 100% or below -100% is reversed the next day. Finally, we exclude the stocks which have 90% zero return days. So this leaves 552 stocks to consider.

Table 2.1: Datastream error filter information

Filter standard	**Number of stocks eliminated**
Return index below 0.01	6
Daily share trading volume is larger than the total shares outstanding for over 100 days (set to be the 'missing' value)	40
Daily share trading volume is larger than total shares outstanding for less than 100 days	6
Over 90% zero return days (2866 days)	23
Duplicate situation stocks	2

2.3.3 Elimination of outliers

Firstly, we calculate each stock's average relative spread, Amihud ratio, RtoTR ratio, zero trading volume days and zero return days through the whole period (2001–2013 with 552 stocks). Here are the descriptive results.

Table 2.2: Descriptive results for 552 stocks

	Mean	Median	Max	Min	Mode	Std
Relative spread	0.053048	0.032454	0.363	0.000819		0.0610
Amihud	4.91E-05	9.05×10^{6}	0.00695	5.04×10^{-10}		0.000308
RtoTR	404.347	32.10	55465.5	0.832		3165.60
Zero trading days	462.1449	116.5	0	2677	0	636.36
Zero return days	1111.6	854.5	2844	13	81	904.62

Note: this table presents descriptive data for five liquidity measurements. Relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculted by absolute daily return divided by trading volume in monetary units; Rtotr calculated by absolute daily return divided by turnover ratio; zero trading volume days calculated by zero trading volume of each day; zero return days calculated by zero daily return changes of each day. The mean, median, standard deviation (std) are obtained by the time-series average of daily value. The listed varibales are observed or calculated from a sample of 552 London Stock Exchange stocks from May 24st, 2001 to Dec 31st, 2016. The data are collected from Thomson Reuters Datastream.

We also present the histograms of each measure by stock. The value of each measure is calculated from the average value for the entire period (2001– 2013). For the liquidity measures, the means are larger than the median, implying that there is excess skewness in the cross-sectional means of liquidity measures. Based on the basic descriptive data and each measure’s histogram, we find that our database has outliers, especially in the case of the Amihud ratio and RtoTR ratio. It is clearly seen that there are very long-tailed distributions of outliers of the Amihud ratio and RtoTR ratio. So we plot the scatter charts of these two measures. In the scatter plot in Figure 2.3, most of the data lie clustered together, but several observations stand out from the rest. Therefore, we decide to remove these outliers, and we exclude stocks that have the top 1% value of each measure.

Figure 2.2: Histograms of each liquidity measure by stock (552 stocks)

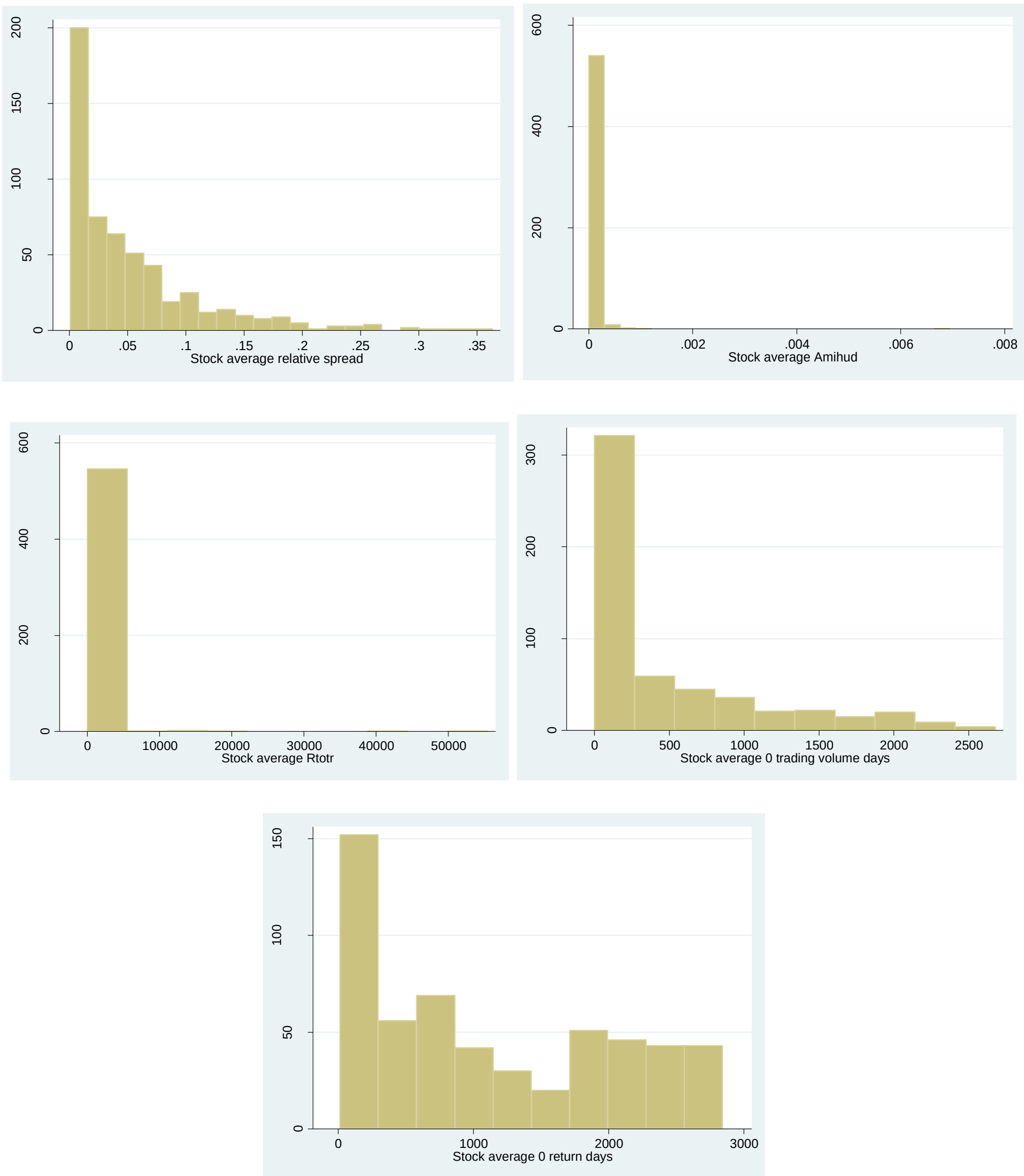
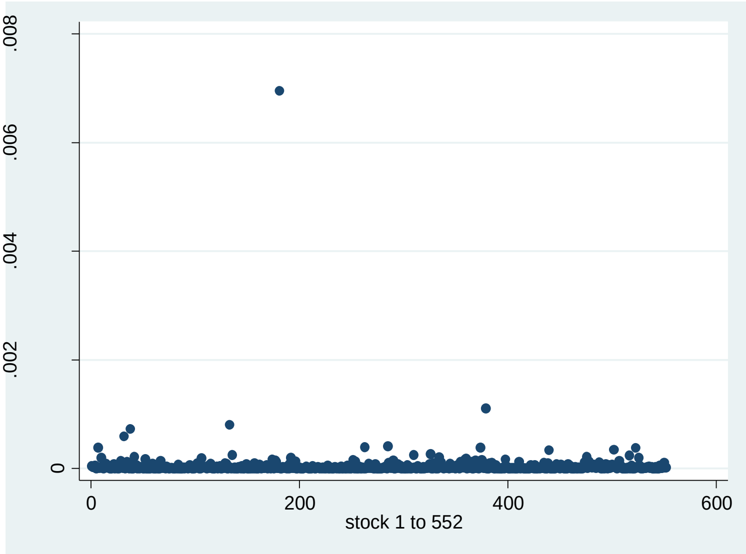
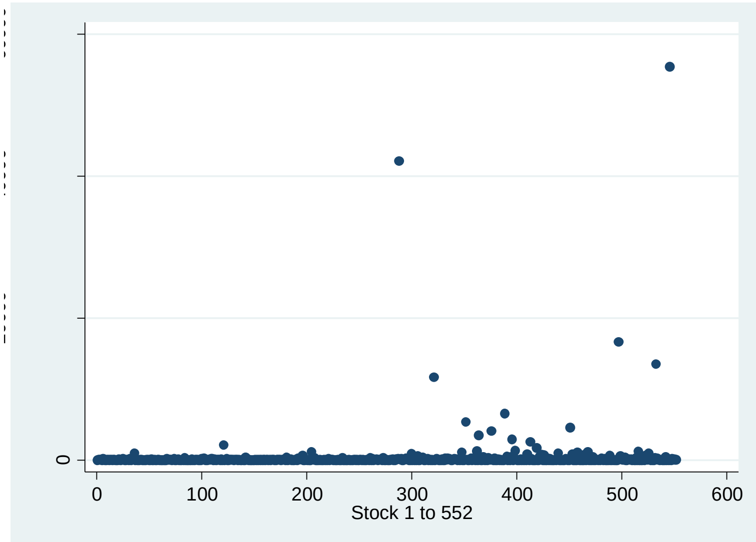


Figure 2.3: Scatter plots of Amihud and RtoTR (552 stocks)





2.4. Data Analysis

2.4.1 Descriptive data

Table 2.3: Descriptive results of 535 stocks

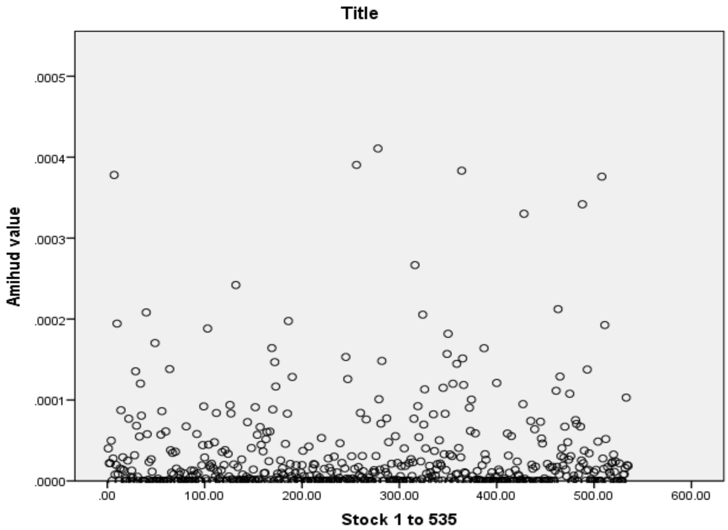
	Mean	**Median**	**Max**	**Min**	**Mode**	**Std**
RS	0.049	0.0313	0.2979	0.000819		0.0541
Amihud	3E-05	7.98×10^{-6}	0.000411	5.04×10^{-10}		5.79×10^{-5}
RtoTR	154.07	30.83	6534.8	0.832		537.07
Zero trading	419.95	100	2348	0	0	583.10
Zero return	1071.7	801	2787	13	81	885.8

Note: this table presents descriptive data of five liquidity measurements. Relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary units; Rtotr calculated by absolute daily return divided by turnover ratio; zero trading volume days calculated by zero trading volume of each day; zero return days calculated by zero daily return changes of each day. The mean, median, standard deviation (std) are obtained by the time-series average of daily value. The listed variables are observed or calculated from a sample of 535 London Stock Exchange stocks from May 24st, 2001 to Dec 31st, 2016.The data are collected from Thomson Reuters Datastream.

Because of overlapping of the stocks that have the top 1% value in different categories, 535 stocks are left. After filtering the outliers, the histograms of Amihud and RtoTR are smoother and the scatter plots are more normally distributed. These are the histograms, scatter plots and descriptive data of 535 stocks, based on which we conduct our analysis.

Figure 2.4: Scatter plots and basic descriptive data of

Amihud and RtoTR (535 stocks)



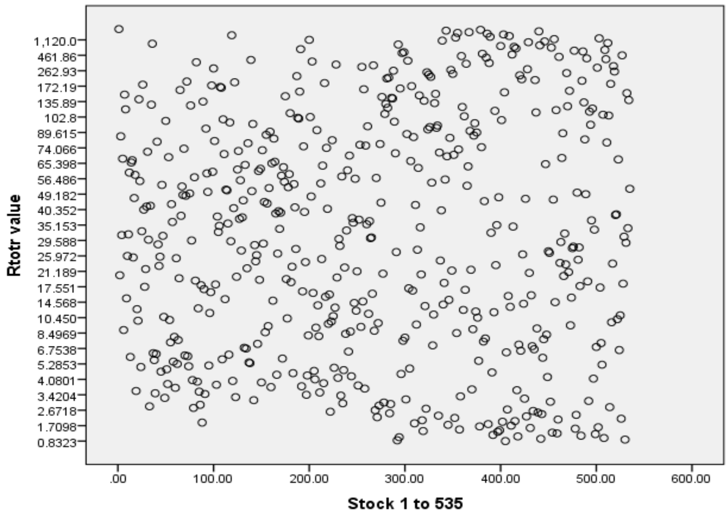
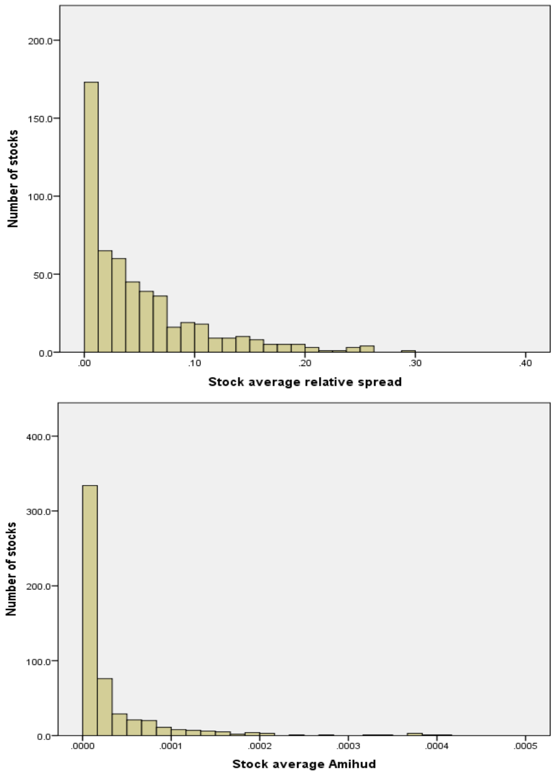
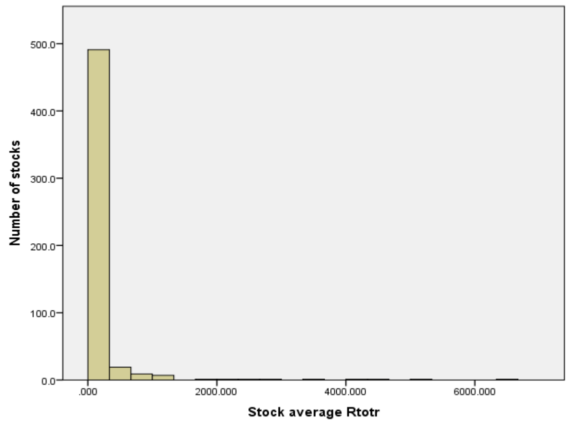
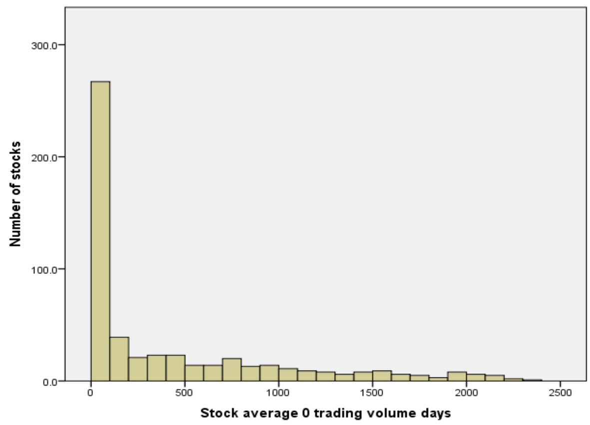
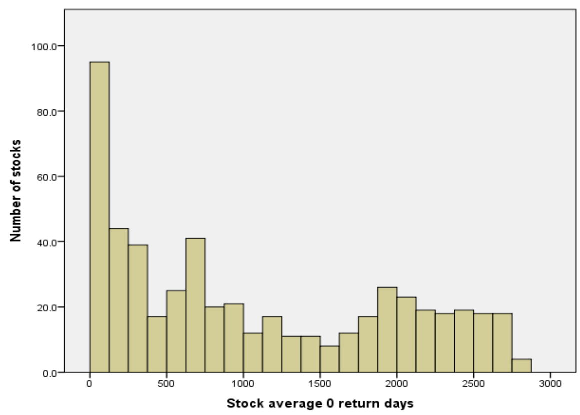


Figure 2.5: Histograms of each liquidity measure by stock (535 stocks)




500.0
400.0
300.0
200.0
100.0
0.0
Number of stocks
.000
2000.000
4000.000
6000.000
Stock average Rtotr


300.0
200.0
100.0
0.0
Number of stocks
0
500
1000
1500
2000
2500
Stock average 0 trading volume days

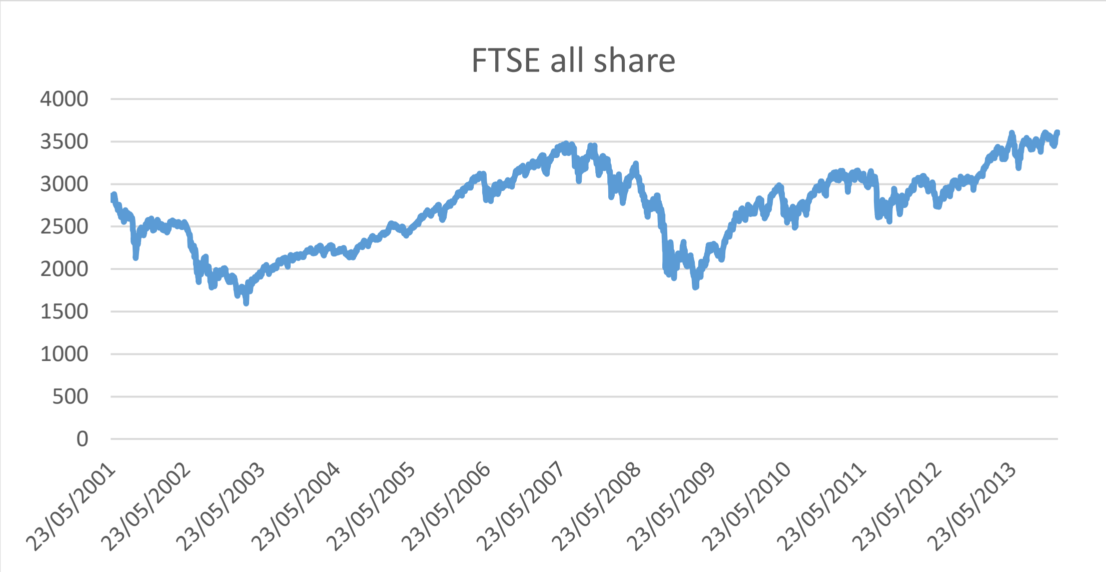

100.0
80.0
60.0
40.0
20.0
0.0
Number of stocks
0
500
1000
1500
2000
2500
3000
Stock average 0 return days

2.4.2 Time-series plots

In this section, we provide an illustrative analysis over the whole period, 2001 to 2013, of different liquidity measurements. Also, we use the FTSE All-Share Index as the stock market benchmark and compare the co-movement of liquidity and the stock market. At the same time, we find the liquidity changes over time under different conditions.

FTSE All-Share Index

Figure 2.6: FTSE All-Share Index from 23.05.01 to 31.12.13

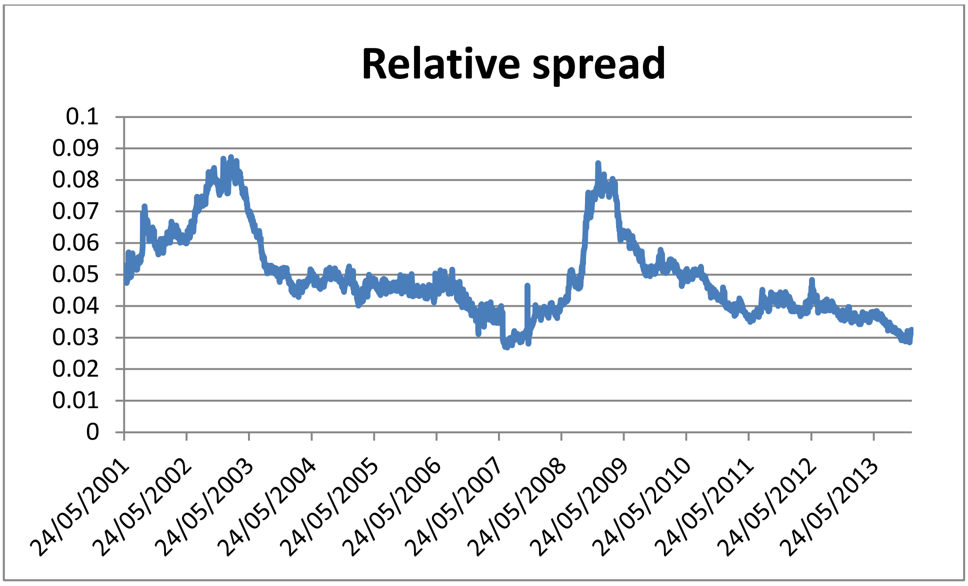


Note: the FTSE All-shares index data is collected from Thomson Reuters Data stream

The chart illustrates the FTSE All-Share Index from 2001 to 2013. It dropped heavily in September 2001. Obviously, the stock market suffered a heavy loss after the 9.11 incident. The markets were in chaos and became less liquid. Then the Index decreased quickly again from 2002 and reached its lowest point in early 2003 (1691 points). The Index recovered in the following years up to mid-2007. Due to the financial crisis, the price index dropped dramatically, especially in 2008 and reached its second lowest point in 2009. It indicates that market is fragile to unparticipant event (Kamara et al, 2008). After that, the price index increased every year, except for several months in 2010 and 2011. Overall, it is clear that the market suffered a bigger loss in 2008 compared to the other period of decline.

Relative Spread

Figure 2.7: Relative spread from 23.05.01 to 31.12.13



Note: Relative spread is calculated by spread between bid and ask price divided by average bid and ask price. The daily relative spread is the average of each stock's relative spread (535 stocks) in the sample. The relative spread is collected from Thomson Reuters Data stream

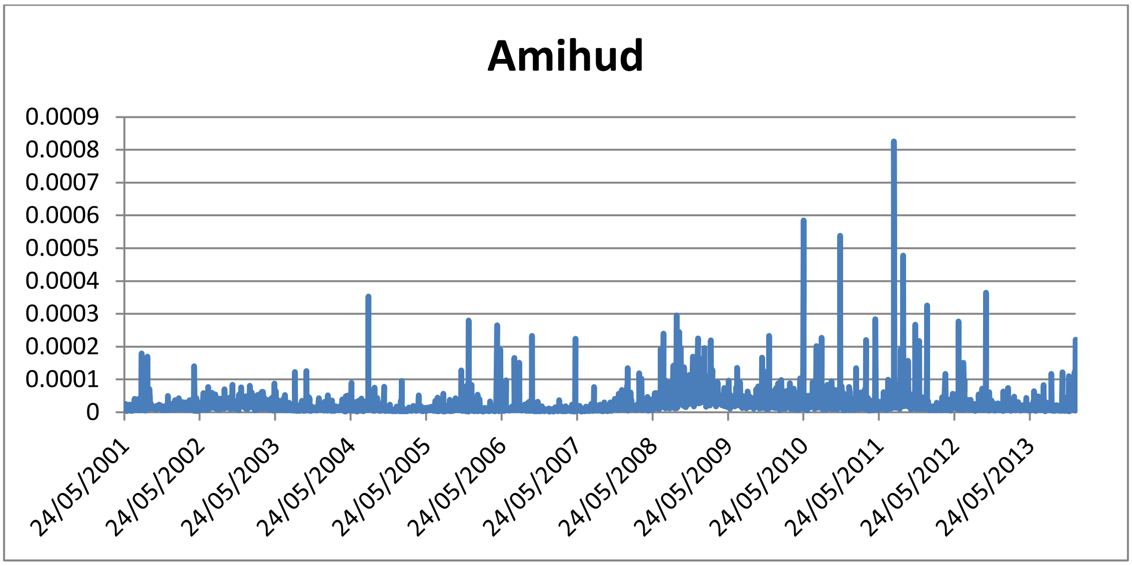
We calculate the average of all stocks' daily relative spread and plot the time-series chart. During 2001 to 2013, it is clear that there are two peaks in this period: in early 2003 and at the end of 2008. The value started to increase from the beginning and rose sharply in September 2001 because of the stock crash after the 9.11 attacks. Then the FTSE All-Share Index dropped quickly from 2002 to early 2003. The relative spread reached its highest value in early 2003. During 2003 and 2007, the FTSE All-Share Index rose steadily, and the relative spread remained stable and decreased to its lowest value in 2007. The widely-used electronic trading system and efficient use of electronic cross-matching in the Stock Exchange's limit order book might be reasons contributing to this.

The figure shows that the relative spread tends to have opposite trends to the FTSE All-Share Index. The relative spread began to increase in late 2007 while the stock market began to crash. The relative spread rose dramatically from 2007 to early 2009 when the FTSE All-Share Index dropped heavily from nearly 3500 to 1800. However, the relative spread fell quickly in 2009 and decreased steadily in the following years. The stock market performed better after the recession. Compared with the FTSE All-

Share Index, we find that the relative spread goes higher while the market return (FTSE All-Share Index) drops. The relative spread reflects the illiquidity of the stock market in the London Stock Exchange. In other words, stock market liquidity has a negative relationship with market price movement.

Amihud

Figure 2.8: Amihud ratio from 23.05.01 to 31.12.13



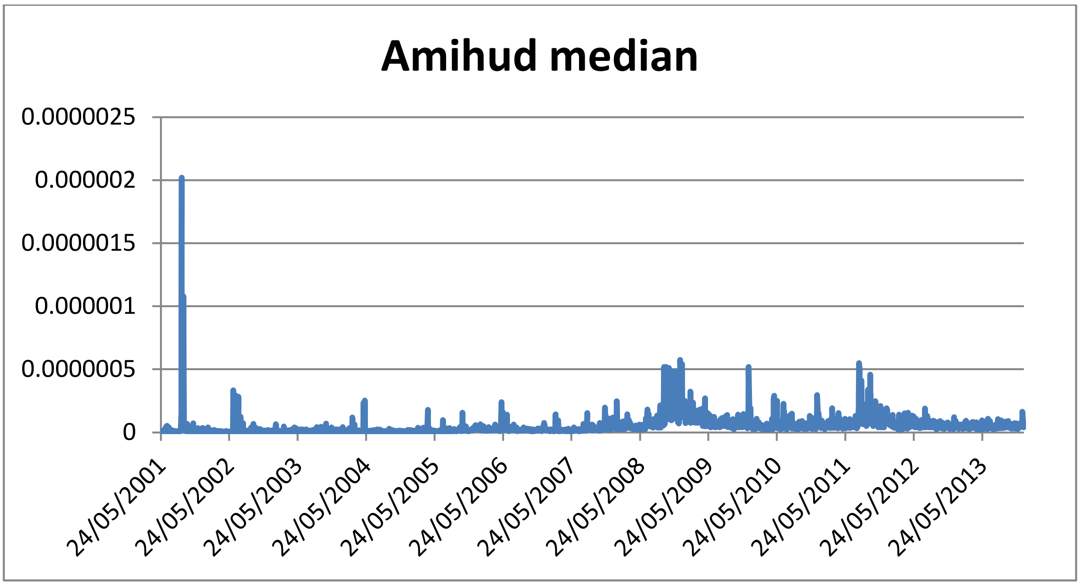
Note: The Amihud ratio is calculted by absolute daily return divided by trading volume in monetary units. The daily Amihud figure plotted is the average of each stock's Amihud ratio (535 stocks) in the sample. The Amihud ratio is collected from Thomson Reuters Data stream

We calculate the average of all stocks' daily Amihud ratio and plot a time-series chart. The Amihud ratio was generally quite low before 2008 compared to the subsequent years. The values after September 2001 were quite high for a few days because of the 9.11 attacks. The values between 2002 and 2003 were also quite high. During this time, the stock market fell heavily. From 2004 to 2007, the Amihud ratio was low except for several high daily values. The Amihud ratio was quite high during 2008 and 2009, due to the financial crisis. In the following years, there were several big values in 2010 and 2011. The average value during 2008 and 2013 was higher than during 2001 and 2007.

With regard to those exceptional high Amihud values during the periods 2004–2007 and 2009–2013, most of the FTSE index returns on the those days are negative which indicates that poor returns lead to the stock market led to low liquidity and high

Amihud ratio on those days. During the period 2004–2007, the days 17/08/2004, 16/05/2007 and 15/12/2005 had high Amihud values, two of them having a negative FTSE index return than other days. During the period 2009–2013, four specific days had a high Amihud values and two of them had a negative FTSE index return. Overall, the Amihud ratio has an almost opposite trend to the FTSE index. Usually, a high Amihud ratio is linked with a lower FTSE index. As discussed before, the Amihud ratio can capture market depth and resiliency in the stock market. It can also reflect the illiquidity of the stock market. So the liquidity of the stock market shows negative links with market price movement.

Figure 2.9: Amihud median from 23.05.01 to 31.12.13



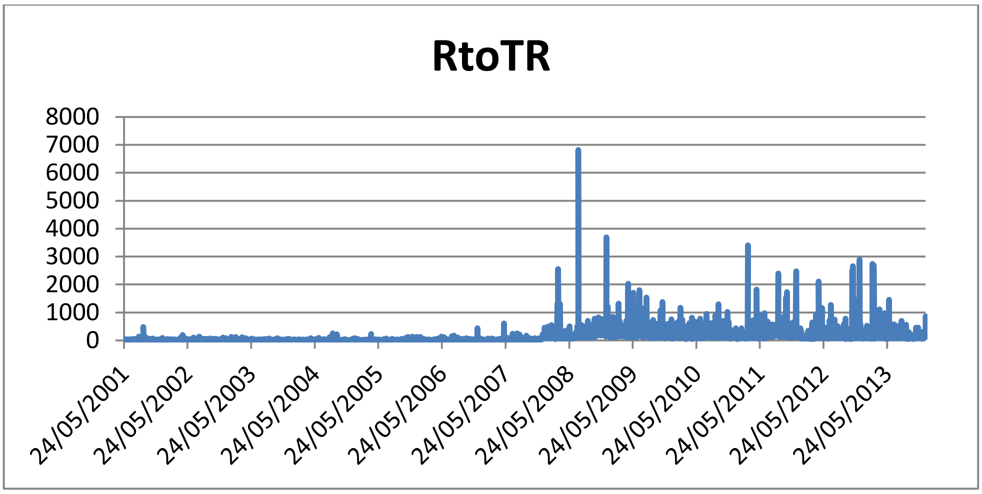
Note: The Amihud ratio is calculted by absolute daily return divided by trading volume in monetary units. The Amihud median is the median value of stocks' Amihud ratio(535 stocks) in the sample. The Amihud ratio is collected from Thomson Reuters Data stream

In contrast to the relative spread, the range of the daily Amihud ratio is very wide. During the whole period (2001–2013), there were many extremely high values. Because of this situation, we use the median of the daily Amihud to illustrate the time-series plot. The median value is smoother than the average value. Unlike the mean of the daily Amihud ratio, the biggest value of the median was in September 2001, due to the market crash during that time, but the values were both high in the two plots compared to the values around that period (2001–2002). Several values in

2002, 2004 and 2006 were higher in both figures compared to other values during 2002–2006. However, in the median Amihud figure, the values between 2008 and 2009 were much higher than the surrounding periods compared to the mean Amihud figure. After 2009, several values were not very high in 2010 and 2011 compared to the mean Amihud figure. Concerning those exceptionally high Amihud median values in different periods, we checked their FTSE index on the same day and found that most of them had a decreasing FTSE index compared to the previous day. For example, during 2002–2006, the FTSE index on 26/06/2002, 11/07/2002, 17/05/2004, 23/02/2005, 19/10/2005 and 22/05/2006, which had exceptionally high values for the Amihud median, was decreasing, indicating that market value reduces on liquidity on the stock market resulting in an exceptionally high Amihud median value. The results are similar to the previous finding. It indicates that large price drops reduce market liquidity and stocks tend to have higher Amihud ratio.

RtoTR

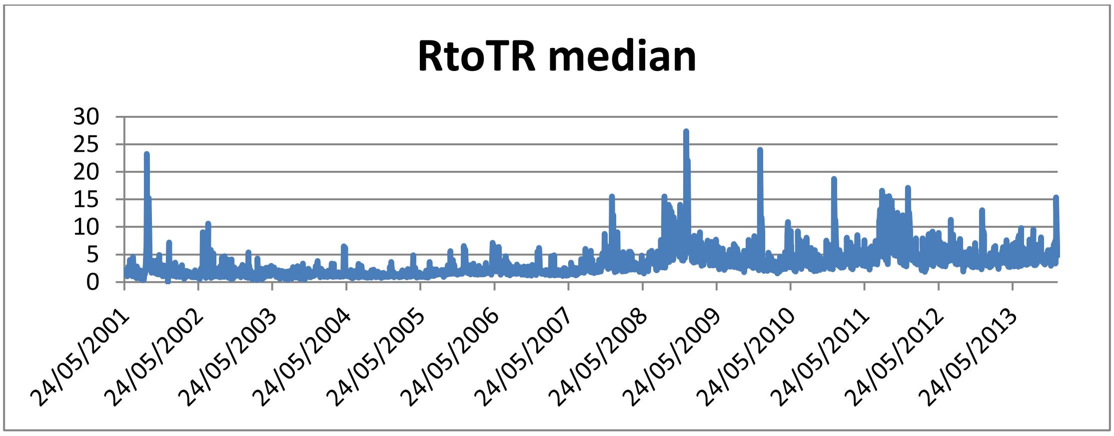
Figure 2.10: RtoTR from 23.05.01 to 31.12.13



Note: Rtotr calculated by absolute daily return divided by turnover ratio. The Rtotr is the average value of stocks' Rtotr ratio(535 stocks) in the sample. The Rtotr ratio is collected from Thomson Reuters Data stream

We calculate the average of all stocks' daily RtoTR and plot a time-series chart. It is clear that the values between 2001 and 2007 were much lower than those after 2008. We double-checked the data and found that the turnover rate (trading volume divided by shares outstanding) before 2007 was much lower than that after 2008. The RtoTR began to increase from 2008 and reached a peak in 2008. Between 2009 and 2011, the values were still quite high on many days. With regard to those exceptionally high values after 2009, we found that most of those days had a high RtoTR value at the same time as the FTSE All-Share index decreased. This indicates that reduced price on the stock market results in exceptionally high RtoTR values.

Figure 2.11: RtoTR Median from 23.05.01 to 31.12.13

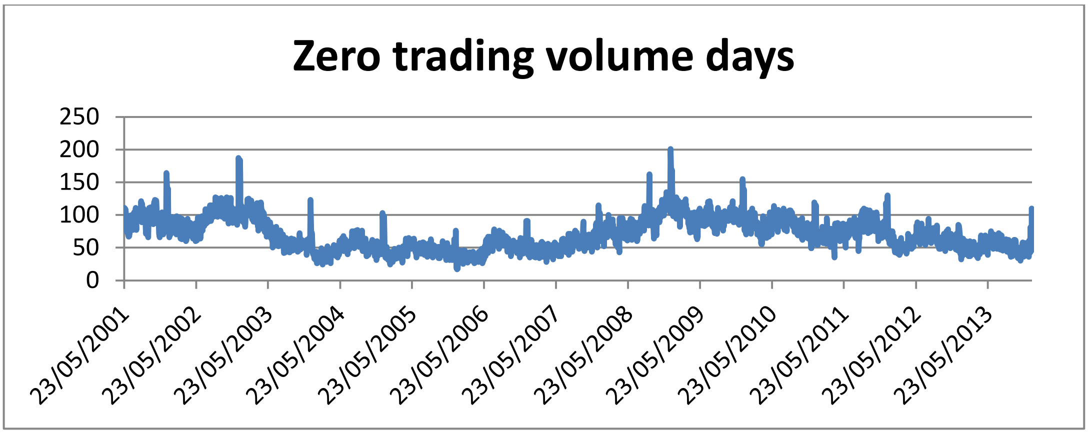


Note: Rtotr calculated by absolute daily return divided by turnover ratio. The Rtotr is the median value of stocks' Rtotr ratio(535 stocks) in the sample. The Rtotr ratio is collected from Thomson Reuters Data stream

As with the Amihud ratio, the range of the daily RtoTR ratio is very wide. During the whole period (2001–2013), there were many extremely high values. Because of this situation, we used the median of the daily RtoTR to illustrate the time-series plot. In this plot, the difference between the values during 2001–2007 and the values during 2008–2013 is not great. There were several high values in 2001 and 2002. Still, the values began to increase in 2008 and the values in 2011 were quite high. The results are quite similar to the other results. A higher RtoTR ratio is related to a lower market price. Interestingly, we find that the median of the daily RtoTR was quite high at Christmas each year. This may be because there is less trading volume before Christmas. The trading volume has a negative effect in the RtoTR ratio equation, so it may lead to a higher RtoTR ratio before Christmas.

Zero Trading Volume Days

Figure 2.12: Zero trading volume days from 23.05.01 to 31.12.13

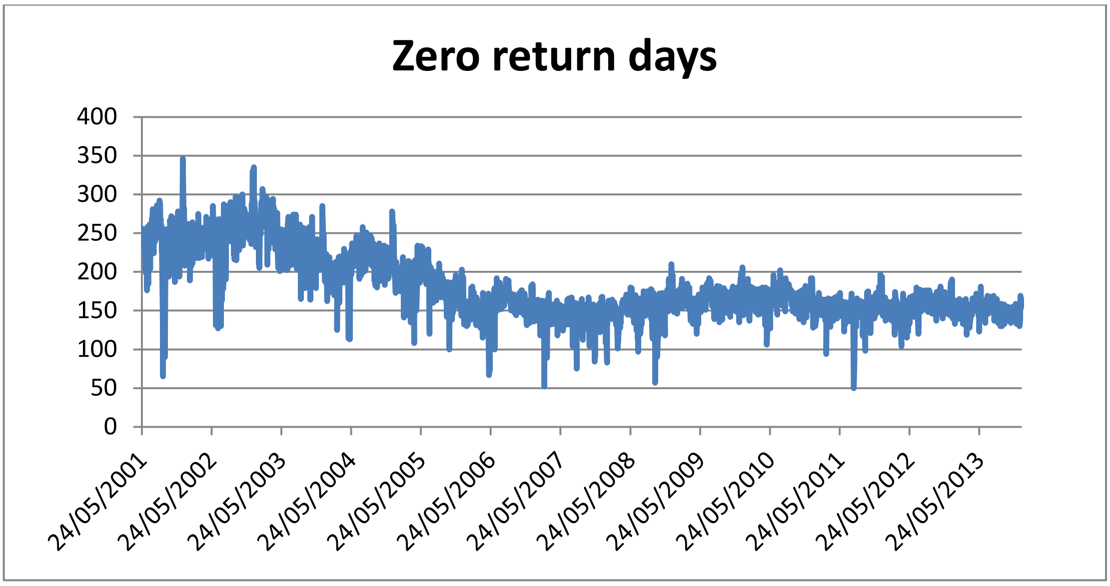


Note: Zero trading volume days is the total daily number of stocks with zero trading volume days (535 stocks) in the sample. Trading volume is collected from Thomson Reuters Data stream

We calculate the sum of all stocks' daily zero trading volume days and plot a time-series chart. As for zero trading volume days, it increased from 2001 to the end of 2002 and suddenly dropped in the early part of 2004. The stock market suffered a crash after the 9.11 attacks and dropped from 2002 to 2003. During 2004–2007, the zero trading volume days fell continuously. After that, they increased every year until the end of 2008. Then, they decreased steadily to 2013. Compared with the FTSE All-Share Index, zero trading days have the opposite co-movement. Higher zero trading days have a price drop of the stock market. This shows that the stock market is less liquid when the market price goes down. Also, interestingly, the zero trading volume days are quite high around Christmas Day each year probably because of seasonal holidays. This supports the earlier finding that the RtoTR ratio is also high before Christmas. Obviously, there is less trading in general before Christmas.

Zero Return Days

Figure 2.13: Zero return days from 23.05.01 to 31.12.13



Note: Zero return days is zero return days calculated by zero daily return changes of each day. Zero return days is the total daily number of stocks' zero return days (535 stocks) in the sample. Return is collected from Thomson Reuters Data stream

We calculate the sum of all stocks' daily zero return days and plot a time-series chart. Clearly the zero return days were quite high in the first period (2001–2003) and then dropped every year to the end of 2006. Then they remained stable during 2007–2013 (at 150 to 200 days). Unlike other liquidity measures, the links between zero return days and market price movements are blurred. It is hard to find any clear links between market price movement and market liquidity conditions. Meanwhile, the graph also proves that the zero return days are higher than usual before Christmas. This means that the market is relatively illiquid before Christmas.

Five liquidity measures are tested in this section. The relative spread can capture market tightness and transaction costs; the Amihud ratio and RtoTR ratio can capture the price impact which represents market depth; zero trading days and zero return days are more intuitive and easier to measure. Although each liquidity measure can explain liquidity from one perspective, the results show that liquidity measures and market price movement tend to move in opposite directions.

In order to test the significance of time-varying liquidity, we give a simple regression showing how the liquidity measures vary over time. We average each day's liquidity measure value and set time measured in days t (1,2,3….3186) and d (dummy variable for financial crisis). If the day is in the crisis period, the value will be set to be 1; otherwise the value is 0.

$$\text{Each liquidity measure} = \alpha + \beta_1 t + \beta_2 d + \varepsilon$$

Where t is each day and d is dummy variable for days in financial crisis period (07/2007-12/2009).

Table 2.4: Regression of time-varying liquidity measures

	Constant	t	d	R^2
RS	0.061** (159.2)	-8×10^{-6}** (-15.6)	0.005** (11.4)	0.327
Amihud	18.1** (5.7)	-0.006** (0.636)	84.2** (6.7)	0.01
Rtotr	-35.4** (-4.0)	0.097** (20.0)	114.2** (10.3)	0.154
Zero trading	71.5** (89.5)	-0.003** (-7.6)	21.1** (21.0)	0.127
Zero return	236.5** (238.8)	-0.033 (-60.5)	-22.4 (-18.0)	0.58

Note: The table presents cross-sectional regression between five liquidity measures and day. Relative spread (RS) calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary units; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. All figures are averages of daily value from 2001 to 2013. The data are collected from Thomson Reuters Datastream. ** indicates statistical significance at the 0.05 level (2-tailed).

The table shows that there are certain relationships between liquidity and time. It can be seen that liquidity is significantly time-varying. It supports the finding of Amihud and Mendelson (1987) that liquidity changes over time. The reason for time-varying liquidity may be due to the trading environment, such as the trading system (Berkman and Eleswarapu, 1998, Kalay et al, 2002), or to economic conditions. The significance of the dummy variables of financial crisis also show that different economic conditions could affect liquidity.

In conclusion, the stock market in the London Stock Exchange seems to have been quite liquid before the financial crisis, but there were some less liquid periods after the 9.11 incident. The good liquidity may be due to the technology innovation in the London Stock Exchange. A number of stocks began to join the SETS from 2001 where liquidity was significantly increased (Naik and Yadav, 2004, Chakravarty et al., 2005). The financial crisis that began from 2007 dried up market liquidity. After the economic recession, the market started to recover from 2010 onwards. This shows that liquidity measures do change over time and that the time period is related to different market conditions. The liquidity largely depends on the economic environment.

The charts of relative spread and zero trading volume days show opposite trends to the chart of the FTSE All-Share Index. When the FTSE All-Share Index is high, the relative spread and zero trading volume days exhibit low values. Charts of the Amihud ratio and RtoTR ratio can show basic liquidity information on the stock market. Zero return days look interesting and there are many of them before 2006. Usually, when the market price goes down, the market becomes less liquid and the five liquidity measurements have high values.

2.4.3 Correlation

2.4.3.1 Cross-sectional correlation analysis

We calculate each stock's average daily relative spread, Amihud ratio, RtoTR ratio, zero trading volume days, and zero return days through the whole period (2001–2013). Each variable is calculated in this equation:

$$Variable_s = \frac{1}{d}\sum_{d=1}^{3186} Variable_{sd}$$

where Variable_s is each average variable value of each stock s, d represents the valid days of each measure, and Variable_{sd} is the daily value of each variable of each stock.

And here is the cross-sectional stock correlation matrix.

Table 2.5: Cross-sectional liquidity measures correlation (535 stocks)

	RS	**Amihud**	**RtoTR**	**Zero trading**	**Zero return**
RS		.847**	.135**	.744**	.832**
Amihud	.847**		.104**	.598**	.623**
RtoTR	.135**	.104**		.134**	.162**
Zero trading	.744**	.598**	.134**		.876**
Zero return	.832**	.623**	.162**	.876**	

Note: The table presents cross-sectional correlations between five liquidity measures. Relative spread (RS) calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary units; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. All figures are averages of daily value from 2001 to 2013. The data are collected from Thomson Reuters Datastream. ** indicates statistical significance at the 0.05 level (2-tailed).

We compute and analyse the Pearson correlation for the variables relative spread, Amihud ratio, RtoTR ratio, zero trading volume days, and zero return days for the entire period (2001 to 2013). Pearson's correlation is the covariance of the two variables divided by the product of the standard deviation. All the correlation coefficients are significant.

Relative spread measures trading costs. The relations with the other four liqudity measures are all positive. Among the five liquidity measures, the correlation between the relative spread and RtoTR ratio is lower (only 0.135) than with the other liquidity measures (over 0.7). One possibility is that the RtoTR involves a turnover ratio, which measures trading frequency not directly trading costs. The correlation between the relative spread and Amihud ratio is the highest (0.847). This shows that the Amihud ratio has a stronger link than other liquidity measures with the relative spread. Compared to other liquidity measures, the RtoTR ratio has the lowest correlation coefficient with each liquidity measure. This shows that the RtoTR may have the weakest power of measuring stock liquidity.

Based on Lesmond et al. (2005), zero return days can measure stock liquidity, because informed traders only trade when the gain from their inclusive information is large enough to offset the trading cost. The highest value of correlation is 0.744 with zero trading volume days, followed by relative spread at 0.832.

A zero trading day can measure the occurrence of the no-trade phenomenon more directly than the zero return days (Kang and Zhang, 2014). Except for the RtoTR ratio, the correlation coefficients with the other measures are all over 0.5.

In summary, the liquidity measures are positively correlated with each other. These five measurements can measure stock illiquidity. The relative spread, Amihud ratio, zero trading days and zero return days have stronger relationships among each other. In contrast, the RtoTR ratio appears to have a lower correlation with other liquidity measures. Based on the statement of Gujarati (1988), if the corrlation coefficients are below 0.8, there would be no multicollinearity problem. Most of coefficients are less than 0.8, except for three coefficients bewteen zero return, zero trading and relative spread. The correction of this problem is fixed later in the thesis.

2.4.3.2 Time-series correlation

As previously discussed, liquidity changes over time, especially when a financial crisis is encountered. The performance of different liquidity measures varies in different market conditions. So we run time-series correlation to find the results.

We add trading volume, turnover rate (defined as the trading volume divided by shares outstanding) and the absolute value of returns on the FTSE All-Share Index (defined as the absolute daily return change: $|R_t - R_{t-1}|$) into the correlation matrix. There is no size bias using the turnover in numbers and it proves to be a good measure of liquidity. The turnover rate is widely used to measure liquidity (Bailey and Jagtiani, 1994, Datar et al., 1998). Generally, high turnover stocks are more liquid because demand is high relative to the number of outstanding shares available for trading. The absolute value of daily return can measure the daily volatility of the market price changes. The higher absolute return of the FTSE All-Share Index indicates that the market is more volatile and less liquid.

Next, we calculate the average daily stocks' relative spread, Amihud ratio, RtoTR ratio, zero trading volume days, and zero return days over 535 stocks in the market from 2001 to 2013 (3186 days).

$$Variable_s = \frac{1}{s}\sum_{s=1}^{535} Variable_{sd}$$

where $Variable_s$ is the average variable value of each stock in the market, s represents the number of valid stocks for each variable, and $Variable_{sd}$ is the variable daily value of each stock.

Table 2.6: Time-series stock correlation matrix 2001–2013

	RS	**Amihud**	**RtoTR**	**Zero trading**	**Zero return**	**Volume**	**Turnover**	**FTSE**
RS		.314**	-.126**	.547**	.653**	.237**	-.244**	.163**
Amihud	.314**		.595**	.479**	-.070**	-.158**	.324**	.261**
RtoTR	-.126**	.595**		.428**	-.447**	-.466**	.672**	.213**
Zero trading	.547**	.479**	.428**		.293**	-.172**	.144**	.284**
Zero return	.653**	-.070**	-.447**	.293**		.129**	-.590**	-.113**
Volume	.237**	-.158**	-.466**	-.172**	.129**		-.184**	.055**
Turnover	-.244**	.324**	.672**	.144**	-.590**	-.184**		.148**
FTSE	.163**	.261**	.213**	.284**	-.113**	.055**	.148**	

Note: The table presents time-series correlations between liquidity measures and market variables from 2001 to 2013. Relative spread (RS) is calculated by spread between bid and ask price divided by average bid and ask price; Amihud is calculated by absolute daily return divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Volume is the trading volume in number. Turnover is the trading volume in number divided by the shares outstanding. FTSE is the absolute return of FTSE all share index. The data are collected from Thomson Reuters Datastream. ** indicates statistical significance at the 0.05 level (2-tailed).

Compared with the cross-sectional correlation matrix, the time-series stock correlation matrix results are more interesting. The time-series correlation coefficients among the liquidity measures are mostly similar, but the coefficients are less correlated. All the correlation coefficients are significant.

More specifically, relative spread has a positive correlation with the Amihud ratio, zero trading days and zero return days, with correlations of 0.314, 0.547 and 0.653 respectively during the whole period (2001–2013). Relative spread is a good measure of liquidity from time-series viewpoint (Jones, 2002). Zero return days is the measure most closely correlated with relative spread. RtoTR has a negative value of coefficient with -0.126. One possibility is that the RtoTR ratio tends to capture more information about trading frequency (because the RtoTR ratio includes the turnover ratio) rather than trading costs. Interestingly, zero return days turn to have negative correlation coefficients with the Amihud ratio and RtoTR ratio in the time-series correlation.

Relative spread has a positive correlation coefficient with trading volume. One possibility is that the investors have to trade stock during a financial crisis, no matter how high the transaction costs. The coefficient of zero return days is also positive. The other three liquidity measures have negative coefficients on trading volume maybe because there were many high volume periods and stocks are liquid during that time.

The coefficients on the turnover rate are interesting. Relative spread and zero return days have negative coefficients while the other three measures have positive results. In theory, the turnover rate measures trading frequency and should be negatively related with these five liquidity measures. But the results may indicate that the turnover rate needs further tests.

As for the FTSE index, except for zero return days, the other four liquidity measures are positively related with the absolute return of the FTSE. This proves that higher volatility of the stock market is associated with less liquidity. Zero trading days has the highest time-series correlation at 0.284, followed by the Amihud ratio at 0.261.

The entire time period from 2001 to 2013 is too long to measure liquidity conditions in the stock market. Thus the results need to be explored more deeply to explain some anomalies. Financial markets seem to act entirely differently when they are stressed. In order to fully understand the changing liquidity and the consistency of liquidity measures because of the financial crisis in 2008, we divide the whole period into three parts: before the financial crisis (2001–2006), during the financial crisis (2007–2009) and after the financial crisis (2010–2013). It is worth repeating both the time-series and cross-sectional correlation analysis. The results from time-series correlation may differ from cross-sectional correlation (Goyenko et al., 2009). This may be because of some measurement error which could have an effect on individual stocks.

Table 2.7: Time-series stock correlation matrix 2001–2006

	RS	Amihud	RtoTR	Zero trading	Zero return	Volume	Turnover	FTSE
RS		.462**	.312**	.794**	.774**	-.215**	-.496**	.349**
Amihud	.462**		.598**	.364**	.250**	-.038	-.248**	.302**
RtoTR	.312**	.598**		.387**	.069**	-.104**	-.321**	.300**
Zero trading	.794**	.364**	.387**		.749**	-.305**	-.630**	.313**
Zero return	.774**	.250**	.069**	.749**		-.354**	-.555**	.156**
Volume	-.215**	-.038	-.104**	-.305**	-.354**		.760**	.040
Turnover	-.496**	-.248**	-.321**	-.630**	-.555**	.760**		-.137**
FTSE	.349**	.302**	.300**	.313**	.156**	.040	-.137**	

Note: The table presents time-series correlations between liquidity measures and market variables from 2001 to 2006. Relative spread (RS) calculated by spread between bid and ask price divided by average bid and ask price; Amihud ratio calculated by absolute daily return divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Volume is the trading volume in number. Turnover is the trading volume in number divided by the shares outstanding. FTSE is the absolute return of FTSE all share index. ** indicates statistical significance at the 0.05 level (2-tailed).

Unlike the results of the whole period table, the coefficients among all the liquidity measures are positive and significant during 2001–2006. Compared with the whole period (2001-2013) results, the coefficients between relative spread and RtoTR become positive. Zero trading volume days are most correlated with relative spread (0.794) and RtoTR is least correlated with relative spread (0.312). The coefficent between zero return days and relative spread is also quite high at 0.774. This proves that zero trading days and zero return days are closely associated with relative spread.

In contrast to the whole period results of the time-series correlation matrix, trading volume and turnover rate are negatively correlated with all liquidity measures. Zero trading volume days and zero return days both perform well at measuring trading volume and turnover rate. This supports that trading volume and turnover rate are negatively related with liquidity.

Also, the absolute value of the FTSE daily return is positively related with all liquidity measures. The zero return days coefficient changes to positive but with the smallest value of 0.156. Relative spread has a high time-series correlation at 0.344 in this period. This shows that zero return days may not be a good measure of capturing market volatility. The results support that stock market volatility is positively related with illiquidity.

Table 2.8: Time-series stock correlation matrix 2007–2009

	RS	Amihud	RtoTR	Zero trading	Zero return	Volume	Turnover	FTSE
RS		.720**	.730**	.783**	.516**	-.395**	.501**	.172**
Amihud	.720**	1.000	.787**	.652**	.248**	-.304**	.487**	.228**
RtoTR	.730**	.787**	1.000	.717**	.351**	-.369**	.561**	.244**
Zero trading	.783**	.652**	.717**	1.000	.649**	-.476**	.430**	.163**
Zero return	.516**	.248**	.351**	.649**	1.000	-.471**	.079*	-.135**
Volume	-.395**	-.304**	-.369**	-.476**	-.471**	1.000	.086*	.126**
Turnover	.501**	.487**	.561**	.430**	.079*	.086*	1.000	.290**
FTSE	.172**	.228**	.244**	.163**	-.135**	.126**	.290**	1.000

Note: The table presents time-series correlations between liquidity measures and market variables from 2007 to 2009. Relative spread (RS) calculated by spread between bid and ask price divided by average bid and ask price; Amihud ration calculated by absolute daily return divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Volume is the trading volume in number. Turnover is the trading volume in number divided by the shares outstanding. FTSE is the absolute return of FTSE all share index. The data are collected from Thomson Reuters Datastream. ** indicates statistical significance at the 0.05 level (2-tailed).

During the financial crisis (2007–2009), compared with the results before the financial crisis, the correlation coefficients of relative spread with Amihud and RtoTR increase considerably to 0.720 and 0.730 respectively, while the zero return days coefficient drops from 0.774 in the preceding period to 0.516. The correlations between each liquidity measure are positive in this period.

Surprisingly, the coefficients among the turnover rate and liquidity measures are all positive. The stock market crashed because of the financial crisis and the market became less liquid compared to other periods. So the values of the liquidity measures are considerably higher and the turnover rate should be lower. This can be seen from the coefficients between the turnover rate and trading volume. Before the financial crisis, the coefficient was 0.76, but during the financial crisis, it dropped to 0.086. It indicates that there is almost no correlation. Selling orders are major parts of trading volume. The transaction costs that usually appear to be a vital aspect during normal conditions will become insignificant if there are a number of large expected losses or gains during periods of stress. This confirms Summers (2000) analysis that turnover is likely to increase during liquidity crunches, as occurred during the Tequila Crisis, the Asian Crisis and the Brazilian Crisis. The result shows that the turnover rate cannot measure market liquidity during a financial crisis.

Trading volumes are still negatively related with each liquidity measure and, comparing the coefficients with those before the crisis, the coefficients in this period are smaller.

All the coefficient values among the liquidity measures and the absolute value of the FTSE All-Share Index drop during the financial crisis, and especially zero return days has a negative coefficient with the FTSE. The RtoTR ratio has the highest time-series correlation at 0.244 in this period, followed by the Amihud ratio at 0.228. As discussed before, the difference between the volatility magnitudes of different measures widened during the financial crisis.

Table 2.9: Time-series stock correlation matrix 2010–2013

	RS	Amihud	RtoTR	Zero trading	Zero return	Volume	Turnover	FTSE
RS		.419**	.205**	.708**	.412**	.465**	.391**	.170**
Amihud	.419**	1.000	.461**	.373**	.062	.182**	.172**	.154**
RtoTR	.205**	.461**	1.000	.283**	.081**	.072*	.009	.120**
Zero trading	.708**	.373**	.283**	1.000	.505**	.350**	.221**	.172**
Zero return	.412**	.062	.081**	.505**	1.000	.086**	-.015	-.161**
Volume	.465**	.182**	.072*	.350**	.086**	1.000	.787**	.278**
Turnover	.391**	.172**	.009	.221**	-.015	.787**	1.000	.221**
FTSE	.170**	.154**	.120**	.172**	-.161**	.278**	.221**	1.000

Note: The table presents time-series correlations between liquidity measures and market variables from 2010 to 2013. Relative spread (RS) calculated by spread between bid and ask price divided by average bid and ask price; Amihud ratio calculated by absolute daily return divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Volume is the trading volume in number. Turnover is the trading volume in number divided by the shares outstanding. FTSE is the absolute return of FTSE all share index. The data are collected from Thomson Reuters Datastream. ** indicates statistical significance at the 0.05 level (2-tailed).

After the financial crisis, the relative spread is still most correlated with zero trading volume days, while the coefficient between the RtoTR and relative spread is only 0.205.

It is surprising to find that the coefficients between each liquidity measure and the trading volume are all positive. This may be explained by the stock market recovery. Investors perhaps began to join in the market rise and trade stocks much more frequently.

The coefficients on turnover are all still positive, except for zero return days. The correlations are lower are those during the financial crisis.

As for the absolute value of the FTSE All-Share Index, zero trading volume days has the highest time-series correlation at 0.172 in this period, followed by relative spread at 0.170. The correlation coefficients of the FTSE All-Share Index are positively related with liquidity measures, except for zero return days. But the coefficients are still smaller than those before the financial crisis.

In conclusion, zero trading volume is the best estimator of the relative spread in different periods, followed by the Amihud ratio. This proves that relative spread and zero trading volume days both have the advantage of measuring trading costs. RtoTR is the most inrelevant measure compared with the other liquidity measures.

The turnover rate is not a reliable measurement to measure liquidity, especially when a financial crisis occurs. Selling orders may lead to a high turnover rate when the market price decreases. The coefficients among the absolute value of the FTSE All-Share Index and liquidity measures are mostly positively correlated. The higher volatility of the stock market is related to the lesser stock liquidity, and the financial crisis may weaken the relationship. The capabilities of the different liquidity measures are affected by the market conditions. This finding shows that relative spread and zero trading volume days, which directly capture trading costs, perform well in the periods before and after the financial crisis.

2.4.4. Portfolio Analysis

To check the links between liquidity measures, we calculate each stock's average relative spread, Amihud ratio, RtoTR ratio, zero trading volume days, zero return days, market value, turnover rate and trading volume through the whole period (2001–2013, 535 stocks).

Table 2.10: Portfolios based on Relative spread

	Relative spread	**Amihud**	**RtoTR**	**Zero trading volume days**	**Zero return days**	**Market value**	**Turnover rate**	**Trading volume**
p1	0.003	3.04E-08	4.087	0.458	93.47	10080	0.017	8176.0
p2	0.011	1.38E-06	47.99	26.93	381.29	697.33	0.007	1055.7
p3	0.032	1.37E-05	239.82	231.12	950.47	159.38	0.0023	262.2
p4	0.062	2.43E-05	240.52	696.74	1734.9	52.55	0.0029	210.07
p5	0.143	0.000118	244.43	1205.7	2292.9	13.40	0.0025	263.6
p5-p1	0.14	0.000118	240.3	1205.3	2199.5	-10066	-0.0145	-7912

This table reports the characteristics of portfolios constructed on the basis of the Relative spread. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the quintile portfolio containning the stocks with the lowest relative spread and P5 is the quintile portfolio containning the stocks with the highest relative spread. P5-P1 stands for the spread between P5 and P1. The portfolios are equally weighted.

We sort stocks into quintile portfolios based on relative spread. Portfolio 1 is the smallest relative spread group of stocks and portfolio 5 is the highest relative spread group of stocks. Relative spread is one of the most intuitive liquidity measures, which can measure trading cost. In other words, portfolio 1 is the most liquid group of stocks and portfolio 5 is the most illiquid group of stocks. The averages of the Amihud raio, RtoTR ratio, zero trading volume days, zero return days, market value, turnover rate and trading volume are calculated.

It is clear that Amihud, RtoTR, zero trading volume days and zero return days have the same trend as relative spread. Moving from portfolio 1 to portfolio 5, the average value of each measure significantly increases. These four measures' biggest values are all in portfolio 5 and the smallest values are all in portfolio 1. In contrast, market value, turnover rate and trading volume have the opposite trend. Moving from portfolio 1 to portfolio 5, the average value of each variable considerably decreases, though not strictly monotonically.

Table 2.11: Portfolios based on Amihud ratio

	Amihud	**Relative spread**	**RtoTR**	**Zero trading volume days**	**Zero return days**	**Market value**	**Turnove r rate**	**Trading volume**
P1	2E-08	0.0033	3.75	0.49	94.2	10180	0.0181	8281.1
P2	7.72E-07	0.013	26.01	27.82	397.34	677.95	0.0054	1004.5
P3	8.75E-06	0.038	165.5	279.88	1110.6	147.24	0.0035	320.81
P4	2.68E-05	0.059	284.6	665.32	1596.4	65.64	0.0024	156.75
P5	0.000121	0.138	301.11	1185.6	2248.5	18.69	0.0026	271.52
P5-P1	0.000121	0.135	297.35	1185.1	2154.2	-10162	-0.016	-8009

This table reports the characteristics of portfolios constructed on the basis of the Amihud ratio. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the quintile portfolio containning the stocks with the lowest Amihud ratio and P5 is the quintile portfolio containning the stocks with the highest Amihud ratio. P5-P1 stands for the spread between P5 and P1. The portfolios are equally weighted.

We sort the stocks into quintile portfolios based on the Amihud ratio. Portfolio 1 is the smallest Amihud ratio group of stocks and portfolio 5 is the highest Amihud ratio group of stocks. Amihud (2002) proposes that the Amihud ratio is negatively correlated with stock liqudity. In other words, portfolio 1 is the most liquid group of stocks and portfolio 5 is the most illiquid group of stocks.

The results show that these other four measures have the same trends as the Amihud ratio and confirm the relationship between the Amihud ratio and liquidity. In contrast, market value, turnover rate and trading volume have the opposite trends compared to the Amihud ratio. Moving from portfolio 1 to portfolio 5, the average value of each variable considerably decreases, though not strictly monotonically. The results are the same as for the relative spread.

Table 2.12: Portfolios based on Rtotr ratio

	RTOTR	**Relative spread**	**Amihud**	**Zero trading volume days**	**Zero return days**	**Market value**	**Turnover rate**	**Trading volume**
P1	3.163	0.0037	4.23E-08	0.49	108.12	9326.	0.019	8070.2
P2	11.95	0.0311	1.1E-05	164.95	705.48	1413.1	0.006	1341.9
P3	33.60	0.0639	3.3E-05	532.15	1429.6	140.15	0.003	234.87
P4	77.82	0.0768	5.48E-05	705.91	1601.8	99.85	0.002	217.76
P5	686.4	0.0709	5.31E-05	716.92	1543.7	110.0	0.001	158.70
P5-P1	683.2	0.067	5.3E-05	716.42	1435.5	-9216	-0.018	-7911.5

This table reports the characteristics of portfolios constructed on the basis of the Rtotr ratio. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the quintile portfolio containning the stocks with the lowest Rtotr ratio and P5 is the quintile portfolio containning the stocks with the highest Rtotr ratio. P5-P1 stands for the spread between P5 and P1. The portfolios are equally weighted.

We sort the stocks into quintile portfolios based on the RtoTR ratio. Portfolio 1 is the smallest RtoTR ratio group of stocks and portfolio 5 is the highest RtoTR ratio group of stocks. Florackis et al. (2011) propose that the RtoTR ratio is negatively correlated with stock liqudity. In other words, portfolio 1 is the most liquid group of stocks and portfolio 5 is the most illiquid group of stocks.

The results show that the other four measures have the same trends as the RtoTR ratio and confirm the relationship between the RtoTR ratio and liquidity. In contrast, market value, turnover rate and trading volume have opposite trends compared to the RtoTR ratio. Moving from portfolio 1 to portfolio 5, the average value of each variable considerably decreases, though not strictly monotonically. The results are the same as for the relative spread and the Amihud ratio.

Table 2.13: Portfolios based on Zero trading volume days

	Zero trading volume days	**Relative spread**	**Amihud**	**RtoTR**	**Zero return days**	**Market value**	**Turnover rate**	**Trading volume**
P1	0.0277	0.0047	8.2E-08	4.923	119.54	8575.	0.014	6353
P2	7.146	0.015	2.01E-06	48.391	376.63	2202.	0.010	3008
P3	123.61	0.0374	1.54E-05	229.91	918.96	200.3	0.0038	364.53
P4	575.41	0.0732	4.42E-05	209.37	1663.477	78.48	0.002	165.19
P5	1476.99	0.1204	9.36E-05	287.42	2379.27	18.54	0.0014	112.48
P5-P1	1476.96	0.1156	9.35E-05	282.50	2259.724	-8556.	-0.012	-6241

This table reports the characteristics of portfolios constructed on the basis of the zero trading volume days. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the quintile portfolio containning the stocks with the smallest zero trading volume days and P5 is the quintile portfolio containning the stocks with the biggest zero trading volume days. P5-P1 stands for the spread between P5 and P1. The portfolios are equally weighted.

We sort the stocks into quintile portfolios based on zero trading volume days. Portfolio 1 is the smallest zero trading volume days group of stocks and portfolio 5 is the highest zero trading volume days group of stocks. Kang and Zhang (2014) propose that zero trading volume days is negatively correlated with stock liqudity. In other words, portfolio 1 is the most liquid group of stocks and portfolio 5 is the most illiquid group of stocks.

The results show that the other four measures have the same trends as the zero trading volume days and prove the relationship between it and liquidity. In contrast, market value, turnover rate and trading volume have the opposite trends compared to zero trading volume days. Moving from portfolio 1 to portfolio 5, the average value of each variable considerably decreases. The results are the same as for the relative spread, Amihud ratio and RtoTR ratio.

Table 2.14: Portfolios based on Zero return days

	Zero return days	Relative spread	Amihud	RtoTR	Zero trading volume days	Market value	Turnover rate	Trading volume
P1	87.212	0.003	4.46E-08	4.34	3.93	10142	0.0176	8332.6
P2	350.35	0.013	2.66E-06	49.15	21.02	718.80	0.0067	992.33
P3	846.036	0.035	1.49E-05	269.6	167.5	166.45	0.0037	331.45
P4	1741.56	0.071	3.31E-05	226.0	579.5	47.25	0.0025	193.35
P5	2437.2	0.127	0.000106	225.7	1405	15.13	0.0015	177.77
P5-P1	2349.9	0.124	0.000105	221.4	1401	-10126	-0.0161	-8154.8

This table reports the characteristics of portfolios constructed on the basis of the zero return days. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the quintile portfolio containning the stocks with the smallest zero return days and P5 is the quintile portfolio containning the stocks with the biggest zero return days. P5-P1 stands for the spread between P5 and P1. The portfolios are equally weighted.

We sort the stocks into quintile portfolios based on zero return days. Portfolio 1 is the smallest zero return days group of stocks and portfolio 5 is the highest zero return days group of stocks. Lesmond (1999) proposes that zero return days is negatively correlated with stock liqudity. In other words, portfolio 1 is the most liquid group of stocks and portfolio 5 is the most illiquid group of stocks.

The results show that the other four measures have the same trends as zero return days and prove the relationship between it and liquidity. In contrast, market value, turnover rate and trading volume have the opposite trends compared to zero return days. Moving from portfolio 1 to portfolio 5, the average value of each variable considerably decreases. The results are the same as for the other four measures.

Overall, the results prove that the higher the value of each liquidity measure, the lower the market capitalization, trading volume and turnover rate will be. The five liquidity measures are positively correlated and they can measure the illiquidity of stocks. The monotonic correlations are obvious among liquidity measures.

2.5. Comparison of Liquidity Measures

2.5.1 Theoretical framework

Lesmond (2005) introduces a model to compare the liquidity measures in 31 emerging markets. This provides a direct test of the relationship between the bid–ask spread plus commission cost and the several liquidity proxies, as well as market factors that capture liquidity. It sets the bid–ask spread as a dependent variable and market proxies (volatility, price, volume and market value) as independent variables. Then, after adding each liquidity measure as an independent variable, a higher R^2 shows a higher model specification. So the best liquidity measure has the highest R^2. The Roll (1984) measure, Amivest measure, turnover measure, Amihud (2002) measure and LOT measure (Lesmond et al., 1999) are used in the study. In this study, we use the Lesmond (2005) model to test liquidity in the London Stock Exchange.

As we discussed before, liquidity, usually defined as market liquidity, is the ease of trading a financial instrument or the degree to which an asset or security can be bought or sold in the market without affecting the asset's price. More specifically, it has three aspects: tightness, depth and resiliency. In theory, direct trading costs (tightness) can be measured by the bid–ask spread; indirect trading costs (depth and resiliency) can be measured by price impact.

Relative spread is the most intuitive way of measuring transaction costs, which can capture tightness in the market (Amihud and Mendelson, 1986b). The Amihud ratio and RtoTR can capture price impact. Zero trading days and zero return days are more direct liquidity measures.

As for market factors, volatility, price, trading volume in numbers and market value are included in the test (Stoll, 2000). The volatility of the market can capture the risk of an adverse price change because of stock put into the inventory (Lesmond, 2005). Stocks with lower prices seem to have more risks. Lesmond (2005) states that the trading volume of stocks and firm size can be used as proxies for order processing and inventory consideration. Stocks with a higher trading volume and bigger company size can have less inventory risk. Market capitalization is often related with bid-ask spread (Stoll and Whyaley, 1983). Karpoff and Walking (1988) and Bhushan (1994) find that price, trading volume and firm size are negatively related with transaction costs.

2.5.2 Cross-sectional Regression

A cross-sectional regression is a kind of regression model which is conducted to find the relationship between the explanatory variables and explained variables in one period through different units. It is possible to interpret whether the liquidity measures can be explained by a linear function of the market proxies using cross-sectional regression. The Fama and MacBeth (1973) methodological approach sets the basis for the cross-sectional regression methodology. Here is a basic cross-sectional equation and its matrix format:

$$Y = C + \beta X + \varepsilon$$

where *Y* is the dependent variable, *C* is the intercept, β is the slope coefficient, X is the independent variable and ε is the error term.

$$Y = \begin{pmatrix} y1 \\ y2 \\ y3 \\ . \\ . \\ . \\ . \\ yn \end{pmatrix}, C = \begin{pmatrix} c1 \\ c2 \\ c3 \\ . \\ . \\ . \\ . \\ cn \end{pmatrix}, \beta = \begin{pmatrix} \beta1 \\ \beta2 \\ \beta3 \\ . \\ . \\ . \\ . \\ \beta n \end{pmatrix} X = \begin{pmatrix} x1 \\ x2 \\ x3 \\ . \\ . \\ . \\ . \\ xn \end{pmatrix} \varepsilon = \begin{pmatrix} \varepsilon1 \\ \varepsilon2 \\ \varepsilon3 \\ . \\ . \\ . \\ . \\ \varepsilon n \end{pmatrix}$$

Firstly, we set the relative spread as a dependent variable. There are several research works in which the bid–ask spread plus commission fees are set to be independent variables. Lesmond (2005) finds that the results of using bid–ask plus commission fees and of only using bid–ask spread are almost the same. Then the dependent variables are daily market price, daily market stocks' variance, daily market trading volume, daily market capitalisation and daily market turnover rate.

Then we run a cross-sectional regression, for which the equation is shown below:

$$RS = \alpha + \beta_1 VAR + \beta_2 Price_{stock} + \beta_3 Volume + \beta_4 MV + \varepsilon$$

where RS is the relative spread, which was defined earlier. We calculate the average daily stock relative spread from 2001 to 2013 for each stock.

From 2001 to 2013, for each stock, VAR is the average daily return standard deviation; $Price_{stock}$ is the average daily price; $Volume$ is the average daily trading volume; and MV is the average daily market capitalisation. R^2 is the fitness of the regression model. Based on the research of Stoll (2000) and Lesmond (2005), we take logs of the price, trading volume, and market capitalisation variables.

Secondly, the regression takes each liquidity measure into consideration respectively: the Amihud ratio (AMI), RtoTR ratio (RTO), zero trading volume days $(0\,TVD)$ and zero return days $(0RD)$. So the regression will change to:

$$RS = \alpha + \beta_1 VAR + \beta_2\,Price_{stock} + \beta_3 Volume + \beta_4 MV + \beta_5 Amihud + \varepsilon$$

$$RS = \alpha + \beta_1 VAR + \beta_2\,Price_{stock} + \beta_3 Volume + \beta_4 MV + \beta_5 Rtotr + \varepsilon$$

$$RS = \alpha + \beta_1 VAR + \beta_2\,Price_{stock} + \beta_3 Volume + \beta_4 MV + \beta_5 0\ trading\ days + \varepsilon$$

$$RS = \alpha + \beta_1 VAR + \beta_2\,Price_{stock} + \beta_3 Volume + \beta_4 MV + \beta_5 0\ return\ days + \varepsilon$$

The final equation will test all the variables together:

$$\begin{aligned} RS = {} & \alpha + \beta_1 VAR + \beta_2\,Price_{stock} + \beta_3 Volume + \beta_4 MV + \beta_5 Amihud + \beta_6 Rtotr \\ & + \beta_7 0\ trading\ days + \beta_8 0\ return\ days + \varepsilon \end{aligned}$$

Due to the multicollinearity of zero trading days and zero return days, we test a corrected regression without zero return days at last:

$$\begin{aligned} RS = {} & \alpha + \beta_1 VAR + \beta_2\,Price_{stock} + \beta_3 Volume + \beta_4 MV + \beta_5 Amihud + \beta_6 Rtotr \\ & + \beta_7 0\ trading\ day + \varepsilon \end{aligned}$$

Table 2.15: Regression on liquidity measures

α	β_1	β_2	β_3	β_4	AMI	RTO	Zero TD	Zero RD	BP-test (Chi)	DW	R^2
0.104**	1.124**	-0.002	0.003	-0.017**					0.65	1.95	0.727
(11.16)	(8.584)	(-1.127)	(1.448)	(-7.108)							
0.086**	0.603**	-0.002	0.00	-0.011**	0.001**				0.75	1.914	0.818
(11.16)	(5.399)	(-0.959)	(0.162)	(-5.592)	(16.287)						
0.103**	1.112**	-0.003	0.003	-0.017**		4.67×10^{-6}**			0.68	1.988	0.729
(11.138)	(8.499)	(-1.265)	(1.545)	(-7.077)		(1.974)					
0.035**	1.306**	-0.002**	0.005**	-0.011**			4×10^{-5}**		0.81	1.884	0.82
(4.126)	(12.206)	(-1.214)	(2.841)	(-5.236)			(16.536)				
-0.049**	1.215**	0.002	0.007**	-0.007**				4×10^{-5}**	0.89	1.846	0.822
(-4.15)	(11.469)	(1.378)	(4.473)	(-3.412)				(16.842)			
-0.01**	0.884**	0.00	0.004**	-0.005**	0.00**	2.1×10^{-7}	2×10^{-5}**	1×10^{-5}**	0.54	1.786	0.889
(-0.996)	(9.527)	(0.207)	(2.701)	(-2.866)	(15.961)	(0.132)	(7.462)	(5.621)			
0.031**	0.839**	-0.002	0.002	-0.007**	0.001**	9.6×10^{-7}	3×10^{-5}**		0.66	1.835	0.882
(4.432)	(9.2)	(-1.135)	(1.65)	(-4.0)	(16.5)	(0.612)	(16.9)				

Note: the dependent variable is the relative spread. β_1 is the coefficient of VAR which is the average daily each stock return variance from 2001 to 2013.β_2 is the coefficient of $Price_{stock}$ which is the average daily each stock price from 2001 to 2013. β_3 is the coefficient of volume which is the average daily each stock trading volume from 2001 to 2013; β_4 is the coefficient of MV which is the average daily each stock market capitalisation from 2001 to 2013; AMI is the Amihud ratio ($\times10^6$); Rto which is the Rtotr ratio; 0TD is the number of zero trading volume days; 0RD is the number of zero return days. T-values are presented in parenthesis below estimates. BP-test presents the Breusch-Pagen test (Chi-value). DW presents the Durbin-Watson test value. ** denotes significant at the 5% level.

In the table 2.14, the second row of the table shows the coefficients of the four market variables and the regressed R^2. The DW tests for autocorrelation show that there is no autocorrelation issue and BP tests for heteroskedasticity show that there is no heteroskedasticity. Based on the previous finding of multicollinearity between zero trading days and zero return days, the last regression excludes zero return days.

The coefficient of VAR (β_1) which measures the market volatility is positive and significant. It shows that higher volatility stocks are associated with a higher relative spread. Market makers in stocks with higher volatility need more compensation for the volatility risk, so the market makers have to raise the spread. This result supports both Stoll (2000) and Lesmond (2005).

The coefficient of price (β_2) is negative. It confirms Stoll's (2000) findings that price is negatively related to relative spread. Price is a proxy for risk. A lower price tends to be riskier given the effects of price discreteness. The result supports both Stoll (2000) and Lesmond (2005). However, the coefficient is not significant. This may be because the price changes over time during a long time period.

The coefficient of market trading volume (β_3) is -0.001. Trading volume captures the trading frequency, and theoretically the higher trading volume of the market, the better this aspect of market liquidity. This proves that a larger relative spread is correlated with less liquidity in this sense. So the negative coefficient proves that the relative spread can capture the trading frequency and that they are negatively correlated. If the stock's relative spread is high, the stock is less liquid. This result supports both Stoll (2000) and Lesmond (2005), but the coefficient is not significant.

Market value (β_4) has a negative and significant coefficient on relative spread. It shows that higher market capitalization stock is associated with lower relative spread. A higher market value company has less inventory risk and has a deeper market. The findings of Stoll (2000) and Lesmond (2005) show that the firm size is inconsistently related with spread.

Then the Amihud ratio has been involved in the regression model and set to be an independent variable. The R^2 value increases to 0.818. This improves the model fitness. Also, the coefficients are most similar to the original regression results.

Adding RtoTR into the regression does not improve the fitness of the model. And the trading volume and price's coefficients are not significant. The RtoTR ratio captures turnover and it also performs poorly in Lesmond (2005)'s model.

Zero trading days and zero return days also show high R^2 statistic values of 0.82 and 0.822 respectively. The coefficients are largely consistent with the original regression, while the coefficient on trading volume of zero trading days and the coefficient on price and market value of zero return days are not significant.

The most comprehensive regression, containing all the market proxies and liquidity measures, shows interesting results. Except for volatility, the coefficients of the other three market factors become insignificant. Besides, the RtoTR ratio's coefficient still remains insignificant compared with the other three liquidity measures.

Overall, zero return days has the largest R^2 value, which is defined as the goodness of fit of the model. And the coefficients of market factors are robust compared with other liquidity estimators. Zero trading days and zero return days are good at some specific market factors. Based on the study, RtoTR performs worst at measuring transaction costs.

2.5.3 Discussion

This section compares five liquidity measures using the Lesmond (2005) model for stocks in the London Stock Exchange. The regression model is based on Stoll's (2000) variables which are proxies for market characteristics. The study tests the Amihud ratio, RtoTR ratio, zero trading days and zero return days against the relative spread and finds that the zero return days has more explanatory power than the other measures in capturing transaction costs.

The Amihud ratio, zero trading days and zero return days perform well at interpreting the relative spread. By contrast, the RtoTR ratio may not be a good proxy for tranaction costs. The coefficients on liquidity measures and volatility are all positive and significant, showing that stocks with higher volatility are associated with higher illiquidity. The results support Lesmond (2005) that price has a negative correlation with relative spread, while market value is inconsistently related to the relative spread.

However, the coefficients of volume, price and market value are mostly not significant though the coefficients are all negative. Trading volume and price may not explain the liquidity measures to any great extent. One possible explanation is that the regression analysis is cross-sectional. The time period (2001–2013) during which the financial crisis occurred may be too long. The previous results have proved that liquidity changes over time and it dried up dramatically during the financial crisis. The cross-sectional data may not convincingly explain all aspects of the long-term liquidity relationships. Also, the model suffers from the limitation that adding independent variables usually increases the R^2 value. R^2 value does not indicate that the regression model is adequate.

2.6. Conclusion

This chapter explains liquidity in different dimensions and discusses several liquidity proxies in the stock market. Liquidity can be defined as the ease of trading a security in the stock market. In theory, it is associated with three characteristics: tightness (an asset which has low transaction costs is said to be tight), depth (a stock has low transaction costs when there is a larger order), and resiliency (the speed at which it bounces back from imbalance to balance).

Liquidity is hard to capture from a single perspective, so many liquidity measures have been used in different studies: spread-based measures (such as relative spread), volume-based measures (such as turnover), and price-based measures (such as price impact). The combinations of different measures give more dimensions with which to capture liquidity. In this study, the relative spread (directly measured transaction costs), Amihud ratio (capturing price impact and trading volume), RtoTR ratio (capturing price impact and turnover), zero trading volume days (intuitive and easy to measure) and zero return days (intuitive and easy to measure) are chosen to measure liquidity. Correlation and portfolio analysis show that these liquidity measures are positively correlated with each other. The results are broadly in agreement with the current literature.

There is another finding in this chapter. The basic data analysis and time-series graph analysis show that liquidity does change over time. The findings show that market liquidity decreased from 2002 to 2006, possibly due to the upgrading of the trading system in the London Stock Exchange. From 2007 to 2010, the market liquidity dropped heavily but recovered after 2010. The time-series graphs for each liquidity measure give strong evidence that liquidity changes during a time period, which is related with changing market conditions, especially in a financial crisis, during which almost all the liquidity measures illustrate that stock market liquidity suffers heavily. And the correlation figures for the sub-periods investigated shows that turnover cannot capture liquidity during a financial crisis. Selling orders may lead to a high turnover rate when the market price decreases.

The time-series and cross-sectional correlation analysis show that liquidity measures are highly correlated with each other, except the RtoTR ratio. More importantly, the results prove that the turnover ratio may not be a good liquidity proxy because it varies heavily when a financial crisis happens. This raises doubts about a wide range of studies employing the turnover ratio as a major liquidity measure (Lesmond, 2005). In other words, the RtoTR ratio, including the turnover ratio, may not be a trustworthy measure of liquidity in certain periods.

Based on Stoll (2000) and Lesmond's (2005) studies, this chapter provides an empirical comparison of liquidity measures and market proxies (volatility, price, volume and market value) in the London Stock Exchange. Based on the cross-sectional regression model, liquidity measures are positively associated with relative spread, volatility and negatively associated with price, volume and market value. The results support those of Stoll (2000) and Lesmond (2005), except for market value. One possibility is that Stoll (2000) study the market through only one year and Lesmond (2005) cover 31 emerging markets which makes it difficult to conclude a findings about market value. The R^2 statistic shows that the Amihud ratio, zero trading days and zero return days perform have increased explanatory power of transaction costs over the Rtotr ratio. While, the coefficients of price and trading volume are mostly insignificant. It may due to the cross-sectional averaging method. In order to solve this problem, the next chapter tests liquidity issues from a panel perspective and find the relationships bewteen liquidity measures and market proxies.

Chapter 3 Liquidity and market characteristics studied from a new panel perspective

3.1. Introduction

In the equity market, liquidity is the ability to buy or sell a stock quickly without causing a large price impact. Liquidity is set to measure how quickly one might buy or sell the stock with the lowest costs. If the stock is liquid, investors can buy many shares rapidly with lower transaction costs, or investors can sell a number of shares rapidly with little impact on the stock price. The level of transaction costs is one measure of liquidity of the stock. If it costs more money to trade the stock, then the stock seems to be less liquid. It is hard to measure liquidity in the stock market because liquidity is related to a number of attributes, such as tightness, depth and resiliency. Liquidity should be tested in multiple dimensions (Amihud, 2002).

The previous chapter gives comparisons of liquidity measures using time-series graphs, correlation analysis and portfolio analysis. Stoll has (2000) studied friction in the form of spread in the NYSE/AMSE and NASDAQ stocks and used several market characteristics to investigate it. Friction can be measured by how long it takes to trade a given amount of an asset optimally (Lippman and McCall, 1986). Frictions, to some extent, can be seen as illiquidity. Lesmond (2005) followed this study using a similar model to test liquidity in emerging countries. Both studies use cross-sectional data to obtain their results. However, liquidity changes over time and cross-sectional data regressions cannot fully analyse the stock liquidity over a period of time. The timing of the snapshot is not guaranteed to be representative. Our former results have shown that the cross-sectional regression has many insignificant coefficients in the London Stock Exchange. The price and trading volume’s coefficients are insignificant in most results, based on the models of Stoll (2000) and Lesmond (2005).

Motivated by these issues, we use panel data to compare liquidity measures and the relationship between liquidity measures and market characteristics in the London Stock Exchange in this chapter. Panel data includes time-series observations on a number of cross-sectional units. The data sets provide rich sources of information to deal with unobservable effects. Using simple cross-sectional regression or time-series regression may lead to omitted variable bias. Moreover, we use a new method derived from the fixed effects model to explain links between non-stationary variables (price and market value) and liquidity measures.

There are five liquidity measures tested in our research: relative spread, Amihud ratio, Rtotr ratio, zero trading days and zero return days. Based on the stock market's characteristics, we test each liquidity measure using Lesmond's model (2005). The contribution of this study is thus the comparison of panel data estimates with a cross-sectional estimation of the relationship between liquidity and market stock variables (volatility, price, trading volume and market value) in specific periods. The results show that the coefficients from panel data are more often significant compared with those from cross-sectional model. The model using panel data is more convincing. The panel data shows that relative spread, Amhud ratio and Rtotr have positive coefficients relating to volatility while zero trading days and zero return days have negative coefficients. All the liquidity measures have negative relationships with stock price and trading volume. Market value's coefficients are inconsistent differing between the liquidity measures.

The first section of this chapter shows the principles of each liquidity measure and the relationship between them and market characteristics. The second section gives a definition of panel data and the basic structure of the panel regression model. The third section shows the basic principle of the logistical regression model, which has been used in the panel data regression for zero trading days and zero return days. The fourth section shows the results and basic findings of the data and stationary tests for panel data. The fifth section presents the results of the liquidity comparison between cross-sectional data and panel data. The sixth section shows the extension of the fixed effect model and the results for the panel data. The last section gives a discussion and conclusions for this chapter.

3.2. Theoretical considerations

3.2.1 Measures of liquidity

3.2.1.1 Relative spread

The liquidity measure most frequently used worldwide is the relative spread, which is the major way to measure trading cost. The quoted spread, proposed by market makers, covers the costs of ordering processing, inventory storage and adverse information costs. Glosten and Harris (1988), Stoll (1989), Atkins and Dyl (1997) and Menyah and Paudyal (2000) state that the spread is related to the volatility of the stock, the stock trading volume, the stock price and stock market value. Each of these four characteristics is closely related to the stock market structure.

$$Relative\ spread = \left|\frac{ask\ price - bid\ price}{midprice}\right|.$$

Where midprice is the average price of bid price and ask price.

Many exchanges use market makers who can buy or sell stock to potential public customers to maintain liquidity. Thus, to compensate market makers who provide liquidity, the exchanges empower the market makers to post different prices for buying and selling orders. The approach of market makers to buy low and sell high is their major source of compensation for providing liquidity. It also reflects the degree of asymmetry of information between buyers and sellers. Copeland and Galai (1983) and Glosten and Milgrom (1985) state that the additional widened spread is an adverse selection component with the purpose of providing protection when the market makers deal with the informed traders. Market makers will set prices in order to ensure the traded price does not result in a loss due to informed traders.

3.2.1.2 The Amihud ratio and Rtotr ratio

Amihud (2002) proposes the Amihud ratio which is widely used to measure liquidity. Compared to the relative spread, it captures more dimensions of liquidity, such as trading volume and price impact. Liquid stocks will have less prices change when large orders occur. This measure represents the price response to order flow. Amihud focuses on the trading volume because it is the number of shares traded that gives a measure for liquidity rather than the proportion of shares. This is therefore an absolute rather than relative measure

$$Amihud\ ratio = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{iyd}|}{VOLD_{iyd}}$$

R_{iyd} is the return (daily price change) on stock i on day d of year y, and $VOLD_{iyd}$ is the daily trading volume in pounds.

The Rtotr ratio proposed by Florackis et al. (2011) is another liquidity measure involving price impact. Instead of using trading volume as the denominator, the Rtotr ratio uses the turnover rate (trading volume divided by shares outstanding of stock). The turnover rate avoids size bias because turnover rates should not depend on company size, avoiding problems of scale bias compared to the trading volume. Compared with an absolute measure, turnover rate is the trading volume relative to the shares outstanding. This measure captures trading frequency by using the turnover ratio in the equation.

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}}$$

where TR_{itd} is the turnover ratio of stock i at day d and $D_{it}$and R_{itd} are as previously defined.

3.2.1.3 Zero trading volume days and zero return days

Lesmond et al. (1999) create a new liquidity measurement:

$$ZR_{i,t} = N_{i,t} / T_t$$

Where T_t is the number of trading days in month t and $N_{i,t}$ is the number of zero-return days of stock i in month t. If ZR is high, entailing that the stocks have more zero return days in month t, it shows that the stock is more illiquid. Lesmond et al. (1999) believe that marginal or informed traders will trade only when the information value is higher than the marginal trading costs. If the stock is less liquid, the new information must have more time to disseminate and affect price.

Kang and Zhang (2014) believe that the proportion of zero-volume days can measure the occurrence of the no-trade phenomenon more directly than the zero-return measure. The zero-based measure that is ZeroVol, which is defined as follows:

$$ZeroVol = \frac{Number\ of\ days\ with\ zero\ volumes\ in\ a\ month}{Total\ number\ of\ trading\ days\ in\ a\ month}$$

Based on the studies by Lesmond et al. (1999), Liu (2006) and Kang and Zhang (2014) we will use two more intuitive ways of measuring liquidity: zero trading days and zero return days. If the stock has zero trading volume in one day, then the day is a zero trading volume day, while if the stock has zero return in one day, the day is a zero return day. Both liquidity measures show the illiquidity of the stock.

3.2.2 Factors related to liquidity

3.2.2.1 Volatility

Volatility is measured by the standard deviation of stock return in a specific period. Stoll (2000) find that stocks with higher volatility have higher relative spread. In this thesis, we use historical volatility to represent volatility. Highly volatile stocks' returns have more fluctuations in a certain period. In other words, volatility can be seen as an uncertainty about future stock movement which indicate future risk. The variance of returns captures the price risk of holding the stock. There is a greater chance of loss from a price move while investors hold inventory. Higher inventory costs leads to less liquidity. If the volatility of the stock is higher, then market makers want more compensation for volatility risk, which widens the relative spread. The wider spreads lead to a less liquid condition. Hence, we expect that volatility is positively related with relative spread.

The Amihud ratio calculates the daily price responses to one pound of trading volume. Similarly, the Rtotr ratio presents that the daily price responses to one pound of turnover rate. Both measures can be interpreted as a measure of price impact. Both Amihud ratio and Rtotr ratio involve absolute stock return. We expect that bigger stock price impact is associated with higher volatility of the stock. If there is a big price impact on stock, then the buyer or the seller would pay more money to buy the stock or earn less by selling the stock. Thus, the stock becomes less liquid. In other words, the Amihud ratio and Rtotr ratio are positively related to volatility.

Zero trading days and zero return days are defined by this rule: if there is no trading volume or zero return in one day, that day is a zero trading day or zero return day. If there is a zero trading day or zero return day, the data of that day is set to be 1, otherwise the data is set to be zero. Clearly, these two measures are discrete in contrast to the other liquidity measures which are continuous. Thus, zero trading days and zero return days require different treatment from the relative spread, the Amihud ratio and Rtotr ratio.

Generally, based on the definition of zero trading days, less liquid stocks tend to have more zero trading days. In reality, the relationship between zero trading days and volatility is complex. If there are many zero trading days in one period, then the standard deviation of stock return would likely be quite small. For example, if we consider a 10-day period in which 9 days are zero trading days and only 1 day has trading volume (such as might occur with small stocks) which is accompanied by a moderate change in stock price. In this situation, the standard deviation of stock return is relatively small (Figure 3.1). In contrast, if there are several trading days accompanied by price moves in the same period (highly-traded stocks, but with larger trading volume bound), then the standard deviation of stock return would be quite large (Figure 3.2). Hence, the volatility of stock is likely to be negatively related to zero trading days.

Figure 3.1: stock with zero trading volume situation (9 days of zero trading days)

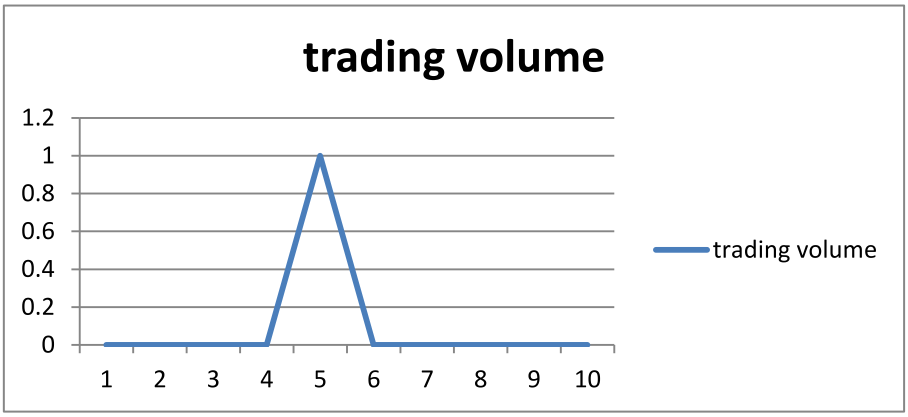
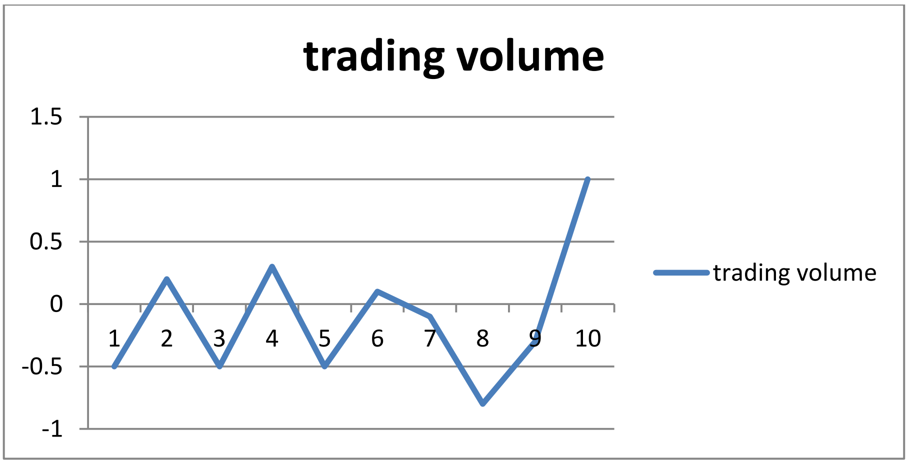
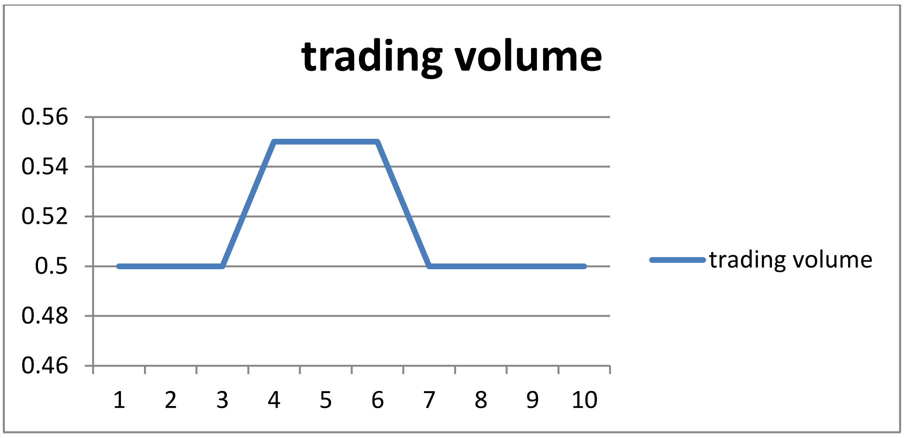


Figure 3.2: stock with zero trading volume situation (a number of trading days)



However, there is another situation that needs to be considered when the stock is traded frequently and the trading volume of each day is relatively small (tight trading volume bound). In this situation, the standard deviation of stock return would be small. (Figure 3.3). So volatility may be positively correlated with zero trading days.

Figure 3.3: stock with daily trading volume situation (zero days of zero trading days)



We expect similar results for zero return days. If there are several zero return days in one period, then the standard deviation of stock return would likely be quite small. By contrast, if there are several return change days during the same period, then the standard deviation of return would be quite large. Hence, the volatility of stock return will tend to be negatively related with zero return days.

3.2.2.2 Price

Price is a fundamental stock characteristic. The price we use is the closing price of stock in London Stock Exchange. Stoll (2000) states that price captures the effect of discreteness and is a proxy for risk. Low price stocks are likely to be riskier because most low price stocks are small companies. But in reality, some companies do stock splits or pay stock dividends, which causes a decrease in the stock price. Theoretically, low price stocks are riskier and market makers need more compensation for the risk; hence the relative spread is larger.

If the stock price is lower and riskier, then the magnitude of price impact is larger. Specifically, low priced stocks are usually smaller companies stocks which are less traded than larger company stocks. Usually, a small company with a lower stock price will have a bigger price impact of orders. Orders which are higher than usual are likely to reflect more private information leading to larger price movements. Judging by the equation of Amihud and Rtotr ratio, which involve price impact, there is a greater impact on price where the initial price is low.

As Lesmond et al (1999) state, if the transaction costs are higher than the expected trading profit, then investors will not trade a stock, thus there would be more zero trading days and zero return days. Higher transaction costs have been proved to be related with lower price (Stoll 2000, Lesmond, 2005). So, zero trading days and zero return days which measure liquidity are expected to be negatively related to price.

3.2.2.3 Trading volume

Trading volume is related to liquidity (Brennan et al., 1998). Trading volume shows how many stocks have been traded in one day and this is a very simple and easy way to measure stock liquidity. Traditionally high trading volume stocks are quite liquid. Market makers want less compensation if the trading volume is higher because there are less inventory risks and adverse selection costs. The relative spread is narrowed when the stock’s trading volume is high. Hence, relative spread is negatively related to trading volume.

Theoretically, trading volume is a part of the denominator in the equations for the Amihud and the Rtotr ratios. If other factors are constant, when trading volume increases, the Amihud ratio and Rtotr ratio will decrease. Also, when smaller trading volume on a stock cause price impact forcing price distortion, it indicates that the stock is less liquid. Obviously, trading volume is negatively related to both Amihud and Rtotr ratio.

Stock with higher trading volume will generally have less zero trading days based on the definition of zero trading days. Hence, trading volume is negatively related to the number of zero trading days. When a stock has low trading volume, it is likely that the stock returns are likely to be small. If there is no return change, then that day is defined as a zero return day. Clearly, trading volume is likely to be negatively related to the number of zero return days.

3.2.2.4 Market value

Market value reflects the market depth of the stock. Usually, a high value company has a deep market depth for the stock. High market value stocks are frequently traded by a number of customers. The stock becomes a focus for analysts who try to reduce information asymmetry. Hence, these stocks will have less adverse selection costs. Thus relative spread is smaller and negatively related to market value. Market value also reduces the inventory risk because it increases the probability of finding a trade counter party. The liquidity of higher market value stocks is likely to be much better than that of lower market value stocks.

Small firm company is more likely to be less liquid because of more inventory risk and asymmetry information. Hence, the Amihud ratio and Rtotr ratio are negatively related to market value.

High market value stocks are more liquid and frequently traded. Obviously, zero trading days and zero return days are likely to be negatively related to market value.

Based on the statements above, the models to be estimated, and the expected sign of the independent variables, will be:

$$Relative\ spread = f(+Volatility, -Price, -Volume, -MV)$$

$$Amihud\ ratio = f(+Volatility, -Price, -Volume, -MV)$$

$$Rtotr\ ratio = f(+Volatility, -Price, -Volume, -MV)$$

$$0\ trading\ days = f(+Volatility, -Price, -Volume, -MV)$$

$$0\ return\ days = f(+Volatility, -Price, -Volume, -MV)$$

Overall, the relative spread and the Amihud ratio and Rtotr ratio are expected to be positively related to volatility. By contrast, zero trading days and zero return days are expected to be negatively related to volatility. All the liquidity measures are expected to be negatively related to stock price, trading volume and market value.

3.2.2.5 Data definition

Relative spread, RS

Spread divided by the average of the bid and ask price.

Amihud ratio

Absolute daily return divided by daily trading volume in pounds.

Rtotr ratio

Absolute daily price change divided by daily turnover ratio.

Zero trading volume days

Measured by the shares traded in a day. If there is no share traded, then the day is a zero trading volume day.

Zero return days

Measured according to whether the stock has a return in a day. If there is no return, then the day is a zero return day.

3.3 Overview of panel regression

In the previous chapter, we tested the liquidity of the London Stock Exchange from 2001 to 2013 using cross-sectional data based on the models of Stoll (2000) and Lesmond (2005). Stoll (2000) firstly links relative spread and market characteristics (volatility, price, trading volume and market value) in the NYSE/AMSE and NASDAQ markets from 1997 to 1998. The results show that relative spread is positively related to volatility and negative related to price and trading volume. Based on the method of Stoll (2000), Lesmond (2005) makes a comparison of liquidity measures, while also testing the links between relative spread and market characteristics in 31 emerging markets from 1993 to 2000. Both of Stoll (2000) and Lesmond (2005) use cross-sectional regression to obtain results.

However, the trading volume and price are not shown to be significant in the UK market. It may due to the length of the investigation period because our period covers over 10 years and liquidity changes over time. In order to solve these issues, we use panel data instead of time-series or cross-sectional data. The panel data regression takes individual firm effects into consideration. More individual specific unobservable effects can be captured from panel data.

3.3.1 The definition of panel data

In the econometric field, there are three major types of analysis: time-series analysis, cross-sectional analysis and panel data analysis.

Time-series data is a series of observations in which a variable related to a unique entity (for example, a stock, one person, a unit and so on) is investigated over time. Time-series data can be collected at regular time intervals, such as daily data, but the data only has a temporal dimension; for instance, the daily stock price changes over the last two years.

Cross-sectional data is a series of observations that consists of a number of variables collected at the same single point in time. Cross-sectional data only has one spatial dimension; for instance, the prices of several firms recorded on one day.

Panel data, also known as longitudinal data, is a dataset in which the behaviour of entities is collected across time. Panel data combines the time-series and cross-sectional data into one data set. Panel data has both spatial and temporal dimensions; for instance, changes in the daily stock prices of a number of firms over the last two years.

There are two types of panel data: balanced panel data and unbalanced panel data. Balanced panel data is when each cross-sectional unit has the same number of time-series observations. If there are any observational differences between the cross sections over time, the panel data is defined as unbalanced panel data.

3.3.2 Advantages of panel data

There are several advantages to using panel data instead of cross-sectional data or time-series data. Commonly, there are much more data points when using panel data. More degrees of freedom reduce the collinearity between explanatory variables (Hsiao, 2014). Also, important economic questions can be solved through the use of panel data which cannot be explained using time-series or cross-sectional dataset. As panel data includes two dimensions: a cross-sectional dimension and a time-series dimension. It involves computation that is complicated and captures more of the underlying relationships than either of the two other methods. So the results can be more efficient and powerful. Thirdly, time and individual variations in behaviour are unobservable in cross-sectional or time-series models.

3.3.3 Structure of Panel Data

There are two major models for panel data: the fixed effects model and random effects model.

The fixed effects model is based on the assumption that the individual specific effect is correlated with independent variables. Each entity is different so the entity's error and the constant (which captures individual characteristics) should not be correlated with the others. The fixed effects model removes the effect of the time-invariant factors.

Here is the basic equation:

$$y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it}$$

Where Y_{it} is the dependent variable observed for individual i at time t, X_{it} is the independent variable measured at time t (regressor matrix), β is the coefficient vector, α_i is the time-invariant individual fixed effect and ε_{it} is the error term. In the fixed effects model, α_i can be correlated with X_{it}.

The random effects model requires the assumption that individual specific effects are uncorrelated with the independent variables. The random effects model can be estimated by using the generalised least square (GLS). Baltagi (2008) states that the random effects model is suitable when the individuals are drawn randomly from a large population. When the random effects assumption is valid, the random effects model is more efficient than the fixed effects model. Moreover, the number of variables to be tested stays the same when sample size grows. It allows the estimation of the impact of a parameter that does not change over time for a unique cross-sectional unit. Here the model specification is:

$$y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it} + U_i$$

$$y_{it} = X_{it}\beta + \alpha_i + W_{it}$$

Where Y_{it} is the dependent variable observed for individual i at time t, X_{it} is the time-variant $1 \times k$ regression matrix, W_{it} is equal to $\varepsilon_{it}+U_i$ presenting between-entity error. This U_i suggests that the individual error components are not correlated with each other.

The Hausman test can be used to determine whether the fixed effects model or the random effects model is most appropriate (Hausman, 1978). The Hausman test can examine whether independent variables and constant terms are correlated or not. For instance, if the independent variable and constant term are uncorrelated, then both estimators are consistent and one would expect that the gap between them to be relatively small. On the other hand, if the independent variable and constant terms are correlated, then the random effect will be biased and one would expect the gap to be large. The Hausman test examines the significant of the difference between fixed effects model and random effects model. Here is the form of Hausman test in panel model:

$$W = (b_1 - b_0)' \,(Var(b_0) - Var(b_1))(b_1 - b_0) \qquad \sim \chi^2 \,(k-1)$$

Where b_0 and b_1 are two estimators of linear model. B_0 can be seen as β of the fixed effects model and b_1 represents β of the random effects model. The null hypothesis it that both estimators are consistent (no correlation between regressors and effects), but b_1 is efficient. The Alternative hypothesis is that b_0 is inconsistent. This Wald test statistic is distributed as a Chi squared distributed as a Chi squared with degrees of freedom equal to the number of restrictions.

Therefore, the random effects model is better if the Chi squared value fail to reject the null hypothesis. While if the Chi squared value rejects null hypothesis, the fixed effects model is better.

3.4. Logistic regression

The existence of zero trading days and zero return days are categorical and tested as dependent variables while testing market characteristics. There are only two situations of zero trading days and zero return days. The ordinary least squares (OLS) cannot deal with independent variables which are categorical data. Hence, we need to run a logistic regression instead of a linear regression.

The basic logistic regression was proposed by Cox (1958). Logistic regression estimates the links between a categorical dependent variables and independent variables by estimating probabilities using a logistic function, also known as the cumulative logistic distribution (Hosmer et al, 2013). Based on the characteristics of the dependent variables, there are four situations: binary, ordinal, nominal and count. The binary responses (0 or 1) are modelled with a binary logit regression, which is suitable for our research. Tobit models are a form of linear regression. Specifically, if a continuous dependent variable needs to be regressed, but is skewed to one direction or truncated, the Tobit model is used. The characteristics necessary for a Tobit Model to be suitable do not exist for zero trading days and zero return days as these are binary variables. In our research, zero trading days and zero return days are defined by this rule. If there is no trading volume or return changes in one day, then that day is a zero trading day or a zero return day. There are only two situations of these two data measures . If the day is a zero trading day or zero return day, the value of that day is set to be 1, otherwise the data is set to be 0. Hence, the binary logistic regression is appropriate to test zero trading days and zero return days. So:

$Yi = 1$ If the day is a zero trading day or zero return day

$Yi = 0$ If the day is not a zero trading day or zero return day.

In terms of explaining the independent variables, we still use the coefficients of the results. The R square statistic is used to identify the goodness of fit in the linear regression which is appropriate given the OLS approach. When analysing data with a logistic regression, an equivalent statistic to the R square does not exist. Given that the logistic regression uses a maximum likelihood approach, then the Pseudo R square is suitable to imitate the R square to evaluate the goodness of fit of the logistic model. The Pseudo R square = 1- L1/L0 Where L0 and L1 are the constant-only and full model log-likelihoods, respectively.

3.5. Basic information

3.5.1 Basic descriptive results

Table 3.1: Statistical information

	Mean	Median	Max	Min	Mode	Std
RS	0.049075	0.031339	0.297945	0.000819		0.054174
Amihud	3×10^{-5}	7.98×10^{-5}	0.000411	5×10^{-10}		5.7×10^{-5}
Rtotr	154.0781	30.83789	6534.894	0.832318		537.0728
Zero trading	419.9533	100	2348	0	0	583.1065
Zero return	1071.733	801	2787	13	81	885.8695
Volatility	0.027885	0.024715	0.153106	0.009482		0.012536
Price	5.12006	5.302756	8.842876	-0.8861		0.062238
Volume	5.582492	5.375829	10.98154	-0.06468		2.099828
MV	5.127593	4.989932	11.54154	0.404965		2.297175

Note: this table presents descriptive data of five liquidity measurements. Relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Volatility is measured by standard deviation of stock return. Price is logarithm of stock closing price. Volume is the logarithm of stock trading volume in number. MV is the logarithm of stock market value. Except volatility, all figures are averages of daily value from 2001 to 2013. The data are collected from Thomson Reuters Datastream.

3.5.2 Portfolio analysis

To check the links between liquidity measures and market proxies, we calculate each stock's average relative spread, the Amihud ratio, the Rtotr ratio, zero trading volume days, zero return days, standard deviation, price, market value, and trading volume for the whole period (2001-2013, 535 stocks). The process is classifying stocks into decile portfolios based on volatility (standard deviation), price, trading volume, market value and analysing the relationships between liquidity measures and them.

Table 3.2: Decile portfolios based on Standard Deviation

Portfolio	Standard deviation	RS	Amihud	RTOTR	Zero trading volume days	Zero return days
P1	0.014766	0.026158	7.24×10^{-5}	146.7755	525.7273	1036.964
P2	0.018368	0.018074	8.65×10^{-6}	93.00028	230.7736	675.6226
P3	0.02028	0.021744	7.56×10^{-6}	90.77357	233.4717	677.9057
P4	0.021956	0.027117	1.05×10^{-5}	88.21857	292.1481	816.6852
P5	0.023858	0.032717	1.2×10^{-5}	218.7089	326.537	927.2037
P6	0.025698	0.03582	1.83×10^{-5}	89.50889	343.7037	956.1667
P7	0.028303	0.045723	2.18×10^{-5}	102.824	423.9259	1058.981
P8	0.032238	0.070574	5.09×10^{-5}	217.2191	575.3519	1439.519
P9	0.039077	0.088607	6.23×10^{-5}	269.3997	580.6852	1476.852
P10	0.056339	0.12952	0.000107	227.6334	677.36	1682.7
P10-P1	0.041574	0.103362	9.94×10^{-5}	80.85788	151.6327	645.7364

This table reports the characteristics of portfolios constructed on the basis of the Standard deviation which is calculated by the stock return over the whole period. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest standard deviation and P10 is the decile portfolio containning the stocks with the highest standard deviation. P10-P1 stands for the spread between P10 and P1.

We classify stocks into decile portfolios according to the standard deviation of the return through the whole period (2001-2013) which is defined as volatility. The portfolios are equal-weighted. Portfolio 1 is the smallest standard deviation group of stocks and portfolio 10 is the largest standard deviation groups of stocks.

It is clear that the relative spread and Amihud ratio have the same trend as standard deviation. Moving from portfolio 1 to portfolio 10, the average value of each measure increases significantly. The biggest values of these two measures are in portfolio 10. Moving from portfolio 1 to portfolio 10, the average value of Rtotr increases considerably, though it is not strictly monotonic. It indicates that stocks having higher volatility risk have a higher relative spread and Amihud ratio. In other words, the more volatile stocks are less liquid.

Interestingly, zero trading days and zero return days both have a higher value with the smallest standard deviation portfolio (Portfolio 1). As we discussed before, when there is a large number of zero trading days and zero return days during the period, the standard deviation of the stock return may be quite small (Figure 3.1) because there is almost no price movement during the period. This may happen with small stocks. From portfolio 2 to portfolio 10, the zero trading days and zero return days increase and have the same trend as the standard deviation. Generally, stocks with higher zero trading days and zero return days are less liquid. The results indicate that higher volatility is related to higher numbers of zero trading days and zero return days (Figure 3.3). In conclusion, portfolio 1 is the most liquid group of stocks, while portfolio 10 is the most illiquid group of stocks.

Table 3.3: Decile portfolios based on Price

Portfolio	Price	RS	Amihud	RTOTR	Zero trading volume days	Zero return days
P1	13.85731	0.134633	0.000116	99.34275	936.4286	2144.214
P2	39.58954	0.083459	5.29×10^{-5}	150.5284	739.1852	1761.815
P3	75.2642	0.061035	3.2×10^{-5}	120.6726	676.5185	1554.481
P4	120.7835	0.047689	2.2×10^{-5}	198.5783	475.6296	1213
P5	177.9586	0.038758	2.08×10^{-5}	150.8078	352.1111	959.1111
P6	235.3317	0.026764	1.49×10^{-5}	99.75926	261.8889	753.7963
P7	313.3022	0.02343	5.63×10^{-6}	133.6507	183.1111	636.2593
P8	456.5103	0.02129	8.66×10^{-6}	96.82153	147.9444	528.6296
P9	752.1743	0.025571	1.28×10^{-5}	142.9847	226.7037	606.1852
P10	1897.685	0.021359	9.06×10^{-6}	378.7923	145.2766	437.9574
P10-P1	1883.828	-0.11327	-0.00011	279.4495	-791.152	-1706.26

This table reports the characteristics of portfolios constructed on the basis of the price which is calculated by average price through whole period. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest price and P10 is the decile portfolio containning the stocks with the highest price. P10-P1 stands for the spread between P10 and P1.

We sort stocks into decile portfolios based on price. The portfolios are equal weighted. Portfolio 1 is the smallest price group of stocks, while portfolio 10 is the highest price groups of stocks.

The results show that all liquidity measures have almost the same trends with price, although they are not strictly monotonic. Higher price is related to smaller values of liquidity measures. It shows that stocks with lower price are less liquid. In other words, portfolio 1 is the most illiquid group of stocks and portfolio 10 is the most liquid group of stocks. Price, however, performs relatively inconsistently related the Rtotr ratio.

Table 3.4: Decile portfolios based on Trading volume

Portfolio	Trading volume	RS	Amihud	RTOTR	Zero trading volume days	Zero return days
P1	10.46427	0.091928	5.26×10^{-5}	483.1946	1244.091	2127.309
P2	32.07255	0.078208	4.51×10^{-5}	225.1872	979.9259	1914.259
P3	59.35609	0.062937	4.36×10^{-5}	270.7651	534.537	1421.278
P4	101.388	0.061743	4.68×10^{-5}	112.6475	512.2909	1428.109
P5	176.9298	0.056259	3.8×10^{-5}	163.9596	324.5185	1158.519
P6	321.538	0.055075	2.96×10^{-5}	156.6417	278.7778	1083.093
P7	610.0791	0.034299	2.11×10^{-5}	68.12387	154.3889	692.3704
P8	1404.095	0.019303	4.45×10^{-6}	19.14758	23.77778	309.5
P9	3363.152	0.021814	1.49×10^{-5}	13.05108	76.88679	352.4151
P10	15792.66	0.002471	1.11×10^{-8}	3.379716	0.395833	80.91667
P10-P1	15782.19	-0.08946	-5.3×10^{-5}	-479.815	-1243.7	-2046.39

This table reports the characteristics of portfolios constructed on the basis of the trading volume in number which is calculated by average value through whole period. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest trading volume and P10 is the decile portfolio containning the stocks with the highest trading volume. P10-P1 stands for the spread between P10 and P1.

Here, we sort stocks into decile portfolios based on trading volume. The portfolios are equal-weighted. Portfolio 1 is the smallest trading volume group of stocks, while portfolio 10 is the highest trading volume groups of stocks.

The results show that all liquidity measures have the same trends with trading volume, though not strictly monotonically. Higher trading volume is related to smaller values of the liquidity measures. This shows that stocks with lower trading volume are less liquid. In other words, portfolio 1 is the most illiquid group of stocks, while portfolio 10 is the most liquid group of stocks.

Table 3.5: Decile portfolios based on Market value

Portfolio	MV	RS	Amihud	RTOTR	Zero trading volume days	Zero return days
P1	5.3894	0.1567	0.000145	138.776	1382.818	2439.927
P2	15.0705	0.1032	6.33×10^{-5}	314.509	1081.907	2175.463
P3	29.2604	0.0701	3.18×10^{-5}	146.872	697.4259	1880.611
P4	56.922	0.0544	2.16×10^{-5}	239.137	545.0556	1490.167
P5	115.412	0.0410	2.14×10^{-5}	287.777	229.5741	983.4444
P6	216.969	0.0254	9.32×10^{-6}	261.533	117.6111	694.8148
P7	421.533	0.0171	2.02×10^{-6}	109.350	54.38889	488.4815
P8	918.443	0.0084	4.9×10^{-7}	17.7838	17.85185	245.6296
P9	2426.89	0.0046	5.97×10^{-8}	4.57471	7.722222	104.2407
P10	20237	0.0022	8.1×10^{-9}	4.08347	0.770833	78.89583
P10-P1	20231.64	-0.15452	-0.00015	-134.693	-1382.05	-2361.03

This table reports the characteristics of portfolios constructed on the basis of the market value which is calculated by average value through whole period. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest market value and P10 is the decile portfolio containning the stocks with the highest market value. P10-P1 stands for the spread between P10 and P1.

We then sort stocks into decile portfolios based on market value. The portfolios are equal-weighted. Portfolio 1 is the smallest market value group of stocks, while portfolio 10 is the highest market value groups of stocks.

The results show that all liquidity measures have the same trends with market value, though they are not strictly monotonic. Larger firm size is related to smaller values of the liquidity measures. This proves that stocks with lower market capitalisation are less liquid. In other words, portfolio 1 is the most illiquid group of stocks and portfolio 10 is the most liquid group of stocks. Market value, however, performs relatively badly for measuring Rtotr ratio. The fluctuation of Rtotr ratio portfolios is much more volatile than the other liquidity measures.

In summary, all the portfolios of liquidity measure have co-movement with market proxies, though the Rtotr ratio seems to have somewhat less co-movement. Liquidity measures have the same trend as volatility and have the opposite trend to price, volume and market value. The results support the findings of Stoll (2000), but there is less co-movement of market proxies and Rtotr.

There is another interesting finding to discuss here; namely, that the number of zero trading and return days are not linearly related to volatility. The least liquid stocks have many zero trading days which shows low liquidity on these measures. The most volatile stocks also have many zero trading and return days. Small company stocks may demonstrate this situation; hence, we expect these small, more volatile stocks to appear to be less liquid.

3.5.3 Correlation test

We calculate each stock's average daily relative spread, the Amihud ratio, the Rtotr ratio, the zero trading volume days, the zero return days, the market value, volatility, price, trading volume and market value over the entire sample period (2001-2013). Every variable is calculated using the equation:

$$Variable_s = \frac{1}{d}\sum\nolimits_{d=1} Variable_{sd}$$

Where $Variable_s$ is each average variable value of each stock s, d represents the valid days of each measure and $Variable_{sd}$ is the daily value of each variable of each stock. So the variables are cross-sectional data. The portfolio based analysis shows that the trends of liquidity measures and market characteristics are similar. The spearman rank correlation is used in this section.

Table 3.6: Nonparametric Correlations

	Volatility	Price	Volume	Market Value
Relative spread	.533*	-.660*	-.713*	-.958*
Amihud	.518*	-.641*	-.716*	-.938*
Rtotr	.229*	-.332*	-.711*	-.646*
Zero trading days	.283*	-.530*	-.805*	-.899*
Zero return days	.331*	-.625*	-.783*	-.955*
Volatility	1.000	-.450*	-.055*	-.437*
Price	-.450*	1.000	.161*	.661*
Volume	-.055*	.161*	1.000	.760*
Market Value	-.437*	.661*	.760*	1.000

Note: this table presents descriptive data of five liquidity measurements. The relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return (percentage return) divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Volatility is measured by the standard deviation of stock return. Price is logarithm of stock closing price. Volume is the logarithm of stock trading volume in number. MV is the logarithm of stock market value. Except volatility, all figures are averages of daily value from 2001 to 2013. The data is collected from Thomson Reuters Datastream. * denotes significant at the 5% level.

Table 3.6 shows the correlation matrix between liquidity measures and stock market variables for the entire period (2001-2013). As the correlation matrix among liquidity measures has been presented in the former chapter, we will only give the correlation matrix related to the explanatory variables discussed in this chapter here. All the correlation coefficients are significant.

For volatility, relative spread is most closely related to volatility with correlation coefficients of 0.533, followed by the Amihud ratio with 0.518. Rtotr ratio performs least closely with volatility (0.229). These three measures meet our expectation. Interestingly, the coefficients of zero trading days and zero return days are both positive, with 0.283 and 0.331 respectively. So if the stock has many zero trading days or zero return days and a large trading volume day or large return day happens, then it would be associated with an increase in the volatility of the stock. This situation tends to occur when the stock size is small.

As for price, the results are similar to our expectations. All the coefficients are negative. The stocks with the higher price seem more liquid. The lowest value of correlation coefficient is -0.660 (relative spread), while the correlation coefficient of Rtotr and price is only -0.332.

The results for trading volume are similar to those of price. The liquidity measures are negative correlated with it. The stocks with higher trading volume seem more liquid. The coefficients of zero trading days and zero returns are -0.805 and -0.783.

The coefficients of each liquidity measure with market value are also negative and meet our expectation that a large value stock is more liquid compared with small company. The Rtotr is less correlated with market value with -0.646; this proves that Rtotr is less size-biased compared to the other liquidity measures.

Overall, the correlation coefficients of each liquidity measure and market variables are reasonable and mostly support our expectations.

3.5.4 Stationarity test

Unlike the situation for cross-sectional regressions, before conducting tests on panel data, we are obliged to follow the basic rules of making sure that time-series variables are covariance stationary to avoid the possibility of spurious results.

One of the simple time-series regressions is an autoregressive model which represents a type of random process. The autocorrelation of a time series are the correlations of the series with its own past values. In the autoregressive model, the output variables rely linearly on their previous values and a stochastic term.

A general autoregressive mode AR(p) is defined as:

$$X_t = c + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \beta_3 X_{t-3} + ... + \beta_n X_{t-n} + \varepsilon_t$$

Where c is the constant, β_1, β_2, β_n are the parameters of the model, and ε_t is the white noise.

We can produce a basic AR(1) model:

$$X_t = c + \beta X_{t-1} + \varepsilon_t$$

Where c is the constant, β_1 is the parameter of the model, and ε_t is the white noise.

When plotted, the value of X_t throughout the period will not be smooth, that is, there will be some periods when there will be fluctuation (up and down) due to the consequences of shocks. The principle of testing for stationarity is to verify whether the effect of a shock is permanent or temporary (Hill et al, 2008). For example, if the effect of shock is temporary, then the value of X_t in subsequent periods will go back to its long-run equilibrium. If X_t returns to its long-run equilibrium, then it can be deemed that the data set is stationary. This means that the data generating process is stable as even with the consequences of the shock. X_t still returns to its long-run mean (mean reverting). However, if after the shock, the subsequent X_t does not go back to its long-run equilibrium that indicateds a non-stationary variable. A non-stationary variable has a permanent memory of any shock. Where non-stationary variables are included in a regression there is the possibility that results are spurious Thus, it is required to check the data stationarity. The null hypothesis for the AR process is that it contains a unit root, which is calculated by the sum of AR coefficients (β) being equal to one.

If the series is stationary then the test statistic has a known distribution so we can make inferences. However, as with any time series regression, if there is autocorrelation in the residual then the standard error on the estimated coefficients is biased meaning that we cannot come to conclusions about non-sationarity.

An effective means to purge autocorrelation is to introduce lags of the dependent variable. In this study, the augmented Dickey-Fuller (ADF) test and the Phillips and Perron (PP) test are used to investigate whether the variables are stationary. The tests determine whether the variables have a unit root.

Dickey and Fuller (1979) use the following equation to test if a time series has a unit root.

$$Y_t - Y_{t-1} = (\rho_u - 1)Y_{t-1} + \mu_t$$

Where μ_t is the error term. If the ρ_u is equal to one, then the time series variable has a unit root and the time-series variable would be non-stationary. The ADF test including lags of the order ρ allows for higher-order autoregressive processes.

$$\Delta yt = \alpha + \delta t + qy_{t-1} + \sum_{t=1}^{p} \phi_j \Delta y_{t-1} + \mu t$$

Where α is a drift, δt is time tread, ϕ_j is the lag of the dependent variable. If ADF statistical value (coefficient q) is significantly less than the zero, then the null hypothesis of a unit root is rejected and the conclusion is that y_t is stationary. The alternative hypothesis is that there is a unit root.

Perron and Phillips (1988)'s tests are similar to the ADF test, although they allow for auto-correlated residuals (Brooks, 2014). The advantage of the Phillips-Perron test is that it is non-parametric and does not require selecting the level of serial correlation as in ADF (Maddala and Wu, 1999). It rather takes the same estimation scheme as in DF test, but corrects the statistic to conduct for autocorrelations and heteroscedasticity.

The zero trading days and zero return days are defined by the following rule. If there is no trading volume or zero return changes in one day, then that day is a zero trading day or zero return day. If there is a zero trading day or a zero return day, then the data of that day is set to be 1, otherwise the data is set to be 0. Clearly, these two data measures are discrete and cannot be tested using ADF test or PP test. Therefore, we initially test the other three liquidity measures (relative spread, Amihud ratio and Rtotr ratio) and four market characteristics (volatility, price, trading volume and market value).

Table 3.7: Stationary tests of variables using ADF and PP test

	ADF (p-value)	PP	ADF (1st diff)	PP (1st diff)
Relative spread	0.00	0.00		
Amihud	0.00	0.00		
Rtotr	0.00	0.00		
Volatility	0.00	0.00		
Price	0.45	0.64	0.00	0.00
Trading volume	0.00	0.00		
Market value	0.51	0.66	0.00	0.00

Note: The table shows the results of stationary test using augmented Dickey-Fuller (ADF) test and the Phillips and Perron (PP) test. The second and third columns show the p-value of both test results. The null hypothesis is that the variable contains a unit root. The fourth and fifth columns show the p-value of both tests after first differencing.

The table gives the results of the stationary test results of the variables (Appendix A about full results)[3]. In theory, if the statistical p-value is 0, then there is no unit root for the variable. Thus, the variable is stationary and can be used in the panel regression. The table above shows that all the stocks' liquidity measures and volatility and trading volume are stationary (p-value=0); price and market value may have non-stationary problem (p-value≈1). Both the Augmented Dicker-Fuller test and Philips-Perron test show the same results. To use price and market value as variables, we have first to do differencing of price and market value.

The first difference of a time series is the series of changes from one period to the next. If Y_t denotes the value of the time series Y at period t, then the first difference of Y at period t is equal to $Y_t - Y_{t-1}$. After first differencing, the ADF test and PP test are significant, and thus the differenced variables can be used in the panel regression model. However, price and market value are not relevant market characteristics after first differencing. There is no economic significance in our models of liquidity. We need the original price and market value to test liquidity measures. In conclusion, it is

[3] We use the STATA 14 as calculation software. There are many tools available for testing stationarity in STATA14, such as the Levin-Lin-Chu (2002) test and the Im-Pesaran-Shin (2003) test. But these methods need strongly balanced data and do not allow individual series gaps

only useful to use volatility and volume as explanatory variables in the panel regression,

3.6. Econometric methods and results

3.6.1 Method

As we have discussed before, zero trading days and zero return days are binary data in panel data set, we use binary logistic regression only in the panel regression of zero trading days and zero return days. Furthermore, based on the stationary tests, we can only run volatility and volume as independent variables using panel regression. In terms of choosing which panel model, the Hausman test results show that the fixed effects model should be chosen in this study (Appendix B).

Fixed effect regression models:

RS=α+β_1VAR+ β_2Volume+ε

Amihud=α+β_1VAR+ β_2Volume+ ε

Rtotr=α+β_1VAR+ β_2Volume+ ε

Zero trading days=α+β_1VAR+ β_2Volume+ ε

Zero return days=α+β_1VAR+ β_2Volume+ ε

Where:

RS is the relative spread for a stock in specific period

Amihud is the Amihud ratio for a stock in specific period ($\times 10^6$)

Rtotr is the Rtotr ratio for a stock in specific period

Zero trading days is the number of zero trading volume days for a stock in a specific period. In the panel data set, we set a zero trading day as 1, otherwise it is 0 if it is not a zero trading day.

Zero return days is the number of zero return changes days for a stock in a specific period. In the panel data set, we set a zero return day as 1, otherwise it is 0 if it is not a zero return day.

VAR (panel data) is the standard deviation of 10 days rolling returns for a stock[4]

Volume is the trading volume for a stock

Cross-sectional regression models:

RS=$\alpha+\beta_1$VAR+β_2Price+β_3Volume+β_4MV + ε equation (6.2.1)

Amihud=$\alpha+\beta_1$VAR+β_2Price+β_3Volume+β_4MV + ε equation (6.2.2)

Rtotr=$\alpha+\beta_1$VAR+β_2Price+β_3Volume+β_4MV + ε equation (6.2.3)

Zero trading days=$\alpha+\beta_1$VAR+β_2Price+β_3Volume+β_4MV + ε equation (6.2.3)

Zero return days=$\alpha+\beta_1$VAR+β_2Price+β_3Volume+β4MV + ε equation (6.2.3)

VAR (cross-sectional data) is the standard deviation of returns at horizon for stock from 2001 to 2013

Price is the average value of closing price for stock from 2001 to 2013

Volume is the average value of trading volume for stock from 2001 to 2013

MV is the average value of market capitalisation for stock from 2001 to 2013.

Based on the former statement (Section 3.2.2), the models to be estimated will be:

$$Relative\ spread = f(+Volatility, -Price, -Volume, -MV)$$

$$Amihud\ ratio = f(+Volatility, -Price, -Volume, -MV)$$

$$Rtotr\ ratio = f(+Volatility, -Price, -Volume, -MV)$$

$$0\ trading\ days = f(-Volatility, -Price, -Volume, -MV)$$

$$0\ return\ days = f(-Volatility, -Price, -Volume, -MV)$$

[4] 10 days rolling return can be seen as an overview of previous return movements.

3.6.2 Results

Table 3.8: Panel data results (2001-2013) using fixed effects model

	C	Volatility	Volume	F-test	R^2	Pseudo R
RS	0.074*	0.25*	-0.007*	1965.66	0.242	
	(611)	(129.48)	(-268.8)			
Amihud	71.48*	555.8*	-14.75*	8.99	0.0017	
	(48.8)	(23.6)	(-46.39)			
Rtotr	996.7*	2967.1*	-187.2*	30.13	0.0024	
	(66.3)	(14.7)	(-64.2)			
Zero trading days	0.54*	-6.7*	-1.37*			0.5366
	(81.1)	(-39.34)	(-369.22)			
Zero return days	1.28*	-5.8*	-0.51*			0.2863
	(5.98)	(-58.3)	(-626.7)			

Note: this table presents panel regression results of five liquidity measurements. The relative spread is calculated by the spread between the bid and ask price divided by average bid and ask price; the Amihud is calculated by the absolute daily return divided by the trading volume in a monetary unit; the Rtotr is calculated by the absolute daily return divided by the turnover ratio; the zero trading volume days is counted by the zero trading volume of each day; and the zero return days is counted by the zero daily return changes of each day. The volatility is the standard deviation of 10 days rolling returns for stock. The volume is the logarithm of stock trading volume in number. The data is collected from Thomson Reuters Datastream. The White (1980) t-statistics are below the coefficients in parentheses. * denotes significant at the 5% level.

Table 3.9: Cross-sectional data results (2001~2013)

	C	Volatility	Price	Volume	MV	R^2
RS	0.104*	1.124*	-0.002	0.003	-0.017*	0.727
	(11.16)	(8.584)	(-1.12)	(1.448)	(-7.1)	
Amihud	29.008*	836.49*	-1.217	4.153*	-9.658*	0.472
	(3.37)	(6.89)	(-0.59)	(2.27)	(-4.26)	
Rtotr	95.8	2726.998	65.400	-40.012	-25.20	0.067
	(0.563)	(1.14)	(1.6)	(-1.1)	(-0.56)	
zero trading days	1631.70*	-4353.21*	-7.408	-40.826*	-160.8*	0.539
	(12.5)	(-2.4)	(-0.24)	(-2.48)	(-4.7)	
zero return days	3464.17*	-2055.16*	-113.28*	-98.9*	-234.5*	0.816
	(27.8)	(-2.17)	(-3.8)	(-3.7)	(-7.14)	

Note: this table presents the cross-sectional regression results of five liquidity measurements. The relative spread is calculated by the spread between the bid and ask price divided by the average bid and ask price; the Amihud is calculated by the absolute daily return divided by the trading volume in monetary units; the Rtotr is calculated by the absolute daily return divided by turnover ratio; zero trading volume days counted by zero trading volume of each day; zero return days counted by zero daily return changes of each day. Volatility is measured by standard deviation of stock return. The price is logarithm of stock price. The volume is the logarithm of the stock trading volume in number. The MV is the logarithm of the stock market value. Except volatility, all the figures are averages of daily value from 2001 to 2013. The data is collected from Thomson Reuters Datastream. The White (1980) t-statistics are below the coefficients in parathness. * denotes significant at the 5% level.

3.6.2.1. R squared statistics

In the panel data table, owing to the fact that zero trading days and zero return days use the logistic regression model, pseudo R square statistics are used to measure the fit of those models. The logistic models of zero trading days and zero return days are both jointly significant (P-values are less than 0.05).

The relative spread has the highest R square statistic with 0.242 showing the good fit of the model. The Amihud ratio and the Rtotr ratio only have a 0.0017 and 0.0024 R square statistic value, which are much lower than that for the relative spread. It indicates that relative spread can be better explained by volatility and trading volume. Trading costs are much related with volatility risk and trading frequency.

In the cross-sectional table, all the liquidity measures use OLS regression. The R square value shows the fitness of the model.

The highest R square statistic is the zero return days with 0.816, followed by the relative spread (with 0.727) and zero trading days (with 0.539). Obviously, zero return days and zero trading days shows a good fit for the model, which proves Lesmond et al. (1999) and Bekeart et al.'s finding (2007) that if the value of the information signal is insufficient to outweigh the costs accompanied by transacting, then the market participants will choose not to trade. The Amihud ratio's R square statistic is 0.472, but the R square statistic of Rtotr ratio is only 0.067. The low R square statistic suggests that the Rtotr cannot be explained by the four market characteristics.

3.6.2.2. Fixed effects panel data results

Relative spread

Consistent with Lesmond (2005), the coefficient on volatility is positive and significant proving that a stock with higher volatility has a higher relative spread. Market makers anticipate the high volatility of the stock and set a higher relative spread to compensate for higher volatility risk. Volatility is measured by the 10-days rolling return deviation and it can be seen partly as due disagreement of traders about the future of the stock. The result indicates that when disagreements are likely, market makers raise the relative spread to protect themselves.

The trading volume is also negatively and significantly related to the relative spread, showing that a larger volume of trade is accompanied by a smaller spread. Obviously, the market maker has less inventory risk holding a highly traded stock, so it narrows down the relative spread.

The Amihud ratio

The coefficient of the Amihud ratio and volatility is positive and significant. It indicates that a higher Amihud ratio is associated with higher volatility. The Amihud ratio takes the price impact into consideration, while more volatile stock price movement leads to higher absolute return resulting in a higher Amihud ratio. Higher volatility stock is less liquid, so the Amihud ratio is higher.

Trading volume is negatively and significantly related with the Amihud ratio. A stock with a large trading volume is less affected by the price impact because the price impact occurs when stock flow orders are overwhelmingly larger than normal. It would need very high trading volume to trigger heavy price impact when the stock is traded heavily in daily life.

Rtotr

The coefficient on volatility is positive and significant. It implies that a higher Rtotr is associated with higher volatility. Higher volatility stock is less liquid, so the Rtotr ratio is higher.

As for trading volume, as we expect, it is negatively related to the Rtotr ratio. Similar with the Amihud ratio, large trading volume stocks are more liquid and are less influenced by the price impact.

Zero trading days

As we expect, the coefficient of zero trading days and volatility is negative and significant. When the volatility is low and there should be many zero trading days during such a period. Hence, a high volatility stock would have less 0 trading days.

The coefficient of trading volume is negative and significant. Obviously, small trading volume stocks or even non trading stocks would have more days of zero trading volume.

Zero return days

As we expect, the coefficient of zero return days and volatility is negative and significant. When the stock return changes slightly or there are no price change, the volatility is low and there should be many zero return days during that period. Hence, high volatility stocks would have less zero return days.

The coefficient on trading volume is negative and significant. Obviously, small trading volume stocks or even non trading stocks would have further days of zero return.

Overall, the coefficients on volatility and trading volume support our expectations: volatility is positively related to relative spread, the Amihud ratio and the Rtotr ratio; volatility is negatively associated with zero trading days and zero return days, while the trading volume is negatively related to all five liquidity measures.

3.6.2.3. Cross-sectional result

Relative spread

The coefficient of volatility with relative spread is positive and significant in the cross-sectional table. It indicates that stock has a higher relative spread when the stock return is more volatile. A highly volatile stock forces market makers to raise the relative spread to compensate for volatility risk, which supports Lesmond's results (2005). Price has a negative coefficient with relative spread, but the coefficient is insignificant. The sample period is from 2001 to 2013 and cross-sectional regression is an average value of price for the entire period. This long period average value eliminates much information. Surprisingly, the coefficient of trading volume is positive and insignificant. Market value has a negative and significant coefficient which we expect. Large companies have a smaller relative spread because market makers have less liquidity risk.

Amihud ratio

The coefficient of volatility is positive and significant, proving that stock with higher volatility is associated with a higher Amihud ratio. The coefficient of price is negative but insignificant. Amihud ratio is more likely affected by price changes, not direct price. Also, the cross-sectional regression of price is taking average value through a long period which may not be appropriate. The trading volume is positive and significant related with Amihud ratio. The coefficient of market value is negative and significant. Larger company stocks have a smaller Amihud ratio, due to the firm size.

Rtotr ratio

Interestingly, all the coefficients of the four market characteristics are insignificant. This may be because the overall fitness of the entire Rtotr ratio model is quite low so that market variables cannot explain the Rtotr ratio.

Zero trading days

The coefficient on volatility is negative and significant, as we expect. It indicates that a higher volatility stock is associated with a small number of zero trading days. Price has a negative coefficient, but is insignificant. Trading volume is also negatively related with zero trading days. It indicates that more zero trading days are associated with less trading volume. Market value is negatively and significantly related with zero trading days. Large value companies are traded much more frequently in the market and have less zero trading days.

Zero return days

The coefficient on volatility is negative and significant. It supports our expectation. Price, trading volume and market value are negatively and significantly related with zero return days. Stocks with higher price, or trading volume, or large capitalization are more liquid according to this measure.

Overall, the regression model for the Rtotr ratio performs quite poorly as all the coefficients are insignificant. The four market characteristics cannot explain the Rtotr ratio. Rtotr is more focusing on the trading frequency not directly trading costs. The results of volatility indicate that less liquid stock tend to have higher volatility.

The coefficients on price are almost all negative, but insignificant. It could be explained by long period cross-sectional regression, which may be inappropriate to deal with price. Price may not be a suitable variable to test cross-sectional regression. In conclusion, the coefficients in the cross-sectional investigations largely support our expectations with the exception of those for Rtotr

3.6.3 Comparison of panel and cross-sectional results

Relative spread

Comparing the coefficients on relative spread, all of the coefficients in the panel data table are significant. It indicates market characteristics are meaningful, while in the cross-sectional table, the coefficients on price and volume are insignificant. This indicates that price and volume cannot explain the relative spread over a long investigation period (2001-2013), especially one including a financial crisis.

More specifically, the coefficients on volatility through both methods are positive and significant. This proves that volatility is positively associated with relative spread. Stock has higher relative spread, which is positively affected by higher volatility risks.

Amihud ratio

The coefficients on volatility are similar in both approaches. Higher volatility stock has a larger Amihud ratio, while more volatile and illiquid stock would have strong price impact. The coefficient on volume is negatively related with the Amihud ratio in panel results, while it is positive in cross-sectional results. It may because the average value of cross-sectional data cannot include detail information of regression model.

Rtotr

Since all the coefficients in cross-sectional data are insignificant, it is hardly worth comparing the coefficients between panel and cross-sectional results. But it proves that panel data is more efficient than cross-sectional data.

Zero trading days

The cross-sectional results support our expectation. All of the coefficients of volatility and volume are negatively related with zero trading days. It is obvious that more zero trading days lead to low volatility and low trading volume.

Zero return days

Similar to zero trading days, both panel and cross-sectional results are closer to our expectation. All of the coefficients of volatility and volume are negatively related to zero return days.

3.7. New method testing price and market value

As the results from the Augmented Dickey Fuller test and the Phillips-Perron test above show, we cannot run panel regression using price and market value as independent variables because both variables are non-stationary. Only stock volatility and trading volume have been involved in the panel regressions aiming to explain the five liquidity measures.

Price and market value variables are, however, essential intuitive variables necessary to capture liquidity. Thus, we still want to test the relationship between them and liquidity measures. We predict that the intercept of previous panel regression contains information about price and market value. To obtain this we want to decompose the intercept into price and market value through simple cross-sectional regression.

3.7.1 Theoretical frameworks

As we have previously discussed, we should choose whether to use a fixed effects model or random effects model to do panel regression. The Hausman tests show that the fixed effects model is more appropriate for this study (Appendix B). In theory, the fixed effects model regression intercepts are different for each entity. The fixed effects regression is set to generate the same coefficient estimates and standard errors as ordinary regression when the indicator (dummy) variables are included for each group. The basic fixed effect model is

$$y_{ij} = X_{ij}b + v_i + e_{it}$$

and V_i are the fixed parameters to be estimated. This is the same if we add dummies in the equation as

$$y_{ij} = X_{ij}b + v_1 d_{1i} + v_2 d_{2i} + ..e_{it}$$

where d_1 is 1 when i=1 and 0 otherwise, d_2 is 1 when i=2 and 0 otherwise, and d_1, d_2, d_n are just dummy variables indicating the groups, and v_1, v_2, ..., are their regression coefficients, which we must estimate. After obtaining these dummy variables, we can calculate each stock intercept within the model[5].

Each stock intercept presents the individual effect of each stock. We assume that each stock intercept may include price and market value information which are unobservable through panel regression due to the problem of these being non-stationary variables. Therefore, we set fixed effects to be dependent variable and price and market value to be independent variables. We can then observe the relationship using OLS regression.

3.7.2 Methods and results

Firstly, we obtain the results of panel regression using the fixed effect model without involving price and market value from the previous study. We then use STAT 14 to create the dummies and obtain each stock intercept using the former regression with

[5] The extension of fixed effects model follows the rules of Stata 14.

volatility and volume as explanatory variables. We then obtain each liquidity measure which has 535 intercepts of the entire group.

Relative spread= intercept + β_1VAR + β_2Volume +ε

Amihud ratio= intercept + β_1VAR + β_2Volume +ε

Rtotr ratio= intercept + β_1VAR + β_2Volume +ε

Zero trading days= intercept + β_1VAR + β_2Volume +ε

Zero return days= intercept + β_1VAR + β_2Volume +ε

Secondly, we decompose each stock intercept into price and market value, which serve as explanatory variables using cross-sectional regression analysis.

There are 105 stocks which have 0 days of zero trading days during the period (2001-2013). Thus only the other 430 stocks have valid intercepts (different from 0) from the previous regression. Hence, during this stage, the regressions involving zero trading days use only 430 stocks, while the other four liquidity measures have 535 stocks.

Relative spread intercept = constant + β_1Price + β_2MV+ μ

Amihud ratio intercept = constant + β_1Price + β_2MV+ μ

Rtotr ratio intercept = constant + β_1Price + β_2MV+ μ

Zero trading days intercept = constant + β_1Price + β_2MV+ μ

Zero return days intercept = constant + β_1Price + β_2MV+ μ

Table 3.10: Decompose intercepts into price and market value

	Constant	Price	MV	R^2	F value	Number of stocks
Relative spread	0.054*	-0.013*	-0.006*	0.468	233.9	535
	(10.4)	(-10.1)	(-8.0)			
Amihud	15.847*	-19.245*	14.17*	0.406	181.3	535
	(3.2)	(-15.7)	(18.4)			
Rtotr	-261.99*	-91.047*	175.275*	0.286	106.8	535
	(-3.1)	(-4.3)	(13.4)			
Zero trading	1.831*	-0.581*	0.071*	0.334	92.5	430
	(9.8)	(-12.9)	(2.1)			
Zero return	1.272*	-0.463*	-0.101*	0.742	765.0	535
	(16.1)	(-23.7)	(-8.2)			

Note: this table presents cross-sectional regression results of five liquidity measurements and two non-stationary variables. The relative spread calculated by spread between bid and ask price divided by average bid and ask price; the Amihud calculated by absolute daily return divided by trading volume in monetary unit; the Rtotr calculated by absolute daily return divided by turnover ratio; the zero trading volume days counted by the zero trading volume of each day; and the zero return days counted by zero daily return changes of each day. The price is logarithm of stock closing price. MV is the logarithm of stock market value. Except volatility, all the figures are averages of daily value from 2001 to 2013. The data is collected from Thomson Reuters Datastream. The White (1980) t-statistics are below the coefficients in parentheses. * denotes significant at the 5% level.

R squared

All the R square values show that price and market value can explain fixed effects. Zero return days have the highest R square value of 0.742, while the Rtotr has the lowest R square value. Surprisingly, the R square value of Rtotr is 0.286 which is higher than the original cross-sectional results (Table 3.10).

Price

For relative spread, price is negative and significant indicating that stocks with higher prices are associated with smaller relative spreads. The result is also supported by Lesmond (2005).

As for the Amihud ratio and Rtotr ratio, the coefficients are negative and significant. The stock has a higher price leading to a smaller Amihud ratio and Rtotr ratio.

Zero trading days have a negative and significant coefficient of price. This proves that low price stock is associated with more non-trading days.

Zero return days also have a negative and significant coefficient of price, proving that low price stock is associated with less zero return days.

Market value

For the relative spread, the coefficient of market value is negative and significant. This indicates that higher market value stocks are associated with a lower relative spread.

The coefficient of market value in the Amihud regression is positive and significant. The coefficient of market value in the Rtotr regression is also positive and significant. It is interesting that the higher Amihud and Rtotr ratio are associated with a higher market value. However, the result supports Lesmond (2005) that market value is inconsistently related with the Amihud ratio.

As for zero trading days, the coefficient statistic is positively related with market value. It proves Lesmond's (2005) finding that market value is inconsistent with the measurement of zero trading days. To some extent, this may be due to the reduced number of stocks in the regression as there are 105 stocks which are invalid due to unobservable dummy intercepts.

Finally, zero return days is negatively and significantly related to market value. This proves that higher market capitalisation stocks are associated with a smaller number of zero return days.

3.8. Discussion and conclusion

In this study, we have focused on the comparison of panel and cross-sectional results explaining stock liquidity in the London Stock Exchange in specific periods from 2001 to 2013. In order to fully understand the liquidity measures, we have extended the model of Lesmond (2005) where relative spread is the only dependent variable and tested the other liquidity measures through a cross-sectional regression model. We use a range of liquidity measures (relative spread, the Amihud ratio, Rtotr ratio, zero trading days and zero return days) as dependent variables and test the relationship between the five liquidity measures and market characteristics (volatility, price, trading volume and market value) both in panel and cross-sectional regression. The previous chapter has shown that price and trading volume are insignificant using cross-sectional regression and it may be due to the long time-period of the investigation. Using a panel regression model can solve this problem.

Important economic questions can be solved through the use of longitudinal data which cannot be explained using cross-sectional data. For example, individual firm effects cannot be tested in cross-sectional data. Also liquidity changes over time so only time-series data can fully explain liquidity. So a panel model may be more suitable for further research. Due to the non-stationary problem of price and market value, we only use volatility and volume as the explanatory variables running the panel regression.

Through the panel regression, we find that market makers need more compensation in case of volatility risk, while highly volatile stock with less liquidity condition tends to have larger price impact. The volatility captures the information of uncertain historical return. Both results support the published literature (Stoll 2000, Lesmond 2005). The negative relationship between volatility and zero trading days and zero return days indicates that low volatile stocks are less traded in the market. Also, the results support that less liquid stock has low trading volume.

In terms of price and market value, which cannot be used directly due to them being non-stationary variables, we find a specific method to create dummy intercepts which can be explained by price and market value through cross-sectional regression. Price is negatively and significantly related to all five liquidity measures. The estimated models for Relative spread, Amihud ratio and zero trading days also show a good level of fit. Compared to other liquidity measures, price and market value have less power in explaining the Rtotr ratio. Interestingly, the relationships between liquidity measures and market value are inconsistent. Stoll (2000) and Lesmond (2005)'s results also show that market value is hardly able to capture the relationship precisely.

Through the cross-sectional regression, most of the results are similar to the panel regression results and support the published literature (Stoll 2000, Lesmond 2005). However, many coefficients of price and trading volume are mostly insignificant.

Comparing the above to the results of Stoll (2000) with a 1-year duration and Lesmond (2005) with 7-year duration, the explanation may be that the information is diminished by using cross-sectional regression averaging over a long period, which includes the financial crisis in 2008.

In conclusion, we differ from Lesmond (2005) in as much as price and trading volume are insignificant in the cross-sectional results from 2001 to 2013 in the London Stock Exchange. It may due to the long-time duration of the dataset. The panel data does provide a powerful explanation of the results, where price and trading volume are significant.

Chapter 4 A new model to test the effect of liquidity on return distribution and autocorrelation, skewness and kurtosis

4.1 Introduction

The previous chapters focus on the comparison of stock liquidity measures and the relationship between liquidity measures and market characteristics (volatility, price, trading volume and market value). There are five liquidity measures (relative spread, Amihud ratio, Rtotr ratio, zero trading days, zero return days) which can be proxies for stock liquidity. Each liquidity measure has its own advantages. A major of researchers have focused on the relationship between illiquidity and excess stock return using different liquidity measures (Amihud, 2002, Pastor and Stambaugh, 2003, Acharya and Pederson, 2005). The literature shows that the illiquidity risk premium does affect the expected return in the stock market. More researches focus on transaction costs and asset price (Constantinindes, 1986, Vayanos, 1998). However, a few research studies focus on the link between the distribution of stock returns and illiquidity. Higher moments of return (like skewness and kurtosis) have been shown to have a relationship with illiquidity under certain circumstance. Amaya et al (2015) state that illiquidity is positive related to realized kurtosis. Overall, when it comes to return skewness, kurtosis and autocorrelation, prior research mainly concentrates on the relationship between skewness or kurtosis and stock returns.

As for the autocorrelation of stock returns, Campbell et al (1993) propose that the first daily autocorrelation of stock returns is lower on high-volume days than on low-volume days. Avramov et al (2006) confirm the findings of Campbell et al (1993) using turnover rate. However, we have found no studies showing direct links between autocorrelation and liquidity measures. A few papers address somewhat related matters. Lesmond et. al. (1999) develop a model to connect transaction costs and daily stock returns on the NYSE and AMEX exchanges. The assumption is that the value of information related to the transaction costs is what causes price movement (Lesmond et al, 1999). So marginal traders would only make transaction when the return is higher than the costs. Ng et. al. (2008) show that transaction costs contribute to post-earnings announcement drift. The results show that higher transaction costs would be compensated for larger return. Both papers show that transaction costs have effects on returns from the time-series viewpoint.

Motivated by the previous findings and observations, we address several questions: (i) Are there any links between stock liquidity and higher moments of return (skewness and kurtosis)? (ii) Will less liquid stocks tend to have higher autocorrelation making the market more predictable and less efficient? (iii) How transaction costs affect price movements and return distributions?

In order to examine these issues, we establish empirical and theoretical frameworks to find the relationships. In particular, we create models and simulations to show that larger transaction costs cause leptokurtosis and higher first lag autocorrelation. Then we confirm our findings using cross-sectional regression models on UK stock data.

The structure of this chapter is based on following sections. We give basic information about skewness, kurtosis and autocorrelation in section 4.2. Section 4.3 discusses previous related literatures. Section 4.4 gives a theoretical model to discuss the relationships between transaction costs and autocorrelation Section 4.5 discusses the links between transaction costs and return distribution through theoretical works and simulations. Section 4.6 shows the results of empirical work testing the expected relationships. The last section contains our conclusions and further discussion.

4.2 Skewness, kurtosis and autocorrelation

In probability theory and statistics, skewness is defined as a measure of the asymmetry of the probability distribution of a random variable about its average value. It is computed using each observation's cubed deviation from the mean standardized by dividing by the standard deviation cubed to make the measure free of scale.

The monthly stock skewness is defined as:

$$skewness = \frac{\sum_1^n (R_t - \overline{R_t})^{\ 3}}{(n-1)s^3}$$

Where n is the number of valid observation day in one month, s is the standard deviation of the monthly return, R_t is the daily return, $\overline{R_t}$ is the mean return in one month.

The value of skewness can be positive, negative or undefined. A return distribution with positive skewness has more small losses and a few extreme gains. In contrast, a return distribution with negative skewness has more small gains and a few extreme losses. The positively skewed distribution has a long tail on its right side and so is called right-tailed. The negative skewed distribution has a long tail on its left side and is called left-tailed. If the distribution is symmetric (e,g. a normal distribution), the skewness is zero.

In probability theory and statistics, kurtosis is a measure that shows when a distribution is more or less peaked than a normal distribution. A distribution which is more peaked than normal is defined leptokurtic. And a distribution which is less peaked than normal is defined as platykurtic. It is calculated by using the average deviation from the mean raised to the fourth power and then standardizing that average by dividing by the standard deviation raised to the fourth power. A normal distribution has a kurtosis of three.

The monthly stock kurtosis is defined as

$$Kurtosis = \frac{\sum_1^n (R_t - \overline{R_t})^{\ \ 4}}{(n-1)s^4}$$

Where n is the number of valid observation day in one month, s is the standard deviation of the monthly return, R_t is the daily return, $\overline{R_t}$ is the mean return in one month.

Autocorrelation can be defined as the correlation of a time series with its own past and future values. Also, it can be called "lagged correlation" or "serial correlation". For example, lag 1 correlation is the correlation between the values (v_1, v_2, v_3….v_n) and 1 time lag values (v_2, v_3, v_4…$v_{(n+1)}$). If the autocorrelation value is positive, it can be presented a specific form of persistence. In other words, it measures the trend that the values would stay same from one observation to the next.

The autocorrelation of a time series with constant expected return is given by

$$\frac{E[R_t \cdot R_{t-1}]}{E[R_t] \cdot E[R_{t-1}]} = \frac{E[R_t \cdot R_{t-1}]}{\mu^2}$$

Where μ is a constant equal to the expected return[6].

4.3 Prior work

Liquidity does affect asset pricing. Amihud and Mendelson (1986a) find that expected asset return is an increasing function of illiquidity costs. In other words, higher illiquidity costs or transaction costs leads to higher stock expected return due to liquidity premium. Lesmond et al (1999) created a limited dependent variable model to estimate transaction costs based on the frequency of zero returns. The literature discusses that the marginal traders would not trade if the value of information does not exceed the transaction costs results in a zero return. The price movement can be explained by the comparison of the value of information and the costs of trading. Based on Lesmond et al (1999), Lesmond et al (2004), Korajczyk and Sadka (2004) and Hanna and Ready (2005)'s studies which use relative spread plus commissions as trading costs Ng et al (2008) examine the effect of transaction costs on the post-earnings announcement drift and prove that company with higher transaction costs has higher abnormal returns in this situation. This shows that transaction costs affect the time series properties of returns. Thus the prior literature has shown that transaction costs affect time-series returns. In general, the stock price reacts more slowly to market information if the stock is less liquid (Diamond and Verrecchia, 1991). Hou and Moskowitz (2005) find that information delay is affected by trading expenses.

The literature mentioned above implies that there is likely to be a connection between serical correlation and liquidity but there are only a very limited number of papers specifically dealing with this connection. The first paper explicitly linking serial correlation of returns and liquidity is Morse (1980) where he finds that high-volume periods tend to have positively autocorrelated returns. Campbell et al (1993) find that the first daily autocorrelation of stock returns is lower on high-volume days than on low-volume day in the New York Stock Exchange. It can be seen that autocorrelation is lower when the market is less liquid compared to when the market liquid is liquid. Avarmov et al (2006) state that high turnover stocks exhibit higher negative serial

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[6] It is based on the Amini et al (2010). If the statistic value is small, it indicates that R_t and R_{t-1} are independent or that there could be one of a set of nonlinear links between them.

correlation than low turnover stocks on weekly based data. Also, the high turnover, low liquidity stocks have more negative serial correlations in cross-sectional regressions.

Mech (1993) discuss the reasons for autocorrelation. His statement is that mispricing causes autocorrelation. Some stocks do not reflect current market information and transaction costs can induce price adjustment delays (Mech, 1993).
Several papers empirically investigate the connection between autocorrelation and general market frictions or partial adjustment effects whereby prices only partially adjust to new information (Ahn et al, 2002; Anderson et al, 2005; Olbrys and Majewska, 2014). The causes of these frictions or partial adjustment effects are not always consistently defined. They generally include trading costs but also may include behavioural effects, time varying risk premiums and market microstructure effects. This makes it difficult to draw conclusions about connections between trading costs in isolation and autocorrelation from this literature. Ahn et al (2002) deduce that market microstructure effects are of major importance in driving autocorrelation but the findings of Anderson et al (2005) and Olbrys and Majewska (2014) are more supportive of the potential importance of trading costs.

Noise traders are investors who make decisions about buying or selling stocks without using fundamental analysis. These investors usually do not react correctly to market information and make wrong decisions. Also, liquidity trades who are market participants who buy or sell stocks with no regard to the timing of their trade may make inappropriate decisions. The reason for the trading is because of their financial needs outside the financial market. If the stocks have better liquidity conditions, the price would react to the new information quickly and less informed traders would participant in the market because there is less opportunity to gain profit while the price reflects market information instantly.

Price movement should follow a random walk if the market is perfect and liquid (Black, 1971). Fama and French (1988), Lo and MacKinlay (1988) and Poterba and Summers (1988) find that the price movement does not follow a random walk. Autocorrelation can be seen as a sign of pricing inefficiency (Anderson, 2006). We expect that liquid stocks tend to have lower serial correlation resulting from lower transaction costs and less liquid stocks tend to have higher autocorrelation resulting from higher transaction costs. Because the speed and accuracy of converging to the intrinsic price is slower in a less liquid market when new information arrives. Higher transaction costs motivate the investor to trade only when the compensation is higher. So the price deviates from its intrinsic value. Based on the previous discussion and motivated by Ng et al (2008), we have developed models to test how asset prices vary in the presence of trading costs.

The liquidity premium has been shown to be positively related to stock excess return (Amihud, 2002, Lesmond, 2005). Investors need more compensation (more return) for holding an illiquid stock. The illiquidity of the stock will be priced in the stock. The price deviation is caused by market illiquidity (Huang and Wang, 2009). The study assumes that the total underlying value of the stock including news on the dividend is normally distributed. After adding a liquidity factor, the distribution presents negative skewness. The distribution of returns for less liquid stock is negative skewed because negative skewness has more small gains. Small company stocks are less liquid than large company stocks as is shown in previous chapters. Illiquid stocks are less frequently traded than the liquid stocks. Because illiquid stocks have less likelihood of trading, there are more zero return days which lead to higher kurtosis. The literature on stock market liquidity is extensive, but is largely concerned with the relationship between stock liquidity and stock excess return. A very large literature documents skewness and kurtosis in equity markets although reasons for these effects are little understood (Ekholm and Pasternack, 2005). As far as we are aware there is no prior research investing the connections between trading costs, skewness and kurtosis.

A number of papers investigate asset allocation effects allowing for the skewness and kurtosis of stock returns (Chunhachinda et al, 1997; Guidolin and Timmermann, 2008). Several papers investigate the connections between skewness, kurtosis and asset prices. Harvey and Siddique (2000) show that conditional skewness helps explain the cross-sectional variation of expected returns across assets even after allowing for size and book-to-market factors. Conrad et al (2013) use options prices to show that individual securities' risk-neutral volatility, skewness, and kurtosis are related to future returns. They find a negative (positive) relation between ex ante volatility (kurtosis) and subsequent returns in the cross-section, and more ex ante negatively (positively) skewed returns have higher (lower) returns. Amaya et al (2015) show that buying stocks in the lowest realized skewness decile and selling stocks in the highest realized skewness decile generates a significant average return of 19 basis points the following week. They further show that the relationship between realized kurtosis and the next week's stock returns is positive but not always significant.

4.4 Model specifications

Assumptions:

Some market participants are rational and skilled, and also aware of the intrinsic value of stocks. Investors would sell stocks if the stock price is sufficiently greater than value, and buy stocks if the stock value is sufficiently greater than price. Their selling decisions depend on trading costs as represented by bid-ask spread. We further assume that there are sufficient noise and liquidity traders to act as counterparties for transactions with rational market participants without themselves referencing intrinsic value. The development below refers to rational market participants.

Define:

V_t as the value of a security at time t

P_t as the price of a security at time t

CP_t as the bid-ask price of a security at time t

Assume for simplicity $CP_t \approx CP_{t+1}$

At any time market participant can sell a security for $P_t - 0.5\ CP_t$. At any time market participant can buy a security for $P_t + 0.5\ CP_t$

For the selling opportunity (price is still higher than value after trading cost):

$$\text{If } P_t - 0.5CP_t \geq V_t \qquad \text{equation (4.1)}$$

The market participant has the opportunity to sell the security to make a profit

And market participant can continuously sell the security until equation (4.2) holds.

$$P_t - 0.5CP_t = V_t \qquad \text{equation (4.2)}$$

For the buying opportunity (value is still higher than price after trading cost):

$$\text{If } P_t + 0.5CP_t \le V_t \qquad \text{equation (4.3)}$$

The market participant has the opportunity to buy the security to make a profit. And market participant can continuously buy the security until equation (4.4). This is because there is no profit opportunity.

$$P_t + 0.5CP_t = V_t \qquad \text{equation (4.4)}$$

There is no selling opportunity if equation (4.5) holds:

$$\text{If } P_t - 0.5CP_t < V_t \qquad \text{equation (4.5)}$$

There is no buying opportunity if equation (4.6) holds

$$\text{If } P_t + 0.5CP_t > V_t \qquad \text{equation (4.6)}$$

Under both situations, there is no incentive to buy or sell stock because there is no profit.

Given the deductions above, P_t will in equilibrium in a band such that:

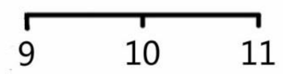
$$V_t - 0.5CP_t \le P_t \le V_t + 0.5CP_t \qquad \text{equation (4.7)}$$

If fCP_t (transaction costs) is higher, it would expand the price movement magnitude.

For better illustrating the model, it is intuitively helpful to show specific figures.

At the beginning, we set bid-ask spread (CP_t) as 2 and security value as 10. So the price could varies from 9 to 11 based on equation (4.7). Figure 4.1

Figure 4.1: Case study



But if price is higher than 11 (10+1), it is the time to sell the stock because the security price is higher than the combination of trading costs and security value.

Also if price is lower than 9 (10-1), it is the time to buy the stock because the security price is lower than the combination of trading costs and security value.

Scenario analysis:

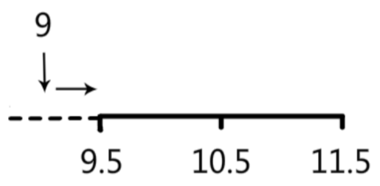
The discussion above shows the situations where there is an incentive to trade. The following scenarios discussions happens when there is an incentive.

Case 1: the lower bound on price given value V_t:

$$P_t - 0.5CP_t = V_t$$

So the original price is 9 right now.

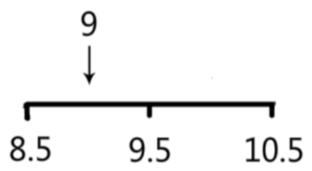
1i) If value increase by a small amount 0.5



If security value increases by 0.5, the value bound would be from 9.5 to 11.5. So the price (originally 9) has to go up to 9.5 to maintain the bound equation 4.7.

The value and price both would increase by the same amount 0.5 when if there is a small increase in value.

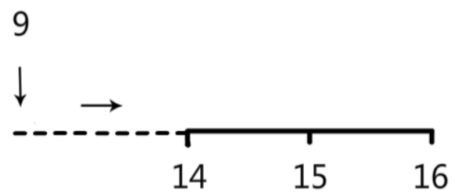
1ii) If value decrease by a small amount 0.5



If security value decreases by 0.5, the value bound would from 8.5 to 10.5. So the price (originally 9) does not need to move because 9 is already in the bound between 8.5 and 10.5)

So the price would not move if there is a small decrease of value.

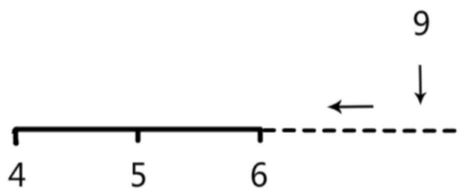
1iii) If value increases by a large amount 5



If security value increases by 5, the value bound would be from 14 to 16. So the price (originally 9) has to go up to 14 to maintain the bound equation 4.7.

The value and price both would increase by the same amount 5 when there is a large increase of value.

1iv) If value decreases by a large amount 5



If security value decreases by 5, the value bound would be from 4 to 6. So the price (originally 9) has to decrease to 6 to maintain the bound equation 4.7.

So the price would decrease less than value when there is a large decrease of value.

In combination of scenarios of Case 1, the price would go up by the same amount when the value goes up, while the price would go down by smaller amount when the value goes down.

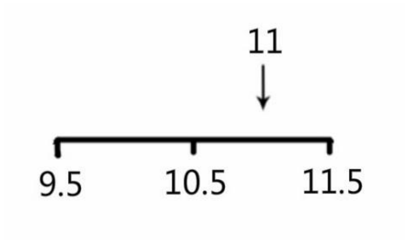
So the aggregate expected return in Case 1 is higher than 0. In other words, the expected return is larger than 0 (for simplicity we have assumed the mean return on value is 0 but the results could easily be generalised to allow for a positive expected return on value).

Case 2: the upper bound on price given value V_t:

$$P_t + 0.5CP_t = V_t$$

So if the original price is 11.

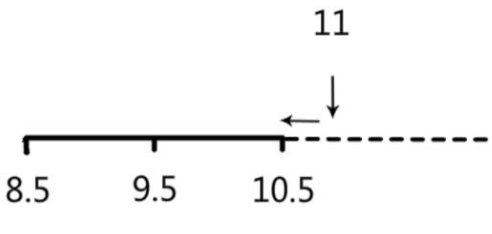
2 i) If value increases by a small amount 0.5



If security value increases by 0.5, the value bound would be from 9.5 to 11.5. So the price (originally11) does not have to move because 11 is already in the bond between 9.5 and 11.5)

So the price would not move if there is a small increase in value.

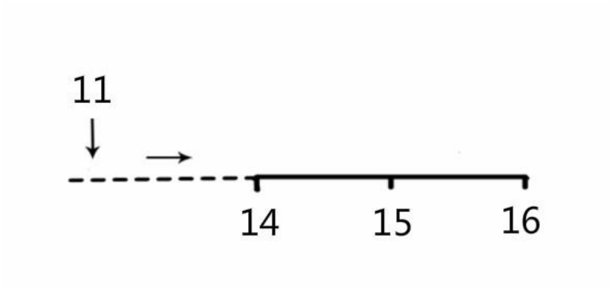
2 ii) If value decrease by a small amount 0.5



If security value decreases by 0.5, the value bound would from 8.5 to 10.5. So the price (originally11) has to decrease to 10.5 to maintain the bound equation 4.7.

So the price decreases by the same amount 0.5 when there is a small decrease of value.

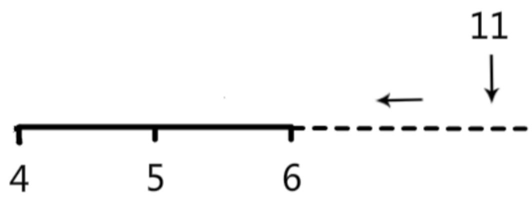
2 iii) If value increase by a large amount 5



If security value increases by 5, the value bound would from 14 to 16. The price (originally11) has to increase to 14 (increase by 3) to maintain the bond equation.

So the price increases by a smaller amount when there is a large increase in value.

2 iv) If value decrease by a large amount 5

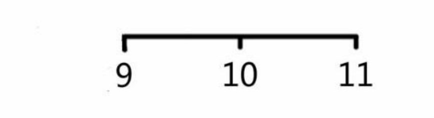


If security value decreases by 5, the value bound would be from 4 to 6. The price (originally11) has to decrease to 6 to maintain the bound equation 4.7.

So the price decreases by the same amount when there is a large decrease of value.

In combination of scenarios of Case 2, the price would go up by a smaller amount when the value goes up, while the price would go down by same amount when the value goes down

Case 3: Price between the lower bound and higher bound (This would only occur if there was no price movement in the previous time period.



Price could be any point between 9 and 11. Under this situation, the sign of the expected future return would depend on whether the initial price is below or above the value of 10. If the price is below value this is somewhat analogous to case 1 and the expected return would be greater than 0. If the price is above value this is somewhat analogous to case 2 and the expected return would be less than 0. Symmetry shows that if price is below value the last price move was probably positive whereas if price is above value the last price move was probably negative.

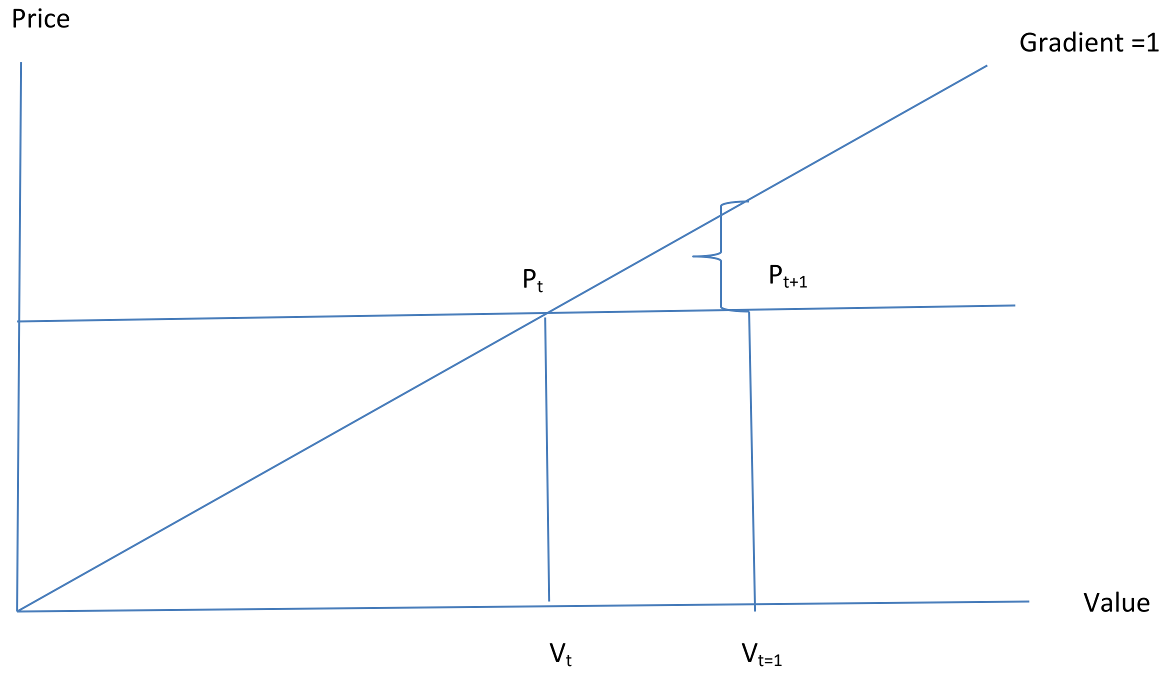
If the price (as opposed to value) movement in the last sample period was positive, such as in scenario 1i), 1(iii) and 2(iii). It shows that the price would move to the lower bound of equation 4.7. And then the price situation would be in Case 1, leading expected returns to be positive. So the next price movement is likely to be upwards.

On the other hand, if the price movement in the last sample period was negative, such as in scenario 1(iv), 2(ii) and 2(iv). It shows that the price would move to the upper bound of equation 4.7. And then the price situation would be in Case 2, leading expected return to be negative. So the next price movement is likely to be downwards.

If the price movement in the last sample period was zero the price would be between the upper and lower bounds of equation 4.7 and by symmetry the expected return is zero and the next price movement is equally likely to the upwards or downwards.

The graphic presentation below shows how the various cases act when value increases from V_t at time t to V_{t+1} at time t+1 . The price at these times will determined by value within bounds determined by trading costs. A similar presentation would apply when value decreases (Figure 4.2). If value increases, price will either increase by the same amount or possibly not change.

Figure 4.2 Summary of price and value with time trend



The autocorrelation of a time series with constant expected return is given by

$$\frac{E[R_t \cdot R_{t-1}]}{E[R_t] \cdot E[R_{t-1}]} = \frac{E[R_t \cdot R_{t-1}]}{\mu^2}$$

Where μ is a constant equal to the expected return.

Now even if the autocorrelation of the value series is zero we can show the autocorrelation of the price series is positive, R_{t-1}

Previous empirical investigations have focused on the relationship between expected return and last sample price movement. It is shown that if the last sample movement (R_{t-1}) was negative, the expected return E [R_t] is negative, which leads to negative return at time t. As discussed before, higher transaction costs would expand the last sample movement magnitude. The strength of this effect depends on the size of the bid-ask spread. For example, we assume that at the beginning, the bid-ask spread is 2 and security value is 10. So the price could vary from 9 to 11 with holding the equation (4.7). But if the bid-ask spread is higher (is 4) and security value is still 10. The price would vary from 8 to 12 with holding the equation (4.7). In other words, the magnitude of price movement expand to 4 not 2. Thus, the price distortion bound from the value is larger. The higher bid-ask spread (transaction costs) would lead to larger bound.

The autocorrelation of this return series can be described as:

$E[R_t \cdot R_{t-1}]$ for the return series

If the last sample movement (R_{t-1}) was negative, the expected return E [R_t] is negative, which leads to positive return at time t. So, the autocorrelation of this return series can be described as:

If $R_{t-1} < 0$

$$E[R_t] < 0$$

$$\therefore E\left[R_t . R_{t-1} \mid R_{t-1} < 0\right] > 0$$

If the last sample movement (R_{t-1}) was positive, the expected return E [R_t] is posititve, which leads to positive return at time t. So, the autocorrelation of this return series can be described as:

If $R_{t-1} > 0$

$$E[R_t] > 0$$

$$\therefore E\left[R_t . R_{t-1} \mid R_{t-1} > 0\right] > 0$$

If the last sample movement (R_{t-1}) was zero, the expected return E [R_t] is zero, which leads to zero return at time t. So, the autocorrelation of this return series can be described as:

If $R_{t-1} = 0$

$$E[R_t] = 0$$

$$\therefore E\left[R_t . R_{t-1} \mid R_{t-1} = 0\right] = 0$$

When applying Bayes Theorem:

$$\begin{aligned} &E[R_t \cdot R_{t-1}] \\ &= E[R_t \cdot R_{t-1} \mid R_{t-1} < 0] P_r[R_{t-1} < 0] \\ &\quad + E[R_t \cdot R_{t-1} \mid R_{t-1} = 0] P_r[R_{t-1} = 0] \\ &\quad + E[R_t \cdot R_{t-1} \mid R_{t-1} > 0] P_r[R_{t-1} > 0] \end{aligned}$$

But by definition:

$$E\left[R_t.R_{t-1} \mid R_{t-1} < 0\right] > 0$$
$$E\left[R_t.R_{t-1} \mid R_{t-1} = 0\right] = 0$$

$$E\left[R_t.R_{t-1} \mid R_{t-1} > 0\right] > 0$$

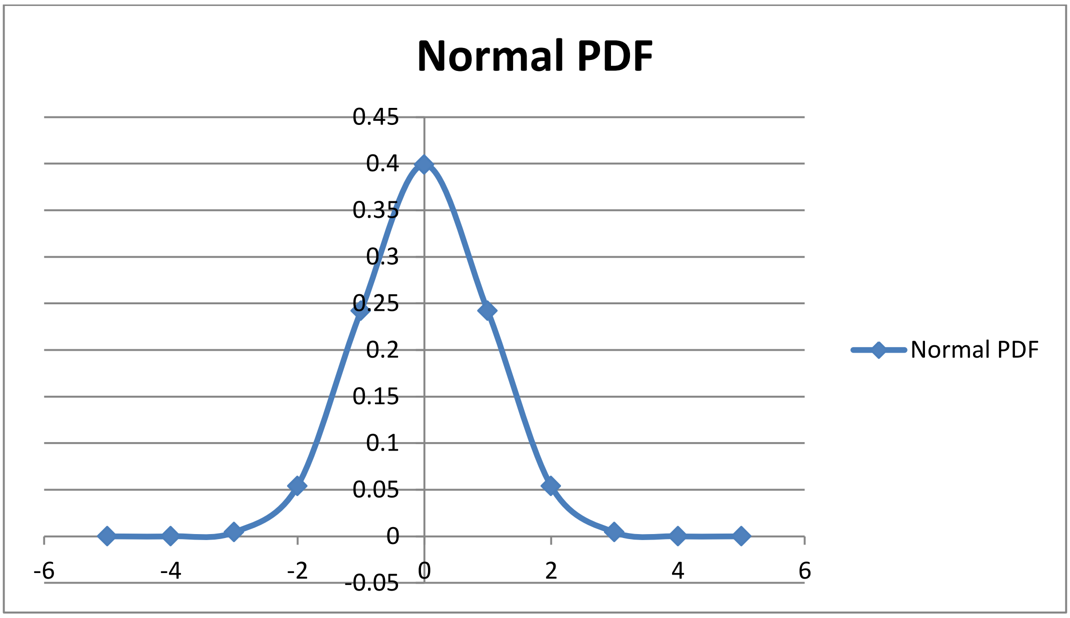
So in aggregate, the autocorrelation is over 0.

In summary, we have created a new model to prove that higher bid-ask spread (as a measure of transaction costs) would cause higher autocorrelation. When there is a higher bid-ask spread, it would lead to larger price movement bound which cause higher autocorrelation. The previous chapters have shown that high transaction costs can be seen as low liquidity and highly correlated with other liquidity measures. In other words, empirically low liquidity stocks by all liquidity measures will exhibit higher autocorrelation.

4.5 Transaction costs and returns distribution

The distribution of stock returns is vital for all kinds of trading and risk management problems. The normal distribution can be seen as a good approximation for returns in theory (Lee et al, 2009). The normal distribution is the familiar bell-shaped curve based on two parameters: mean and standard deviation. Figure 4.2 illustrate the probability density function (PDF) for an example of the normal distribution of price intrinsic value having mean equal to 0 and standard deviation equal to 1. The density of 0 values is around 0.4. This assumption about intrinsic value is made for ease of implementation.

Figure 4.3: Value movement distribution based on Normality (0, 1)



Empirical work has shown that observed returns are not normally distributed. For example, the stock market crash in 1987, the LTCM Hedge fund crisis, the 2008 crisis and many other market events show clear non-normality.

We consider a model, similar to the one in the previous section, where the intrinsic value of a stock moves as a normal distribution but transaction costs cause observed prices to depart from intrinsic value with the size of the departure depending on the magnitude of the transaction costs.

4.5.1 Leptokurtism

We first consider leptokurtism, intuitively higher transaction costs are likely to be associated with a greater proportion of small and zero return days which will cause leptokurtis. Figure 4.3 considers this idea more formally by plotting the price movement distribution based on value movement adjusted for expenses which are set to be one (the standard deviation of the distribution) this level of expenses being chosen for convenience. The figure assumes the intrinsic value and price are initially equal. There are 68% of values drawn from a normal distribution within one standard deviation of the mean. So in Figure 4.3, the density of the 0 value increases to 0.68. If the transaction costs (relative spread) are two (two standard deviation away from the mean) the leptokutism becomes more acute. Figure 4.5 combines Figure 4.3 and

Figure 4.4 to show a direct comparison of changes of distribution due to trading expenses.

Figure 4.4: Price movement distribution based on Value movements adjusted for trading costs as 1

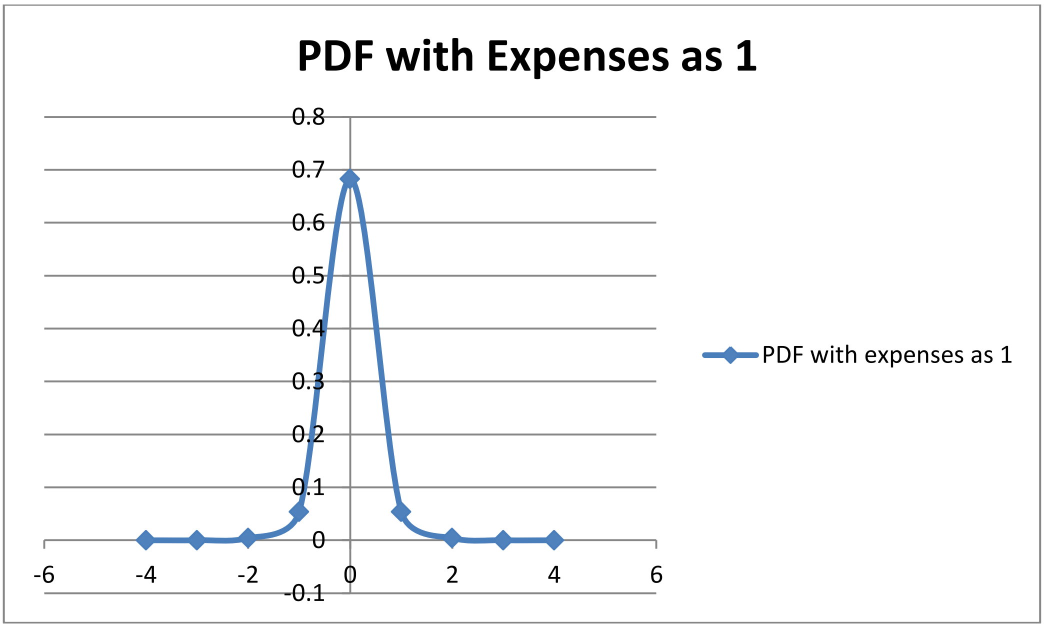


Figure 4.5: Price movement distribution based on Value movements adjusted for trading costs as 2

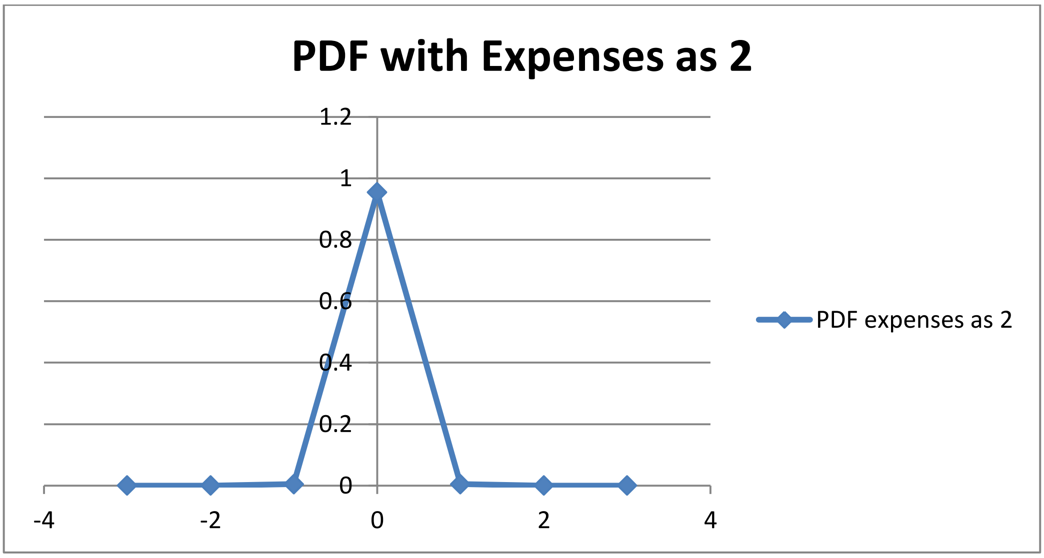
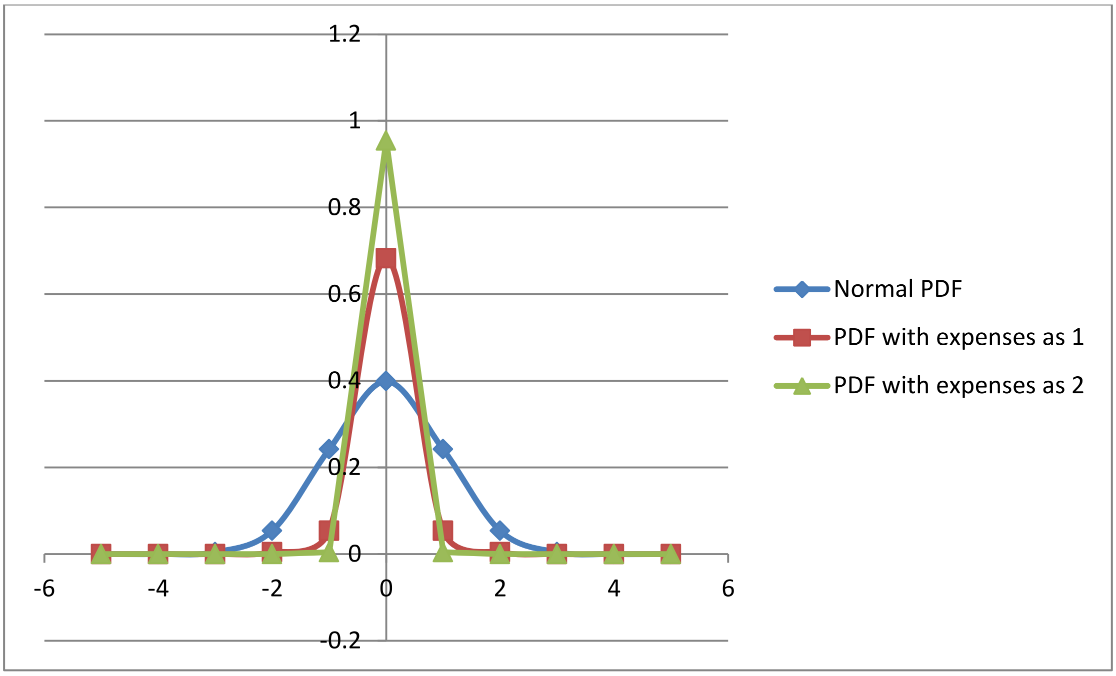


Figure 4.6: Comparison of normal PDF and PDF with expenses



The Figure 4.5 shows that the higher transaction costs (bid-ask price) lead to a higher density of zero value. Thus, a higher probability of small and zero return which leads to leptokurtosis.

We run simulations to see how our analysis of the connection between kurtosis and trading costs holds up. We randomly create four set of 1000 numbers which follow a standard normal distribution (mean is zero and standard deviation is 1). These numbers can be seen as raw return for 1000 stocks with zero trading costs. Then we add expenses, such as 0.01, 0.05, 0.1, 0.25, 0.5,1, in order to get a new net return for 1000 numbers. Lastly, we average the kurtosis values for new net returns which are calculated with different expenses. The results show that higher transaction costs are associated with higher kurtosis. (Appendix C)

4.5.2 Skewness

If we assume that intrinsic value moves in line with a normal distribution as discussed in 4.5.1 we can clearly see that trading costs do not alter the symmetry of the distribution so will not affect skewness.

We further run simulations to check our analysis of the connection between skewness and trading costs (Appendix C). We still use the same four set of 1000 numbers which are created in the last section. And the increasing expenses are also the same. Finally, we average skewness values for the new net returns which are calculated under different trading expenses. The results are inconsistent in terms of a simple relationship between expenses and skewness. Specifically, when the original sample's skewness is positive, the higher expenses seem to lead to higher positive skewness. On the contrary, when the original sample's skewness is negative, the higher expenses seem to lead to lower negative skewness.

4.6 Empirical results

In this section we check whether our proposed connections between trading costs and the properties of stock returns are confirmed by data from the UK stock market.

4.6.1 Data

In the previous chapters, we have already done the filter work of data selection. In this chapter, we still use the same data sample which is 535 UK domestic stock listed on the London Stock Exchange from May 2001 to December 2013. We calculate each variable monthly based on daily data. All the variables have the same definitions as in previous chapters.

4.6.2 Basic descriptive data

Table 4.1 Descriptive data of return distribution

	Mean	Median	Max	Min	Mode	Std
RS	0.049	0.031	0.297	0.000819		0.05417
Amihud	3.00E-05	7.98E-06	0.000411	5.04E-10		5.79E-05
Rtotr	154.078	30.837	6534.894	0.83231		537.072
Zero trading	419.953	100	2348	0	0	583.106
Zero return	1071.733	801	2787	13	81	885.869
Skewness	0.17882	0.19004	0.66356	-1.71		0.20356
Kurtosis	3.91811	2.94185	12.8672	0.0982		3.033
Autocorrelation	-0.0245	-0.0227	0.10434	-0.1818		0.0491

For skewness, the mean value of 535 stocks is 0.17 and median is 0.19. It shows that most stocks have positive skewness. Comparing the max value and min value, many stocks may have extreme negative skewness but the max skewness value is not extremely high. Also, it shows that there is no symmetry of distribution which is a common assumption in the literature. As for kurtosis, the mean is 3.9 which is higher than the median (almost 3). It shows that most stocks have kurtosis over 3 indicating a leptokurtic situation. Thus stock return distributions are generally not normally distributed.

4.6.3 Correlation analysis

Table 4.2 Cross-sectional nonparametric correlation coefficients

	Relative spread	Amihud	Rtotr	Zero trading days	Zero return days	Skewness	Kurtosis	Auto	Mv
Relative spread	1.000	.943**	.690**	.890**	.937**	-.121**	.906**	.454**	-.950**
Amihud	.943**	1.000	.755**	.901**	.917**	-.139**	.892**	.416**	-.933**
Rtotr	.690**	.755**	1.000	.725**	.700**	.003	.680**	.188**	-.662**
Zero trading volume days	.890**	.901**	.725**	1.000	.943**	-.141**	.929**	.482**	-.899**
Zero return days	.937**	.917**	.700**	.943**	1.000	-.140**	.969**	.536**	-.955**
Skewness	-.121**	-.139**	.003	-.141**	-.140**	1.000	-.128**	.013	.128**
Kurtosis	.906**	.892**	.680**	.929**	.969**	-.128**	1.000	.543**	-.932**
Autocorrelation	.454**	.416**	.188**	.482**	.536**	.013	.543**	1.000	-.516**
Mv	-.950**	-.933**	-.662**	-.899**	-.955**	.128**	-.932**	-.516**	1.000

We report results from cross-sectional regression of skewness and liquidity measures for 535 stocks on the London Stock Exchanges during the period May2001 to December 2013. The relative spread is calculated by the spread between bid and ask price divided by average bid and ask price; Amihud is calculated by absolute daily return divided by trading volume in monetary unit; Rtotr is calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; zero return days counted by zero daily return changes of each day. Skewness is the one-month historical skewness from daily returns. Kurtosis is the one-month historical kurtosis from daily returns. Autocorrelation is the one-month first-lag autocorrelation from daily returns. Mv is the monthly stock market capitalization. ** denotes significant at the 5% level.Correlation (2-tailed)

The cross-sectional correlation results show that liquidity measures are negatively correlated with skewness and positively correlated with kurtosis and lag 1 autocorrelation. In other words, stocks with higher illiquidity have more kurtosis and autocorrelation.

More specifically, the liquidity measures have negative and significant coefficients with skewness except the Rtotr ratio (where the correlation coefficient is negative but insignificant). Also, it is obvious that all liquidity measures have high positive and significant correlations with kurtosis (the coefficients are around 0.8). It shows less liquid stocks tend to be leptokurtic. The less liquid a stock, the higher peaked the return distribution would be. The positive correlation coefficients with autocorrelation means that less liquid stocks have higher lag 1 autocorrelation value.

The liquidity measures are all highly correlated (All over 0.65). Every liquidity measure is highly correlated with relative spread which is the main estimator of transaction costs. These results confirm our theoretical analysis.

4.6.4 Portfolio analysis based on skewness, kurtosis and autocorrelation

We calculate the monthly average of each stock's relative spread, Amihud ratio ($\times 10^6$), Rtotr ratio, zero trading volume days, zero return days, standard deviation, skewness, kurtosis, autocorrelation and market value through the whole period (151 months during 2001-2013, 535stocks).

Table 4.3: Decile portfolios based on Skewness

	Skew	Auto	Amihud	0RD	0TD	RS	Rtotr	Kurtosis	MV
P1	-0.242	-0.001	167.68	15.918	8.903	0.140	410.1	8.907	16
P2	0.043	-0.031	59.059	8.657	3.713	0.063	206.0	4.617	3807
P3	0.104	-0.032	26.258	5.064	1.914	0.033	299.8	2.882	4395
P4	0.146	-0.022	21.044	5.545	1.949	0.037	46.51	3.154	4206
P5	0.175	-0.037	21.549	4.345	1.283	0.032	110.1	2.567	2805
P6	0.203	-0.035	15.244	4.834	1.621	0.029	98.45	2.828	3275
P7	0.243	-0.038	10.061	4.482	1.313	0.024	100.5	2.756	2507
P8	0.291	-0.029	33.426	6.139	1.968	0.043	95.02	3.339	752
P9	0.344	-0.007	20.694	7.031	2.036	0.041	214.0	3.689	280
P10	0.472	-0.011	23.388	8.653	3.055	0.055	183.5	4.462	179
P10-P1	0.713	-0.009	-144.2	-7.264	-5.848	-0.085	-226.5	-4.445	163.08

This table reports the characteristics of portfolios constructed on the basis of the skewness. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest value of skewness and P10 is the decile portfolio containning the stocks with the highest value of skewness. P10-P1 stands for the spread between P10 and P1.

We sort stocks into decile portfolios based on stock monthly skewness. Portfolio 1 is the portfolio with the smallest value of skewness and portfolio 10 is the portfolio with the highest value of skewness.

It is clear that portfolio 1 is the least liquid portfolio based on all five liquidity measures. Moving from portfolio 1 to portfolio 10, the average value of each liquidity measure decreases, but not strictly monotonically. It supports Huang and Wang (2009) that the impact of liquidity leads to a negative skewness distribution. It is interesting that portfolio 1 with negative skewness has smallest market value. It indicates that small stocks tend to have negative skewness.

Table 4.4: Decile portfolios based on Kurtosis

	Kurtosis	Auto	Amihud	0RD	0TD	RS	Rtotr	Skew	MV
P1	0.543	-0.057	0.013	0.511	0.002	0.003	3.629	0.154	16264
P2	1.005	-0.046	1.392	1.145	0.115	0.008	12.97	0.164	4092
P3	1.454	-0.048	2.118	1.440	0.154	0.010	26.74	0.212	1103
P4	1.978	-0.047	9.271	3.202	0.221	0.024	160.7	0.245	430
P5	2.595	-0.048	15.79	4.548	0.729	0.031	198.7	0.262	258
P6	3.337	-0.040	17.22	6.456	1.350	0.042	246.9	0.258	143
P7	4.604	0.005	32.10	9.503	2.552	0.059	132.7	0.296	65.9
P8	6.084	0.027	66.85	12.849	4.666	0.081	323.7	0.177	38.7
P9	7.697	0.011	100.7	14.517	7.271	0.103	292.5	0.095	86.0
P10	10.32	-0.001	160.4	17.142	11.333	0.143	366.	-0.096	11.8
P10-P1	9.783	0.056	160.4	16.63	11.333	0.140	362.39	-0.249	-16252

This table reports the characteristics of portfolios constructed on the basis of the skewness. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest value of skewness and P10 is the decile portfolio containning the stocks with the highest value of skewness. P10-P1 stands for the spread between P10 and P1.

Then we sort stocks into decile portfolios based on stock monthly kurtosis. Portfolio 1 is the group of stocks with the smallest kurtosis and portfolio 10 is groups of stocks with the highest kurtosis.

It is clear to find that kurtosis has same trend with all five liquidity measures. Moving from portfolio 1 to portfolio 10, the average value of each liqudiity measure increases strictly monotonically. Portfolio 1 is the least liquid portfolio and portfolio 10 is the most liquid portfolio. Amaya et al (2015) find that realized kurtosis has positive relation with illiquidity. The results support Amaya et al (2015) and our expectations that low liquidity stock leads to higher return kurtosis.

Table 4.5: Decile portfolios based on Autocorrelation

	Auto	0RD	0TD	Amihud	RS	Rtotr	Skew	kurtosis	MV
P1	-0.114	3.568	0.802	1.032	0.023	221.10	0.188	2.100	2528
P2	-0.077	2.902	0.630	1.634	0.026	187.54	0.210	1.761	7762
P3	-0.058	2.683	0.778	1.877	0.020	66.012	0.180	1.937	4188
P4	-0.041	4.688	1.430	4.142	0.044	88.418	0.197	2.780	1711
P5	-0.028	7.657	3.338	4.634	0.061	81.630	0.201	4.243	1202
P6	-0.017	6.237	2.513	5.003	0.051	99.490	0.106	3.765	2872
P7	-0.004	9.138	4.118	7.528	0.069	155.20	0.137	5.083	1596
P8	0.010	9.873	4.366	5.135	0.071	296.93	0.175	5.304	206
P9	0.029	11.978	5.612	5.098	0.071	255.90	0.193	6.300	118
P10	0.059	12.286	4.298	3.611	0.062	312.56	0.205	6.066	58
P10-P1	0.172	2.579	8.718	3.495	0.039	91.456	0.017	3.966	2469

This table reports the characteristics of portfolios constructed on the basis of the skewness. All stocks listed on the London Stock Exchange from May 2001 to December 2013. P1 is the decile portfolio containning the stocks with the lowest value of skewness and P10 is the decile portfolio containning the stocks with the highest value of skewness. P10-P1 stands for the spread between P10 and P1.

As for autocorrelation, we sort stocks into decile portfolios based on stock monthly autocorrelation. Portfolio 1 is thegroup of stocks with the smallest autocorrelation and portfolio 10 is groups of stocks with the highest autocorrelation.

Most of the liqudity measures have the same trend with autocorrelation, but not monotonically. Specifically, zero return days, zero trading days and relative spread have same trend with autocorrlation. These three measures has the lowest value in portolio 1 and the higher value in portolio 10. The increasing trend is obvious. The results show that the stock with higher autocorrelation tends to be less liquid. It supports our expectation that illiquid stock with higher transaction costs would cause price distortion. At the same time, the table shows that lower autocorrelation stocks have higher market value. It may to because small firm stocks are illiquid and supports our expection from another viewpoint.

4.6.5 Regression analysis

In this section, we use cross-sectional regression to analyse the relation between liquidity and skewness, kurtosis and autocorrelation. Our empirical strategy examines an extensive sample of daily data. We calculate monthly skewness, kurtosis and first lag autocorrelation from daily returns. Also, we use daily data of each liquidity measure to calculate monthly liquidity measure data.

Skewness=α+$\beta_1$each liquidity measure + ε

Kurtosis=α+$\beta_1$each liquidity measure + ε

Autocorrelation =α+$\beta_1$each liquidity measure + ε

Table 4.6: Relationship between liquidity and skewness

Intercept	**0.252*** **(23.19)**	**0.225*** **(25.57)**	**0.168*** **(20.539)**	**0.233*** **(23.085)**	**0.252*** **(19.152)**
Relative spread	-1.478* (-10.06)				
Amihud		-1151.2* (-11.66)			
Rtotr			$-3.82\times10^{-5*}$ (-2.9)		
Zero trading				-0.019* (-9.157)	
Zero return					-0.01* (-7.24)
R^2	0.16	0.203	0.016	0.136	0.09

We report results from cross-sectional regression of skewness and liquidity measures for 535 stocks in London Stock Exchanges during the period May2001 to December 2013. The relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary units ($\times10^6$); Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; zero return days counted by zero daily return changes of each day. Skewness is the one-month historical skewness from daily return. The White (1980) t-statistics are below the coefficients in parentheses. * denotes significant at the 5% level.

The above results show that coefficients of each liquidity measure are all negative and significant. It supports that more liquid stocks have lower stock return skewness which is in line with the findings of Huang and Wang (2009). Less liquid stocks may need more compensation based on liquidity premium theory and the compensation results in negative skewness.

Table 4.7: Relationship between liquidity and kurtosis

Intercept	**1.75*** **(16.2)**	**2.998*** **(25.08)**	**3.796*** **(28.326)**	**1.923*** **(29.568)**	**0.404*** **(7.1)**
RS	43.64* (29.916)				
Amihud		23219.8* (17.78)			
Rtotr			0.001* (3.645)		
Zero trading				0.719* (52.564)	
Zero return					0.497* (80.164)
R^2	0.627	0.372	0.024	0.838	0.923

We report results from cross-sectional regression of kurtosis and liquidity measures for 535 stocks in London Stock Exchanges during the period May2001 to December 2013. The relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary unit ($\times 10^6$); Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. Kurtosis is the one-month historical kurtosis from daily return. The White (1980) t-statistics are below the coefficients in parentheses. * denotes significant at the 5% level.

The coefficients of each liquidity measure are positive and significant. Also the R square values are quite high, expect for the Rtotr ratio. All the results support Huang and Wang (2009), Ameya et al (2015) and our expectation that liquidity has a positive effect on kurtosis. The less liquid stocks exhibits higher kurtosis. The coefficients of zero trading days and zero return days are extremely high and it indicates that more non-trading days lead to higher kurtosis.

Table 4.8: Relationship between liquidity and first lag Autocorrelation

Intercept	**-0.037*** **(-13.5)**	**-0.028*** **(-12.011)**	**-0.025*** **(-11.447)**	**-0.038*** **(-15.596)**	**-0.056*** **(-19.622)**
RS	0.253* (6.813)				
Amihud		9.1e-05* (3.474)			
Rtotr			3.2×10^{-5} (1.012)		
zero trading				0.005* (9.363)	
0 return					0.004* (14.231)
R^2	0.08	0.022	0.002	0.141	0.275

We report results from cross-sectional regression of first lag autocorrelation and liquidity measures for 535 stocks in London Stock Exchange during the period May2001 to December 2013. The relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary unit ($\times10^6$); Rtotr calculated by absolute daily return divided by turnover ratio; Zero trading volume days counted by zero trading volume of each day; Zero return days counted by zero daily return changes of each day. First lag autocorrelation is calculated by the one-month daily return. The White (1980) t-statistics are below the coefficients in parentheses. * denotes significant at the 5% level.

Except for the Rtotr ratio, other four liquidity measures have positive and significant coefficients on autocorrelation. Generally, less liquid stocks have higher transaction costs. The results show that higher transaction costs lead to higher autocorrelation. The trading expense expands the price movement magnitude. Also, the price of illiquid stocks price movement reacts to new information slowly. Price cannot move toward stock intrinsic value quickly and that leads to higher autocorrelation. As for the insignificant coefficient of Rtotr ratio, one possibility is that Rtotr ratio may not a reliable measure of transaction costs. Rtotr captures price impact not directly involving trading costs.

4.7 Conclusion and discussion

In this chapter, we create new models to examine the relationship between transaction costs and return distribution and autocorrelation. The rationale behind the creation of these models is twofold. First, no direct link has been documented between liquidity and return distribution. Though several papers have studied the relation between turnover rate and autocorrelation, the direct relationship between liquidity and autocorrelation is almost uninvestigated. Second, this new model gives a solid theoretical foundation to examining how stock liquidity (capturing transaction costs) affects stock price movement. Illiquid stocks with higher transaction costs are associated with higher return kurtosis. Larger bid-ask spread (higher transaction costs) leads to higher autocorrelation. There is no strong evidence to make the conclusion about the relationship between liquidity and skewness through theory or simulations although we see some empirical links.

We calculate monthly measures based on daily data to examine 535 domestic UK companies on the London Stock Exchange over the period May 2001 to December 2013. We have found empirical links between liquidity and the properties of return distributions and return autocorrelation. In specific, we find that illiquid stock with higher transaction costs have negative skewness and a positive relationship with kurtosis and first lag autocorrelation. Our results support the finding of Amaya et al (2015), Huang and Wang (2009) and our theoretical analysis.

There are some interesting topics are left for future research. We assume the investors who know the intrinsic value of stock and when these investors want to buy or sell the stocks, there are some noise traders or liquidity traders who are willing to be the counter party. These are fairly major simplifying assumptions and perhaps more sophisticated models can be developed to take account of the potentially time varying distribution of investors' beliefs. The further study may also cover the theoretical work of the relationship between liquidity and skewness. This study is more focused on the empirical connection between liquidity and skewness.

Chapter 5 Conclusion

5.1 Conclusions

In the stock market, liquidity can be considered from a number of different angles, although it can be thought of as the speed with which a stock can be bought or sold. Kyle (1985) states that liquidity has three characteristics: tightness, depth and resiliency. Tightness can be seen as bid-ask spread which is the gap between the actual transaction price and quoted price. Depth is a proxy for the extent of the volume that can be traded without affecting stock price. In some prior research, price impact is a measure of market depth. Resiliency captures the speed of the temporarily incorrect prices bouncing back to actual price. Triggered by these liquidity characteristics, researchers have tested a number of liquidity measures in the last three decades. Amihud and Mendelson (1986b) firstly use relative spread to test liquidity. Relative spread is a good measure of transaction costs which is a direct proxy for liquidity. Amihud (2002) proposes a new liquidity measure, the Amihud ratio, and it has becomes a major liquidity measures used in much research. The Amihud ratio is defined as absolute return divided by the trading volume and captures price impact. Florackis et al (2011) amend the Amihud ratio using turnover ratio instead of trading volume to avoid size bias. Lesmond et al (1999) and Kang and Zhang (2014) use zero return days and zero trading volume days to measure liquidity respectively. Both measures are intuitive and easy to use. However, there is no consensus about which measure is the best approach. So, one of the major motivations for conducting research of this nature is the desire to compare these five liquidity measures.

Liquidity changes over time so long time series data is needed to study its evolution and increase the power of relevant statistical tests. Much research uses high-frequency data of short duration causing a problem in assessing the time varying properties of liquidity. In this research, the data period covers from 2001 to 2013 including the financial crisis which gives a good opportunity to test liquidity measures in extreme circumstances. Moreover, most prior studies focus on the US market or emerging markets. The UK stock market has been less covered in the literature to date. Chapter 2 gives a review of the current literature relating to liquidity and liquidity measures. The literature also covers the development of trading systems in the London Stock Exchange. The technical innovations in trading systems aim to increase liquidity in the stock market. We divide liquidity measures into several categories: spread, one-dimensional volume based liquidity measures (turnover, trading volume), multi-dimensional volume based liquidity measures (Amihud ratio, Amivest ratio, Rtotr ratio), non-trading measures and other liquidity measures. The data selection and filters standard are critically and carefully conducted drawing on methods used in previous research. The data are taken from the Thomson Datastream database. Following Ince and Porter (2006) and Lee (2011), we finally choose 535 stocks as sample data. The time-series graphs of the liquidity measures show that liquidity changes over time and the volatility of liquidity widened during the financial crisis. We conduct both time-series and cross-sectional correlation analysis and portfolio analysis which support our expectation that liquidity measures are positive linked with each other and do reasonably represent liquidity. One of the major findings is that the correlation coefficients between turnover rate and liquidity measures vary in different time sub-periods. It supports some recent research that turnover may not be a reliable liquidity measure during financial crises which affects the effectiveness of Rtotr ratio. The findings support Summers (2000) that turnover seems to increase during liquidity crunches rather than decrease to reflect a decline in market liquidity (Froot et al, 2001).

Stoll (2000) uses bid-ask spread to test fictions and create a cross-sectional regression model to test the relationships between bid-ask spread and market variables, such as volatility, price, trading volume and market value. Lesmond (2005) develop the model to determine which liquidity measure performs better at explaining the relative spread and other market characteristics. Volatility, price, trading volume and market value are proxies for liquidity. There are three sets of regressions in Chapter 2. The first one regresses the relative spread on the market liquidity proxies which have been discussed. The second set of regressions is based on the first set of regressions but adding different liquidity measures separately. The higher incremental explanatory power captured by the R^2 value determines which is the better regression model. In other words, after adding each liquidity measure, the liquidity measure with the higher R^2 value performs better at explaining liquidity. The results show that Amihud ratio, zero trading days and zero return days are better than Rtotr ratio at representing liquidity. The last regression includes all the liquidity measures in the regression as explanatory variables. At the same time, the results support the findings of Stoll (2000) and Lesmond (2005) that liquidity measures are positively related to volatility and negative related to price and trading volume. As for market price, the coefficients are negative which is similar to Stoll (2000).

Motivated by Chapter 2, we choose to use panel data to test liquidity measures and market characteristics in Chapter 3. Compared to cross-sectional data, the advantages of panel data are presented: First, the results of the previous cross-sectional regressions show many insignificant coefficients, such as those for price and trading volume. It may be because cross-sectional data is not able to fully analyse stock liquidity over a long period of time. Liquidity does changes over time and financial crises have a particularly heavy impact. The panel data sets can cover the unobservable or missing elements not evident in cross-sectional data.

The underlying methods of analysing panel data are complex. The daily data relating to zero trading days and zero return days are binomial, so we involve logistic regressions instead of linear regressions to analyse the relationship. Also, we have to do stationarity tests (the Augemented Dicky Fuller test and the Phillipe-Perron test) before the use of panel regression. The tests show that price and market value are non-stationary. Because of this situation, we create a new method of testing the relationship between liquidity and price and market value using an extension of the fixed effects model. The previous fixed effects model only includes volatility and trading volume, but we presume that the intercept of the fixed effects model includes remaining information about price and market value. So the extension of a new regression model is based on the regression intercepts of fixed effects model. We set the intercepts as the dependent variables which can be explained by price and market value through a new cross-sectional regression model. This new approach solve the problem that price and market value cannot be tested through panel data due to non-stationarity.

In contrast to the Stoll (2000) and Lesmond (2005) models, in this chapter we mainly focus on the relationship between liquidity measures and market characteristics (volatility, price, trading volume and market value). Volatility measures the risk of adverse price and volatility risk. Price is a proxy for risk and controls for the effects of price discreteness. Trading volume and market value represent inventory risk and probability of finding counter parties. Each liquidity measure is a dependent variable and the four market characteristics are independent variables. The results show that relative spread, the Amihud ratio and the Rtotr ratio are positively related to volatility and negatively related to trading volume. It shows that highly volatile stocks or low trading volume stocks tend to be illiquid. Zero trading days and zero return days have negative coefficients on volatility and trading volume. It is obvious that more non trading days lead to low volatility and trading volume in certain period. After creating a new regression model, the results shows that liquidity measures are negatively related to price. The coefficients on market value are not consistent. Most of our findings are similar to the findings of Stoll (2000) and Lesmond (2005). What is more, the coefficients in panel data are all more significant than those in cross-sectional results of Chapter 2. This supports the advantages of panel data regression.

The contribution of chapter 4 is firstly in discussing the relationship between liquidity and skewness, kurtosis and autocorrelation both from theoretical and empirical viewpoints. In theory, price follows a random walk if the market is efficient and liquid. In the real market, price does not follow a random walk and is not normally distributed. When the market is not liquid, even informed investors may not react fully to the new market information which leads price to sometimes deviate from its intrinsic value. Thus return autocorrelation may be larger. Motivated by Ng et al (2008), we create a model to show that larger transaction costs leads to gaps between market and intrinsic value. Also, if the previous price movement is positive, the next price movement would likely be positive. If the last price movement is negative, the next price movement would likely be negative. Overall, though Bayes Theorem, we prove that higher transaction costs would lead to higher autocorrelation in theory. Less liquid stocks are less frequent traded and may have more zero return days or small return days due to higher transaction costs. Thus, the return distribution would exhibit leptokurtism. It can be explained by examining probability density functions and simulations from normal distributions. The portfolio analysis and regression model support our assumptions. For skewness, there are no direct theoretical results showing the relationship between liquidity and skewness. The regression model results, however show that less liquid stocks are negatively correlated with skewness. Overall, we examine liquidity in the London Stock Exchange through five liquidity measures. The varieties of liquidity measures provide a comprehensive study of liquidity related characteristics. The time-series study supports that turnover rate may not be a reliable liquidity measure during financial crisis. Stoll (2000) and Lesmond (2005) study the relationship between liquidity and market characteristics (volatility, price, trading volume and market value). In this thesis, we examine the relationships using stocks in the London Stock Exchange. Most of results are similar to the results of Stoll (2000) and Lesmond (2005), while the coefficients of price and trading volume are mostly insignificant. One possibility is that Stoll (2000) and Lesmond (2005)'s data are based on relatively short periods of only one year or several years. The averaging cross-sectional method is not suitable to deal with long-period liquidity issue. Therefore, this thesis firstly studies liquidity from a panel perspective and find less liquid stock tends to have higher volatility, lower price and trading volume. What is more, we firstly link liquidity with return distribution (skewness and kurtosis) and autocorrelation. Both theoretical and empirical works find that liquidity is positively related with kurtosis and autocorrelation. It expands the liquidity research to a new relevant field.

5.2 Limitations and further discussion

The thesis studies the liquidity and liquidity measures in the London Stock Exchange based on 535 domestic UK stock from 2001 to 2013. Although the time period is long, more information would be obtained from a longer data period. The nature of how liquidity changes over time and the performance of liquidity measures may need further research using a longer period. The Rtotr ratio has been shown not to be a reliable liquidity measure compared with other liquidity measures in the UK market, especially during the financial crisis. It deserves further studies to test it in different situations. Moreover, there are numerous comparisons of liquidity measures and it may need a standard to compare each liquidity measure.

We have tested the relationship between liquidity measures and market characteristics using panel data. Little other theoretical or empirical research has been done on studying liquidity from a panel data viewpoint. It would be useful further study was done on the best ways to deal with the issue of using panel data in this context such as non-stationary variables.

The relationships between liquidity and skewness, kurtosis and autocorrelation are considered in the current findings. The link between skewness and liquidity is still unclear and would benefit from further investigation. The assumption of the theoretical model we created is based on the existence of rational or informed investors and noise and liquidity traders. It would be interesting to consider the effects of liquidity in more sophisticated models of heterogeneous investors.

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Appendix

Table A1 shows the Augment Dickey-Fuller (ADF) test and Phillips and Perron (PP) test of price. Price is the logarithm of the daily closing price from Datastream. The figures are conducted through STATA 14. Both lag difference are one in both tests. The p-values are below the statistic value in parentheses.

Table A1: ADF and PP tests for Price

Price	ADF	PP	Price after first differencing	ADF	PP
Number of panels	535	535	Number of panels	535	535
Avg number of periods	3181	3181	Avg number of periods	3185	3185
Inverse chi-sqaure (P)	1074.89	1052.79	Inverse chi-sqaure (P)	3.86e+04	3.86e+04
	(0.45)	(0.64)		(0.00)	(0.00)
Inverse normal (Z)	0.91	1.40	Inverse normal (Z)	-187.95	-187.95
	(0.82)	(0.92)		(0.00)	(0.00)
Inverse logit t(L*)	0.59	1.11	Inverse logit t(L*)	-459.72	-459.72
	(0.72)	(0.87)		(0.00)	(0.00)
Modified inv. Chi-square (Pm)	0.11	-0.37	Modified inv. Chi-square (Pm)	810.56	810.56
	(0.46)	(0.65)		(0.00)	(0.00)

Table A2 shows the Augment Dickey-Fuller (ADF) test and Phillips and Perron (PP) test of market value. Market value is the logarithm of the daily market value from Datastream. The figures are conducted through STATA 14. Both lag difference are one in both tests. The p-values are below the statistic value in parentheses.

Table A2: ADF and PP tests for Market value

Mv	ADF	PP	Mv after first differencing	ADF	PP
Number of panels	535	535	Number of panels	535	535
Avg number of periods	3181	3181	Avg number of periods	3181	3181
Inverse chi-sqaure (P)	1068.14	1050.05	Inverse chi-sqaure (P)	3.86e+04	3.86e+04
	(0.51)	(0.66)		(0.00)	(0.00)
Inverse normal (Z)	0.30	0.76	Inverse normal (Z)	-187.95	-187.95
	(0.62)	(0.78)		(0.00)	(0.00)
Inverse logit t(L*)	0.03	0.51	Inverse logit t(L*)	-459.72	-459.72
	(0.51)	(0.69)		(0.00)	(0.00)
Modified inv. Chi-square (Pm)	-0.04	-0.43	Modified inv. Chi-square (Pm)	810.56	810.56
	(0.52)	(0.67)		(0.00)	(0.00)

Table A3 shows the Augment Dickey-Fuller (ADF) test and Phillips and Perron (PP) test of volatility and trading volume. The volatility is the standard deviation of 10 days rolling returns for stock. Trading volume is the logarithm of daily trading volume from Datastream. The figures are conducted through STATA 14. The p-values are below the statistic value in parentheses.

Table A3: ADF and PP tests for Volatility and Trading volume

Volatility	ADF	PP	Trading volume	ADF	PP
Number of panels	535	535	Number of panels	535	535
Avg number of periods	3171	3171	Avg number of periods	3186	3186
Inverse chi-sqaure (P)	3.55e+04	3.49e+04	Inverse chi-sqaure (P)	3.85e+04	3.86e+04
	(0.00)	(0.00)		(0.00)	(0.00)
Inverse normal (Z)	-179.12	-177.14	Inverse normal (Z)	-187.89	-187.95
	(0.00)	(0.00)		(0.00)	(0.00)
Inverse logit t(L*)	-423.69	-415.68	Inverse logit t(L*)	-459.49	-459.72
	(0.00)	(0.00)		(0.00)	(0.00)
Modified inv. Chi-square (Pm)	745.22	730.70	Modified inv. Chi-square (Pm)	810.14	810.56
	(0.00)	(0.00)		(0.00)	(0.00)

Table A4 shows the Augment Dickey-Fuller (ADF) test and Phillips and Perron (PP) test of relative spread, Amihud ratio($\times 10^6$) and Rtotr ratio. Relative spread calculated by spread between bid and ask price divided by average bid and ask price; Amihud calculated by absolute daily return divided by trading volume in monetary unit; Rtotr calculated by absolute daily return divided by turnover ratio. The figures are conducted through STATA 14. Both lag difference are one for both tests. The p-values are below the statistic value in parentheses.

Table A4: ADF and PP tests for Relative spread, Amihud and Rtotr ratio

RS	ADF	PP	Amihud	ADF	PP	Rtotr	ADF	PP
Number of panels	535	535	Number of panels	535	535	Number of panels	535	535
Avg number of periods	3170	3170	Avg number of periods	3186	3186	Avg number of periods	2741	2741
Inverse chi-sqaure (P)	3.46e+04 (0.00)	3.59e+04 (0.00)	Inverse chi-sqaure (P)	3.80e+04 (0.00)	3.82e+04 (0.00)	Inverse chi-sqaure (P)	3.69e+04 (0.00)	3.79e+04 (0.00)
Inverse normal (Z)	-175.31 (0.00)	-179.59 (0.00)	Inverse normal (Z)	-185.78 (0.00)	-186.74 (0.008)	Inverse normal (Z)	-180.95 (0.00)	-185.06 (0.00)
Inverse logit t(L*)	-412.03 (0.00)	-427.87 (0.00)	Inverse logit t(L*)	-453.21 (0.00)	-455.92 (0.00)	Inverse logit t(L*)	-439.53 (0.00)	-452.02 (0.00)
Modified inv. Chi-square (Pm)	724.06 (0.00)	752.80 (0.00)	Modified inv. Chi-square (Pm)	-798.78 (0.00)	803.66 (0.00)	Modified inv. Chi-square (Pm)	774.00 (0.00)	796.86 (0.00)

Table B1 report the results of Hausman tests which are used to test whether to use fixed effects models or random effects model. RS represents relative spread; volatility is the standard deviation of 10 days rolling returns for stock; volume is the average value of trading volume in number for stock. The second column specifies the fixed effects model's coefficients, the third column specifies the random effects model's coefficients, the fourth column is the difference between the coefficients from fixed and random effects model, and the fifth column is the standard deviation of the Hausman test. The last column gives the results of Hausman test.

Table B1: Hausman tests for Relative spread

RS	**Coefficients**				**Chi**	**32.2**
	Fixed (b)	Random(B)	(b-B) difference	Standard deviation	Prob> Chi =0.00	
Volatility	0.249	0.25	-0.001	0.0002		
Volume	-0.007	-0.007	-0.00002	0.00001		

Table B2 report the results of Hausman tests which are used to test whether to use fixed effects models or random effects model. Amihud represents Amihud ratio ($\times 10^6$); volatility is the standard deviation of 10 days rolling returns for stock; volume is the average value of trading volume in number for stock. The second column specifies the fixed effects model's coefficients, the third column specifies the random effects model's coefficients, the fourth column is the difference between the coefficients from fixed and random effects model, and the fifth column is the standard deviation of the Hausman test. The last column gives the results of Hausman test.

Table B2: Hausman tests for Amihud ratio

Amihud	**Coefficients**				**chi**	**360.84**
	Fixed (b)	Random(B)	(b-B) difference	Standard deviation	Prob>chi =0.00	
Volatility	554.13	556.09	-1.959	3.714		
Volume	-14.49	-11.599	-2.898	0.1822		

Table B3 report the results of Hausman tests which are used to test whether to use fixed effects models or random effects model. Rtotr represents Rtotr ratio; volatility is the standard deviation of 10 days rolling returns for stock; volume is the average value of trading volume in number for stock. The second column specifies the fixed effects model's coefficients, the third column specifies the random effects model's coefficients, the fourth column is the difference between the coefficients from fixed and random effects model, and the fifth column is the standard deviation of the Hausman test. The last column gives the results of Hausman test.

Table B3: Hausman tests for Rtotr ratio

Rtotr	**Coefficients**				**Chi**	**199.84**
	Fixed (b)	Random(B)	(b-B) difference	Standard deviation	Prob>chi =0.00	
Volatility	2961	2837	124	16.79		
Volume	-186.7	-174	-12.7	0.898		

Table B4 report the results of Hausman tests which are used to test whether to use fixed effects models or random effects model. 0 Trading represents 0 trading volume days; volatility is the standard deviation of 10 days rolling returns for stock; volume is the average value of trading volume in number for stock. The second column specifies the fixed effects model's coefficients, the third column specifies the random effects model's coefficients, the fourth column is the difference between the coefficients from fixed and random effects model, and the fifth column is the standard deviation of the Hausman test. The last column gives the results of Hausman test.

Table B4: Hausman tests for Zero trading days

0Trading	**Coefficients**				**Chi**	**263.35**
	Fixed (b)	Random(B)	(b-B) difference	Standard deviation	Prob>chi=0.00	
Volatility	-0.316	-0.318	0.0017	0.00008		
Volume	-0.0822	-0.0821	0.00014	8.31e-06		

Table B5 report the results of Hausman tests which are used to test whether to use fixed effects models or random effects model. 0 return represents 0 return days; volatility is the standard deviation of 10 days rolling returns for stock; volume is the average value of trading volume in number for stock. The second column specifies the fixed effects model's coefficients, the third column specifies the random effects model's coefficients, the fourth column is the difference between the coefficients from fixed and random effects model, and the fifth column is the standard deviation of the Hausman test. The last column gives the results of Hausman test.

Table B5: Hausman tests for Zero return days

0 Return	**Coefficients**				**Chi**	**59.09**
	Fixed (b)	Random(B)	(b-B) difference	Standard deviation	Prob>chi =0.00	
Volatility	-1.444	-1.442	-0.0016	0.00024		
Volume	-0.078	-0.078	0.000051	0.00001		

Table C1 shows the simulations of net return changes results from different transaction costs. The 1000 samples (raw return) are randomly simulated under normal distribution (Mean is zero; Standard deviation is one). After calculating different transaction costs (0.01, 0.05, etc), the net return changes based on different transaction costs in following columns, the bottom four descriptive data shows the results of average value of each column.

Table C1: Sample simulation of Skewness and Kurtosis (1st group)

	Expense	0.01	0.05	0.1	0.25	0.5	1
Number	Raw Return	Net Return	Net Return	Net Return	Net Return	Net Return	Net Return
1	0.2473	0.2373	0.1973	0.1473	0.0000	0.0000	0.0000
2	-1.6127	-1.6027	-1.5627	-1.5127	-1.3627	-1.1127	-0.6127
.							
1000	0.2409	0.2309	0.1909	0.1409	0.0000	0.0000	0.0000
Mean	0.0346	0.0342	0.0327	0.0308	0.0252	0.0198	0.0099
STD	0.9901	0.9819	0.9498	0.9104	0.7973	0.6268	0.3570
Skewness	-0.0471	-0.0465	-0.0451	-0.0431	-0.0377	-0.0484	-0.1562
Kurtosis	-0.3530	-0.3272	-0.2196	-0.0749	0.4392	1.6698	6.8096

Table C2 shows the simulations of net return changes results from different transaction costs. The 1000 samples (raw return) are randomly simulated under normal distribution (Mean is zero; Standard deviation is one). After calculating different transaction costs (0.01, 0.05, etc), the net return changes based on different transaction costs in following columns,, the bottom four descriptive data shows the results of average value of each column.

Table C2: Sample simulation of Skewness and Kurtosis (2nd group)

	Expense	0.01	0.05	0.1	0.25	0.5	1
Number	Raw Retun	Net Return	Net Return	Net Return	Net Return	Net Return	Net Return
1	-1.5879	-1.5779	-1.5379	-1.4879	-1.3379	-1.0879	-0.5879
2	0.6407	0.6307	0.5907	0.5407	0.3907	0.1407	0.0000
.							
1000	-0.6247	-0.6147	-0.5747	-0.5247	-0.3747	-0.1247	0.0000
Mean	0.0029	0.0031	0.0039	0.0044	0.0043	0.0053	-0.0001
STD	1.0346	1.0269	0.9966	0.9597	0.8549	0.7007	0.4689
Skewness	-0.7541	-0.7698	-0.8364	-0.9269	-1.2614	-2.1445	-6.0926
Kurtosis	6.8725	7.0841	7.9885	9.2607	14.2819	28.9599	113.5045

Table C3 shows the simulations of net return changes results from different transaction costs. The 1000 samples (raw return) are randomly simulated under normal distribution (Mean is zero; Standard deviation is one). After calculating different transaction costs (0.01, 0.05, etc), the net return changes based on different transaction costs in following columns, the bottom four descriptive data shows the results of average value of each column.

Table C3: Sample simulation of Skewness and Kurtosis (3rd group)

	Expense	0.01	0.05	0.1	0.25	0.5	1
Number	Raw Retun	Net Return	Net Return	Net Return	Net Return	Net Return	Net Return
1	1.7730	1.7630	1.7230	1.6730	1.5230	1.2730	0.7730
2	0.4318	0.4218	0.3818	0.3318	0.1818	0.0000	0.0000
.							
1000	0.3770	0.3670	0.3270	0.2770	0.1270	0.0000	0.0000
Mean	0.0153	0.0150	0.0143	0.0136	0.0114	0.0062	0.0021
STD	1.0174	1.0095	0.9780	0.9395	0.8296	0.6664	0.4129
Skewness	0.0696	0.0720	0.0810	0.0932	0.1398	0.2760	0.9718
Kurtosis	0.6480	0.6969	0.9031	1.1863	2.2438	5.0215	19.9007

Table C4 shows the simulations of net return changes results from different transaction costs. The 1000 samples (raw return) are randomly simulated under normal distribution (Mean is zero; Standard deviation is one). After calculating different transaction costs (0.01, 0.05, etc), the net return changes based on different transaction costs in following columns, the bottom four descriptive data shows the results of average value of each column.

Table C4: Sample simulation of Skewness and Kurtosis (4th group)

	Expense	0.01	0.05	0.1	0.25	0.5	1
Number	Raw Retun	Net Return	Net Return	Net Return	Net Return	Net Return	Net Return
1	-0.3570	-0.3470	-0.3070	-0.2570	-0.1070	0.0000	0.0000
2	-0.5248	-0.5148	-0.4748	-0.4248	-0.2748	-0.0248	0.0000
.							
1000	-0.2193	-0.2093	-0.1693	-0.1193	0.0000	0.0000	0.0000
Mean	0.0271	0.0273	0.0283	0.0296	0.0327	0.0349	0.0246
STD	1.0085	1.0006	0.9694	0.9312	0.8219	0.6584	0.4020
Skewness	0.1754	0.1771	0.1843	0.1939	0.2288	0.3183	0.7423
Kurtosis	0.1039	0.1372	0.2756	0.4613	1.1212	2.6767	8.8411