How Exactly Do Markets Adapt? Evidence from the Moving Average Rule in Three Developed Markets

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Abstract

The seminal study by Brock, Lakonishok and LeBaron (1992) (BLL hereafter) found that the moving average rule had strong predictive power over 90 years in the DJIA, and this result was confirmed by Hudson et al. (1996) for the FT30 in the UK and Chen et al. (2009) for the TOPIX in Japan. However, according to the Adaptive Market Hypothesis, trading rules are only likely to be successful for a limited period of time and, as investors and markets adapt, their predictive power will diminish. We examine the moving average (MA) rule using post-BLL (1987-2013) data and find that after 1986 the rule's predictive power has diminished in all three markets. We investigate the exact process behind the weakening of the predictive power of moving average rules and find that post-1987 markets react to new buy/sell signals not on the days those signals are generated, but the day before. In support of this finding, we show that trading strategies based on anticipation of signals would have yielded superior profits to investors. Hence, trading on anticipated signals constitutes a feasible explanation of price reactions to future, one-day-ahead new signals, and thus in line with the Adaptive Market Hypothesis.

Keywords: Technical analysis; Adaptive Market Hypothesis; Market Efficiency; Predictability

JEL classification: G11, G14, G15

1. Introduction

The Efficient Market Hypothesis (EMH) has been one of the most studied and respected theories in the academic finance literature since its formulation in the 1960s. According to the weak form of the EMH, stock prices reflect all available information in past prices, such that technical analysis trading rules based on historical price data are unprofitable (Fama 1970). However, in recent years, and especially following Brock, Lakonishok and LeBaron, (1992) (BLL hereafter), there has been an explosion of studies that find that technical trading rules based on historical data do possess significant power in forecasting stock returns. The BLL study investigates the profitability of the moving average (MA hereafter) and trading range break rules using DJIA data in the period 1897 to 1986 and finds that the MA rule has had high predictive power over the 90 years period. These results have been examined in great detail and generally found to be quite robust and to hold in many other markets, including the UK and Japan. Studies have analysed the robustness of those results to data snooping bias[1], transaction costs[2], or out-of sample performance. On the latter issue, a number of studies find profits from the rules applied by BLL to be non-existent in the period following that paper (e.g., Lebaron, 2000; Schulmeister 2009; Fang et al., 2013, and Taylor, 2014, for risk-adjusted profits). Some authors attribute this decline in profits to the original results having been spurious in the first place (due to data snooping: Ready, 2002, Bajgrowicz and Scaillet, 2012, biases in closing prices due to nonsynchronous trading: Day and Wang, 2002, or to other statistical biases: Fang et al., 2013). Others attribute the decline to an increase in market efficiency (Sullivan et al., 1999).

The objective of our study is to examine in detail how the predictive ability of the rules have declined and the implications of this decline for general models of market behaviour. A decline in the predictive ability of the rules is not incompatible with the broad notion of market efficiency but particular patterns of decline may be more compatible with the Adaptive Market Hypothesis (AMH hereafter) proposed by Lo (2004). The AMH enables predictability from technical rules to co-exist with the EMH in an intellectually consistent manner. This theory states that investment strategies can be successful or unsuccessful, depending on the particular market environment. Contrary to the EMH, the AMH implies that

[1] Sullivan et al. (1999) find the profits reported in Brock et al. (1992) to be sustained even after an adjustment for data snooping, whereas Ready (2002) applies a different adjustment method and finds the significant profits in Brock et al. (1992) to be spurious.

[2] For instance, Bessembinder and Chan (1998) argue that profits in Brock et al. (1992) would be fully offset by transaction costs.

the performance of investment strategies may decline for a time and then return to profitability, when environmental conditions become more conducive to such strategies. A consequence of this implication is that market efficiency is not an all-or-nothing condition, but varies continuously over time and across markets. Lo (2004) argues that convergence to some ideal state of efficiency is neither guaranteed nor likely to occur. We find results compatible with the AMH in that, whilst the predictive power of the rules have declined, which is consistent with EMH, this decline drives other market changes and so cannot be interpreted as a simple move towards efficiency.

We achieve the objective of our study by examining the evolution of the MA rule in three major financial markets over the period subsequent to the study by BLL. Specifically, we firstly examine the performance of the original MA rules to establish whether they possess predictive abilities and outperform the buy-and-hold strategy. We find that the MA rule is no longer significantly predictive for the DJIA (US market) and FT30 (UK market), and that the level of predictability in the TOPIX (Japanese market) has diminished since the end of the investigation period used by BLL (1992). These findings could be argued to be consistent with the Efficient Market Hypothesis, since the rule is no longer predictive and the market has become 'efficient' in this respect. Secondly, and more importantly, we shed light onto how exactly the market adapted to the knowledge of the effectiveness of the rules. To this end, we analyse differences in return behaviour around days when technical trading rules generate new buy or sell signals, in the pre- vs. post-BLL samples. The results support the notion of investors not only having learned to react immediately to new signals from technical trading rules, but also to anticipate those signals successfully. To further investigate whether anticipation of trading rule signals could have yielded superior returns to investors in the post-BLL period (who, e.g., might have learned about and started acting upon the BLL results), we suggest a version of the MA rule whereby investors predict the trading signal on the following day and trade on that signal today. We find that the trading based on this modified rule outperforms the original MA rule in the post-BLL period, suggesting profitability of technical trading conditional on the level of investors' forecasting ability. Thus, our results taken as a whole provide support for the AMH. A previously successful trading rule is no longer successful as investors have driven away its profitability. However, investors who can adapt the rule and predict the signal it would give on the next day can still successfully use a modified version of the rule. This is in line with the AMH which suggests that market participants are always competing and adapting within the market and that new investment strategies will replace old strategies once the former ones are no longer profitable.

This study does not attempt to answer the question of what exactly were the factors which contributed to the observed decline in the forecasting performance of the MA rules post-1986. As mentioned earlier, some authors argued that technical trading predictability was always spurious or non-existent when transaction costs have been accounted for. Assuming the BLL results were not spurious and could have been exploited given reasonable transaction costs, the decline of technical trading profitability could be due to an increase in market efficiency (Sullivan et al., 1999). This again could be driven by advances in information technology and computing power facilitating investment analysis and order executions; development of derivatives markets which have been shown elsewhere to positively affect the efficiency of price formation on spot markets; or an increase in the fraction of trades by sophisticated institutional traders who also face low transaction costs. Lastly, we entertain the possibility that traders have learned about the profitability of technical trading as unveiled in the BLL study and started to trade on those rules in the post-1986 period, which resulted in the decline of the predictive performance of those rules. In this study, however, we investigate the mechanism but not the causes of the decline in predictive power of the original MA rules.

The rest of the paper is organized as follows. A review of the relevant literature relating to technical analysis in general, the MA rule in particular, and the AMH is presented in Section 2. Section 3 explains the methodology of the different MA rules examined and the two trading rules implemented while Section 4 presents our hypotheses. Section 5 presents the data while empirical results are discussed in Section 6. Section 7 summarises the findings and provides conclusions.

2. Literature Review

2.1 Technical Analysis

Technical analysis has a long history of widespread use by participants in financial markets (Park and Irwin, 2007; Lo and Hasanhodiz, 2010). Menkhoff (2010) finds that the vast majority of fund managers use technical analysis and it is preferred to fundamental analysis. Academics have tended to be sceptical about the use of technical analysis. The scepticism can be linked to the early negative empirical findings regarding the profitability of various technical rules in stock markets (Fama and Blume, 1966, Van Horne and Parker, 1967, 1968, Jensen and Benington, 1970). However, due to more recent positive findings regarding technical analysis rules, there has been a great increase in the literature on technical analysis since the mid-1990s, with Park and Irwin (2007) noting that half of all empirical studies conducted after 1960 were published during the period 1995-2004.

2.2 The MA Rule in the US, UK and Japan.

The MA rule is one of the most popular technical trading rules amongst practitioners and has been extensively studied in the academic literature. One of the first papers to investigate the MA rule was by Cootner (1962) who found that it was much more successful than a simple buy-and-hold strategy if gross profits are considered. However due to the high frequency of trading, the rule is much inferior after allowing for transaction costs. These results were further supported by Van Horne and Parker (1967; 1968), and James (1968).

The study by BLL is one of the most influential works on technical trading rules. The influence is due to the strong findings of consistent and positive results about the forecasting power of technical trading rules, the use of a long price history (90 years of the DJIA) and the application for the first time of the model-based bootstrap method. BLL applied the MA rule to the DJIA data over the 1897-1986 period and the results indicate that buy (sell) signals from the MA rule generates positive (negative) returns across all 26 rules and four sub-period tested. Thus all the buy-sell differences are positive and outperform buy-and-hold returns. All the buy-sell spreads are also positive with an annual return of 19%, which compares favourably with buy-and-hold returns of 5%. Moreover buy signals generate higher average returns than sell signals and have a lower standard deviation than sell signals. This implies that technical trading returns cannot be explained by risk. However, the authors do not adjust for transaction costs, so their results are not sufficient to prove that the MA rules generate net returns greater than the simple buy-and-hold strategy.

The results from BLL have been subject to considerable scrutiny. Bessembinder and Chan (1998) investigate the profitability of the rules by examining the same trading rules as BLL for dividend-adjusted DJIA data over the sample period 1926-1991. Incorporating dividends tends to reduce the returns on short sales and thus decreases the technical trading returns. To avoid data snooping, they test the profitability and significance of the returns of the trading rules on portfolios as well as individual stocks. Even given break-even transaction costs have declined over time, they find that the transaction costs outweigh the returns. Further, Sullivan et al. (1999) examine the results of BLL by applying a bootstrap reality check for the same sample period. They find that the results are not due to data snooping. However, the out-of-sample results are not so successful and the authors conclude that market efficiency has improved in recent years. Ready (2002) also studies the BLL results by comparing the BLL MA rules to technical trading rules formed by genetic programming and finds the best BLL trading rule for the 1963-1986 sample period produces significantly higher excess returns than the average of the trading rules recognized by the genetic programming. However, the BLL MA rule is less successful than the genetically generated rules over the 1957-1962 period. Thus, Ready argues that investors would have been unlikely to choose the BLL MA rule at the end of 1962 given its relatively poor performance and the results attributable to data snooping. Furthermore, Day and Wang (2002) re-examine BLL findings by adjusting for both dividends and the interest earned on the proceeds from short sales. They show that adjusting for transaction costs and the impact of nonsynchronous prices on the reported closing levels of the DJIA eliminates the profits, reducing both the differential returns following buy and sell signals, and that the risk-adjusted excess profits are not statistically significant. Moreover, Atanasova and Hudson (2010) update the BLL results to include data from the DJIA from 1897 to 2009. They find MA rules to be highly predictive on data adjusted to remove calendar effects data and conclude that the removal of calendar effects does not make the rules insignificant. Shynkevich (2012) studies technical trading rules that are adjusted for data snooping bias on the technology industry and small cap sector portfolios from 1995-2010. They find that the MA rule does outperform a buy-and-hold strategy over the first half of the sample, but cannot outperform the buy-and-hold strategy during the second half of the sample. Fang et al. (2013) examine the DJIA and S&P500 out-of-sample data, both pre-and post-dating the original BLL sample, and find no evidence of statistical predictability in any of these additional periods. Recently, Taylor (2014) studies the performance of the technical trading rules of BLL over the period 1928-2012 on all members of the DJIA. The study finds that the risk-adjusted profits available from technical trading rules evolve slowly over time and consistent with the AMH, the risk-adjusted profits are confined to particular episodes primarily from the mid-1960s to mid-1980s, and that the risk-adjusted profits rely on the ability of investors to short-sell stocks.

The MA rule has also been examined in many other markets, including the UK and Japan. In the UK, Hudson et al. (1996) examine BLL's methodology on the FT30 from 1935 to 1994. Although they confirm that these rules have predictive power, they do not generate excess returns after taking account of transaction costs. Fifield et al. (2005) study the MA rule in 11 European stock markets (including the UK) from 1991 to 2000 and found that none of the rules examined outperformed the simple buy-and-hold strategy, suggesting deterioration in the profitability of the MA rule. Further, Metghalchi et al. (2012) examine the profitability of the MA rule in 16 European stock markets (including the UK) from 1990 to 2006. They find that the simple MA rule does have predictive power in all of the countries and that the two trading strategies studied do beat the buy-and-hold strategy.

Evidence from Japan has been sparse and mixed. Bessembinder and Chan (1995) find that the MA rules have explanatory power in all five Asian markets considered, with the explanatory power greater in three emerging markets (Malaysia, Thailand and Taiwan) than more developed markets (Hong Kong and Japan). However, when transaction costs are considered, any gains from these trading strategies are eliminated. Ito (1999) also investigates the trading rules used by BLL on the national equity indices of six Pacific-Basin countries. The results show that the rules have predictive power in Japan, Canada, Indonesia, Mexico and Taiwan, but not in the US. Chong and Ng (2008) study the Nikkei 225 from 1985 to 2006 and also split the whole subsample into two using the year 2000 as the cut-off year. They find the MA rule has no predictive power in any of the samples thus indicating the efficiency of the Japanese stock market in this respect. Further Chen et al. (2009) examine various technical trading rules from 1975 to 2006 in eight Asian markets (including the TOPIX) and find that the short term MA rules are the most profitable for all markets when no transaction costs are implemented. However when transaction costs are taken into account, the most profitable rules are the long-run MA rules, although there is a substantial decline in trading profits.

2.3 The Adaptive Market Hypothesis (AMH)

The AMH has gained increasing attention and support in the recent academic literature. Lim and Brooks (2006) examine the evolving efficiency of developed and developing stock markets through the portmanteau bicorrelation test statistic and find that the degree of market efficiency varies through time in a cyclical fashion. Todea et al. (2009) investigate the profitability of the MA strategy over time windows using linear and nonlinear tests and find that returns are not constant over time, but rather episodic. Ito and Sugiyama (2009) study the time-varying autocorrelation of monthly S&P500 returns and show that the degree of market efficiency varies over time. Kim et al. (2011) examine the AMH using the return predictability of the DJIA from 1900 to 2009 and find strong evidence that return predictability fluctuates over time in a similar way to that described by Lo and that the US market has become more efficient after 1980. Smith (2012) investigates the adaptive nature of eighteen European stock markets and find that each of the markets provides evidence of the time-varying nature of return predictability, which is consistent with the adaptive markets hypothesis. Lim et al. (2013) show that the three major US indices have time-varying properties using a rolling window AR and WBAVR test and argue that markets must go through periods of efficiency and inefficiency. Further, Urquhart and Hudson (2013) examine the AMH through linear and nonlinear tests for dependence of the DJIA, FT30 and TOPIX over a very long period. They find strong evidence of the AMH through the linear tests; however, the nonlinear tests show strong evidence of dependence throughout every subsample of each three markets. Zhou and Lee (2013) examine the predictability of REIT returns and find that it is time varying and declines over time, which is influenced by market conditions. Hull and McGroarty (2014) study 22 emerging markets over a 16-year sample using the Hurst-Mandelbrot-Wallis rescaled range test on stock returns and volatility. They find strong evidence of long memory persistence in volatility over time which is consistent with the AMH. Manahov and Hudson (2014) develop various artificial stock markets using a special adaptive form of the Strongly Typed Genetic Programming based learning algorithm applied to data from the FTSE 100, S&P 500 and Russell 3000 and find that the stock market dynamics are better explained by the AMH than the EMH since different trader populations behave as an efficient adaptive system evolving over time. Furthermore, Urquhart and McGroarty (2014) study four well-known calendar anomalies from 1900 to 2013 and show that each anomaly behaves in a way consistent with the AMH.

3. Methodology

In this section, we firstly present the definition of the MA rule which was applied in BLL and subsequent studies. Next, we explain how the anticipation of future buy and sell signals by investors would result in a modification of the MA rule. Lastly, we introduce trading strategies based on those anticipated signals.

3.1. Moving Average (MA) rule

A moving average is an average of observations of the level of an index over several consecutive time periods. The standard MA rule generates buy (sell) signals on which the investor act. This strategy recommends buying (or selling) on a day when the short-period moving average rises above (or falls below) the long-period moving average. Thus buy and sell signals are generated by crossovers of a long moving average (calculated over L days) by a short moving average (S days, $S < L$). The buy signal is generated when the short-period moving average moves higher than the long-period moving average:

$$\left[\sum_{\lambda=1}^{S} P_{t-(\lambda-1)} \Big/ S\right] > \left[\sum_{\lambda=1}^{L} P_{t-(\lambda-1)} \Big/ L\right] + band \;\Rightarrow Buy\ at\ time\ t \qquad (1)$$

Where P_t is the price at time t. Sell signals are generated when the inequality is reversed:

$$\left[\sum_{\lambda=1}^{S} P_{t-(\lambda-1)} \Big/ S\right] < \left[\sum_{\lambda=1}^{L} P_{t-(\lambda-1)} \Big/ L\right] - band \Rightarrow Sell\ at\ time\ t \qquad (2)$$

When the short-term moving average remains above (below) the long-term moving average on subsequent days, technically "buy" ("sell") signals are generated but no trading takes place. Rather, the initial position is maintained.[3] Hence, trading only takes place following the initial, but not subsequent, signals. A percentage band may be included to reduce the number of signals by eliminating "whiplash" signals when the short and long period moving averages are close[4]. A popular MA rule in the literature is the (1,200), where the short period is one day and the long period is 200 days. However for completeness, three other common variations of the rule are used, namely the (1,50), (1,150) and (1,200). The shorter ~~the size of~~ the moving average, the closer it follows the market, and the longer ~~the size of~~ the moving average, the more it smooth's market fluctuations. Thus a rule with S = 1 is very responsive,

[3] This position depends on the exact trading strategy being implemented. In a simple case, one could go long in an asset following an initial buy signal and remain long as long as "buy" signals are being generated on subsequent days, go and remain short given "sell" signals. Other strategies are possible, however, e.g. as discussed in Section 3.3.

[4] Generally a 1% band is used in the literature.

that is, whenever the actual returns rises above (below) the moving average, the signal is to buy (sell).[5]

3.2. Anticipation of MA signals

Informed investors may become aware of the substantial returns available after a new buy or sell signal has been generated and begin to anticipate signals to take advantage of the expected price movements. To establish the maximum gains from trading on perfectly anticipated next day's signals, we devise a hypothetical trading rule. This perfectly anticipated MA rule perfectly predicts the signal which will be generated by the original MA rule on the following day and trades on that signal today already, to take advantage of the expected price movements. Clearly, *perfect* prediction is not possible without knowledge of the future, so this rule can be regarded as a benchmark for the maximum benefits obtainable from predicting signals rather than a proposal for an implementable trading rule. This allows us to consider the incentives for investors to act to anticipate signals. In reality, the actual, realised returns would vary across investors who possess different forecasting skills, over time, and with market conditions, but be lower than those under perfect foresight. However, a certain, albeit imperfect, level of predictive accuracy is quite possible since the long run moving average is often very different from the current price and so it is fairly certain what the following day's signal is going to be[6]. If we take, for example, a situation where today's index price is 50 and the associated moving average is 45, tomorrow's signal is highly likely to be a buy signal as well. It would take a large change in price (a change of greater than 10%) for a sell signal to be generated, which is extremely unlikely.

3.3. Trading strategies

An important question when dealing with any technical trading rule is whether an investor can utilise the rule to generate returns greater than the market. Thus, the degree to which investors can earn profits that beat the buy-and-hold strategy using two simple trading strategies is analysed.

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[5] It is implicitly assumed that investors can trade at the closing price on the day the signal is generated. In real life, it would be possible if trading took place after the closing price has been announced, maybe OTC. Alternatively, as Ready (2002) argues, investors can anticipate the closing price, and hence the signal, shortly before the closing price is observed, as the price is not likely to move significantly in the last few minutes of trading.

[6] We also considered an imperfectly anticipated rule, whereby investors can perfectly predict future signals if the gap between future close and future MA is large, but not if this gap is small. In the latter case, investors are uncertain about what the next day's signal is actually going to be and follow the present, not future, signal instead. Not surprisingly, the empirical results for the imperfect rule tend to show lower profits than those for the perfectly anticipated signals (not reported to conserve space but available on request).

In the first strategy, the investor is initially assumed to hold a buy position and the investor to hold the buy until a new sell signal is generated. Upon this new sell signal, the trader sells and goes out of the market until the next new buy signal. Upon the last sell signal, it is assumed that the investor liquidates his position. At the end of the sample period, the profit from the different trading rules are calculated and compared with the profit from the naïve buy-and-hold strategy.

The second trading strategy examined follows the "double or out" rule suggested by Bessembinder and Chan (1998). If a neutral signal is generated, there is an investment in the index. If a buy day is indicated, the investment in the index is doubled whereas, if a sell day is indicated, the funds are invested in cash, thus broadly giving a similar risk to that of a buy-and-hold strategy. Bessembinder and Chan (1998) assume investors earn the daily risk-free rate when a sell signal is generated, but since no risk-free rates are available for long periods of the data we examine, to be conservative we assume 'our' investor invests in cash with no return when a sell signal is generated. The roundtrip breakeven costs are calculated for both strategies and represent the percentage roundtrip trading costs that would eliminate the difference between the rule profits and the buy-and-hold strategy[7].

4. Market Adaptation Hypotheses

The fact that the MA rule was successful for such a long period of time suggests that the rule is picking up some intrinsic properties of the market, e.g., an upward (downward) trend in prices whose inception is indicated by the new buy (sell) signal. This property might have been unknown to investors in general before 1987 but since then, more investors may have begun to implement the rule into their investment strategy (maybe as a result of the publication of the BLL study). The situation before the rule became known is illustrated in a stylised way in Figure 1. For simplicity of exposition, the figure assumes that investors are risk neutral and the discount rate is 0. Furthermore, all price movements not predicted by the rules are random and not illustrated in the figure. The overall expected return for investors not aware of the rule, who buy and hold or who randomly buy or sell without reference to the rule, is 0. The solid line in the figure represents pre-BLL expected price movements: trends in price which generate superior returns to MA rules if one buys at any time during the buy

[7] We only report the "double or out" trading strategy to conserve space but results from the simple trading strategy are available upon request.

periods, ideally at its inception (local minimum). Similarly, negative returns are generated if one buys at any time during the sell periods.

[Figures 1 and 2 around here]

When the rule becomes popular among investors, given the EMH, one would expect the excess returns it generates to be ultimately arbitraged away and the market price to settle at the equilibrium price.[8] However, it is not clear how the move to equilibrium might be achieved in practice and indeed whether equilibrium will ever be achieved. After the rule becomes known, some investors would want to take advantage of this new information. If more investors follow the MA rule, it will result in more buying (selling) pressure on the price when a buy (sell) signal is generated. Thus, prices will go up (down) more than they would have done before the MA rules become popular among investors. This means that the stock will become more (less) expensive than it would have been previously, due to the higher buying (selling) pressure at the start of the buy (sell) period (compared to the era when MA rules were not widely traded upon).

The dashed line in Figure 1 represents post-BLL price movements if there was an immediate and perfect reaction to new buy/sell signals, in the sense that investors collectively anticipate the next maximum/minimum price correctly. No profits are then possible if one buys during the buy or sell period. Profits are only possible to those who react first to the new signals, but as signals are public information and, for now, we are assuming that no investor can consistently predict, or anticipate, those signals, no investor should be assumed to be able to systematically be among the first to react. Hence, the widespread use of MA rules, e.g., due to the knowledge of BLL findings, could have changed the behaviour of prices, resulting in the impossibility of systematically obtaining profits from strategies based on MA rules.

A key factor that is unknown is what proportion of investors would start to follow the rule after it became generally known. The consequences of relatively large or small numbers of investors becoming involved are quite different and can generate different scenarios with the

[8] For the ease of exposition, we will be assuming here that the MA rule became more popular among investors because they have learned about its profitability from the results in BLL study. This is a rhetorical device~~figure~~ and one could equally attribute the increased popularity of MA rules to lower transaction costs due to advances in information and communication technology, increased efficiency due to trading in derivatives, increased importance of institutional investors, etc. ~~it is not to say that w~~We do not see the publication of the BLL paper as the only possible cause behind the potential increased implementation of MA rules.

dashed line in Figure 1 being but one possibility. Here, we discuss the various potential price adjustments and theoretical arguments underlying those scenarios, with corresponding price paths around a buy signal shown in Figure 2. The price path in the pre-BLL era is represented by the solid line A (as before, random movements in prices around trends are ignored for simplicity of exposition), an upward trend in price occurs on day *t=0,* which triggers a new buy signal. If there was no significant change post-1986 in investors' behaviour and, consequently, in price movements around days when new buy signals are generated, the price path should be identical to that observed in the BLL sample (as represented by line A). Hence, on any day *t = -1, 0, 1, 2, 3, …* around a new buy (sell) signal, daily returns in the BLL and the post-BLL samples should not be statistically different from each other (graphically, the price curves for BLL and post-BLL periods are identical and perfectly overlapping).

However, the publication of the BLL, paper or another event occurring around the same time, (see footnote 12~~9~~) could have affected investors' behaviour. On days when a new buy signal is generated (and potentially on subsequent days), with investors knowing that buying after a buy signal yields superior returns, one could expect the investors to increase their purchases of the asset in question. This would result in a higher price than what otherwise (i.e., pre-1987) would have been observed, i.e., in a price curve different from the one given by A. For instance, if investors rush to buy an asset they observe to generate a new buy signal at *t=0*, its price could be bid up on day 0, resulting in a higher price level as compared to the pre-1987 era, when none of these extra buyer-initiated trades would have taken place. Curve B represents a hypothetical case where investors (and the price) react strongly, but not immediately, to a buy signal at day 0. This can be considered to be an overreaction if the initial price reaction is partially reversed in subsequent periods. The resulting returns are first higher and then lower than those which would have been observed in the pre-1987 era (curve B initially with a higher gradient and subsequently with a lower (and negative) gradient relative to curve A). Another possible, although unlikely, scenario is that investors correctly assess the anticipated future price of the asset (given the future trend) and bid up its price immediately to this level. This scenario is represented by curve C and is equivalent to that depicted by the dashed line in figure 1. Here, due to the instantaneous reaction of the market to the new buy signal, returns at *t=0* are positive and higher and all returns following day 0 are lower than in the pre-1987 scenario (curve C rises at t=0 and is flatter than A for *t =1, 2, …*). Another possible outcome is that investors underreact to the new buy signal, at *t=0*, hence their buying pressure exerts a somewhat muted impact on the price, resulting in a gradual price rise (curve D). Hence, daily returns following day 0 would be initially higher and subsequently positive but lower than in the pre-1987 scenario.

We also investigate whether, post-1986, some investors have increasingly started not only to react to the buy/sell signals when they are about to be generated (*t=0*), but also anticipate the emergence of new signals on the next day. In the extreme case where investors at day *t=-1* are able to predict the signal of day 0 and react instantaneously and correctly to this prediction, we would expect the price to follow a pattern given by curve E: the price at *t=-1* adjusts with no delays to the signal expected to be generated the following day. In this case, the return at *t-1* would be higher post-1987 than before, the price increment between *t=-1* and *t=0* (i.e., return measured at *t=0*) would be identical in both subperiods, and lower for the subsequent days in the subperiod starting in 1987. If, however, the anticipating investors' price impact is not full and instantaneous at *t=-1* but takes a day to fully materialise (as shown by curve F), the returns in the post-1986 period would be higher in day *t=0* as compared to the pre-1987 price behaviour. Needless to say, the abovementioned scenarios do not exhaust the full spectrum of possible price movements around the new signals and other patterns could also be observed in reality. Nonetheless, from these scenarios and general reasoning we can deduce several testable hypotheses:

Hypothesis 1: If the MA rules work less well in the post-BLL period this is consistent with a move towards greater efficiency at least in respect of these rules, i.e., the rules will be less predictive of future returns.

Hypothesis 2: If returns in the post-BLL period are higher (lower) immediately after a new buy (sell) signal and subsequently lower (higher) and negative (positive) during the rest of the buy (sell) period it appears than investors may be reacting too strongly to the signal.

Hypothesis 3: If returns in the post-BLL period are higher (lower) immediately after a new buy (sell) signal and subsequently lower (higher) and positive (negative) during the rest of the buy (sell) period it appears than investors may be not reacting sufficiently strongly to the signal.

Hypothesis 4: If returns in the post BLL period are higher (lower) immediately before a new buy (sell) signal it appears that investors may be anticipating signals. Associated with this is the possibility that, if investors anticipate signals and hence the related price adjustments, price movements after the signal may be more muted (less positive after a buy signal or less negative after a sell signal) as they have already been somewhat anticipated.

Hypothesis 5: If new profitable rules closely related to the original rules have evolved in the post BLL period the market can be characterised as adapting to the new information rather than simply moving towards greater efficiency.

5. Data

The data used in this study are complete historical records of the daily prices of three long-standing stock market indices, the DJIA, FT30 and TOPIX from the US, UK and Japan respectively. These indices represent three of the most important and well established world markets and provide enough data to examine how successful the MA rule has been before and after the end of the sample used by BLL. We study the moving average rule over the period post-BLL, thus we examine 1st January 1987 to 31st December 2013. The daily return for each index is calculated as a difference in log index values.

Table 1 documents the descriptive statistics of the three indices' full samples as well as the subsample periods studied in this paper. The mean return for the DJIA during the post-BLL period is greater than the mean during the pre-BLL period, while the FT30 shows that the mean return during the post-BLL period is substantially lower than the mean return during the pre-BLL period. The mean for the TOPIX during the post-BLL period is actually negative in line with the poor performance of the market in Japan since 1987. The returns in all markets are non-normal with significant Jarque-Bera statistics.

[Table 1 about here]

6. Empirical Results

6.1. Are MA rules still successful?

Initially, the MA rule is examined over the full samples for each market to determine the overall success of the rule. Panel A of Table 2 presents the MA rule results for the DJIA and the results show that from 1896 to 2013 each rule produced positive buy and negative sell returns, resulting in positive buy-sell differences which are all significant[9]. Although the (1,50,0.01) rule produces the greatest buy-sell difference, it is lower than BLL's results, suggesting that the MA rule has less predictive power since 1987[10]. Panel B documents the MA rule results for the FT30 and shows all buy (sell) returns to be positive (negative) and significant, leading to positive and significant buy-sell differences. The largest buy-sell difference is again associated with the (1,50,0.01) rule. The buy-sell differences are lower than those found by Hudson et al. (1996), again suggesting a weakening of the rule. Panel C reports the TOPIX results and indicate that all rules examined produce positive buy and negative sell returns, and positive buy-sell differences, all figures being significant. Looking at the magnitudes of returns across those three markets, this preliminary analysis suggests that the MA rule is more successful in the TOPIX than the DJIA or FT30 and that the rule's predictability is not as strong as found in previous studies, indicating that the rule is not as predictive since BLL.

[Table 2 about here]

To determine how the MA rule has performed since BLL's study[11], we examine the level of predictability of the rule since that seminal paper documented the success of the rule. Panel A of Table 3 presents the DJIA results and shows that none of the buy or sell returns is significant (and the latter are positive rather than negative), and the buy-sell differences are insignificant and most of them are actually negative in the post-BLL era. This indicates that there is no predictability from the MA rule. Although none of the rules are statistically significant, the fact that most buy-sell differences are now negative shows a complete reversal in the successfulness of the MA rule compared to the BLL results. Panel B shows for the FT30 that all six rules generate insignificant buy and sell returns; however, the buy-sell differences that are still positive and significant at 5%. This would indicate a weakening of

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[9] For consistency with most prior studies including, e.g., BLL, Hudson et al (1996) and Han et al (2013), in this and subsequent tables we calculate our t-statistics as follows. For buy (sells): $(\mu_r - \mu).(\sigma^2/N + \sigma^2/N_r)^{-1/2}$, where μ_r and N_r are the mean returns and number of signals for the buys (sells); μ and N are the unconditional mean and number of observations; σ^2 is the estimated variance for the entire sample. For buy -sell: $(\mu_b - \mu_s).(\sigma^2/N_b + \sigma^2/N_s)^{-1/2}$, where μ_b and N_b are the mean returns and number of signals for the buys; μ_s and N_s are the mean returns and number of signals for the sells.

[10] We study 1987-2013 data while BLL used 1896-1986 data.

[11] To be precise we follow the related literature and investigate the period after the data period examined by BLL, i.e. 1987-2013. Although the BLL paper was published in 1992, it used data up to 1986 and was probably public knowledge before it was officially published in the *Journal of Finance*. Thus, investors will probably have known about the success of the rule before the publication of the paper.

the technical rule in the FT30 since the BLL study and a decrease from the full sample which found each rule generated positive buy-sell differences which were significant at 1%. On the other hand, most of the sell returns, although insignificant, are on average more pronounced in the post-BLL period, leading to higher, not lower, buy-sell differences for the MA(1,200) rules post-BLL. Hence, the evidence for FT30 is mixed. The TOPIX results in Panel C show that all of the six rules generate positive buy-sell differences of which all but one are significant. However, the magnitudes of the buy-sell differences are lower than the full sample results, also indicating a weakening of the MA rule. Further, the buy returns are lower post-BLL, the average sell returns seem to have increased in magnitude following the BLL sample, even though they seem more volatile and, hence, less significant.

Overall, these results show that each market has seen a fall in the predictive power of the MA rule since 1987 compared to the full sample analysis. The MA rule in the DJIA from 1987-2013 does not generate significant positive buy-sell differences, suggesting that investors may have taken advantage of the rule, eroding away the profits. The FT30 results suggest that although positive returns can still be made, they are no longer significant at the 1% level. This erosion in signalling power of the MA rules seems to have predominantly taken place for the buy signals. As for the UK, the decline in predictive power of the MA rules should be primarily contributed to a deterioration of buy signals' strength; sell signals seem to generate higher, not lower, profits, even though their precision appears to have declined, too, as those returns are more volatile and less significant. The TOPIX however, still generates significant positive albeit lower buy-sell differences, indicating that the MA rule is less profitable when used in this market.

[Table 3 about here]

These results of diminished profitability of MA rules in the post-BLL period support our Hypothesis 1 that there was a move towards greater efficiency at least in respect of these rules. This phenomenon could be driven by various forces: an increased awareness of MA rules' historical profitability which resulted in their increase adoption by market participants, lower transaction costs due to technological advance, improved information flows courtesy of derivatives trading, or prevalence of sophisticated institutional investors.

6.2. Was the decline in profitability of MA rules to be expected?

A finding of overall weaker predictive power of MA rules post-BLL does not have to be due to a structural break in the performance of MA rules occurring around year 1987. As an alternative explanation, one could hypothesise that the overall predictive power of MA rules would have been lower anyway in the post 1986 period, e.g., due to a long-term process of improving market efficiency. Hence, we analyse whether the changes in predictive power of MA rules could be explained as a simply continuation of trends originating in the BLL sample. Specifically, we estimate the following model:

$$MW\_MAR_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + (\beta_0 + \beta_1 t + \beta_2 t^2) POST_t + \epsilon_t, \qquad (3)$$

where MW_MAR_t stands for average daily return from a MA strategy (we consider returns following buy and sell signals separately), calculated in 5 year windows and moving by three months in each step, *t* denotes the time trend, and $POST_t$ is a dummy equal to one in the post BLL period (starting 01/01/1987) and zero before that date.[12] If the coefficients $\beta_0, \beta_1, \beta_2$ are jointly significant, this would indicate a structural break in the linear or non-linear trend the MA returns follow; insignificance of βs, on the other hand, would imply that there was no structural change of any form to the predictive power of the MA rules in the post-BLL era, and any difference in average MA returns pre- vs post-BLL should be fully attributed to the existence of long-term trends in MA returns which started before 1987 and simply continued beyond that date. Regression results, obtained by means of quantile regression technique to guarantee their robustness in presence of outliers (Koenker and Hallock, 2001), are presented in Table 4 and the corresponding observed and fitted values of MW_MAR_t are depicted in Figure 3.[13]

[Table 4 and Figure 3 about here]

For the MA(1,50) for the DJIA, the results show a significant change in the trends of average returns following the BLL paper, as indicated by significance of the F statistic. This suggests

[12] We impose that date for the break as the literature is concerned with the change in MA rules' profitability in the post-BLL sample, i.e., starting in 1987. Hence, this date is the most logical~~obvious~~ candidate for the timing of a break. When we allow the data to speak for itself and employ Andrews' (1993) test for unknown break, the results (not reported to conserve space) are generally consistent with the notion that ~~also~~ the break occurred on or shortly (by a few years) after the date selected here.

[13] To conserve space, only the rules without the band are considered here.

that MA return behaviour in the post-BLL era is not a simple continuation of the pre-BLL trends. Specifically, the buy returns decline faster in the early post-BLL period, and sell returns experience an upward shift, especially pronounced around year 2000. Both these changes indicate reduced rule effectiveness. For MA(1,150) and MA(1,200) returns, significant changes in (linear and/or quadratic) trends around year 1987 are also observed. Post-BLL changes for all three rules are highly significant, as indicated by joint significance test results. Overall, these results are in line with the observations from Tables 2-3 that post-BLL buy and sell returns are closer to zero and, consequently, their differences are also closer to zero, and insignificant. Trends in the post-BLL era are not simple continuations of pre-BLL trends, however, suggesting the existence of a structural change in MA returns around the end of the BLL sample.

The results for FT30 MA(1,50) rule indicate that buy returns started to decline post-BLL, whereas sell returns experienced a shift upwards but started to recover (i.e., move down) post-BLL. Results for the remaining two strategies indicate that there were trends in average returns prior to 1987, and those trends changed significantly in the post-BLL era. However, whereas buys have experienced an initial upward shift followed by a decline over time in the post-BLL era, especially for MA(1,150), sells have shifted downwards in the post-BLL period, as compared to the trends they were following prior to 1987, especially the later indicating an improvement rather than deterioration in the signalling strength of MA strategies. Overall, the moving-windows results for the UK are mixed and only weakly support the notion that the predictive power of MA strategies deteriorated following the publication of the BLL results, as buy returns show an indication of a downward trend post-BLL but sell returns indicate an increased, not weaker, signalling strength. Those observations are in line with the results in Tables 2 and 3. In all cases, however, do we find evidence of significant changes in trends of MA profitability around year 1987.

For TOPIX, all but one trends in buy and sell returns undergo significant changes as they enter the post-BLL era. Following an initial jump, buy returns decline rapidly after entering the post-1986 period, at least until the end of the century. This decline is in line with the hypothesis that trading on MA signals intensified post-BLL, eroding the predicative power of MA rules. Sell returns experience a gradual recovery (i.e., a move downwards) at the beginning of the post-BLL period but start to deteriorate around year 2000. Overall, these results suggest that the observed lower average returns in the post-BLL era are due to lower buy returns in that period, as reported in Table 3. This difference between pre- and post-BLL results (Tables 2 and 3) is not due to a simple continuation of pre-1987 trends in MA returns into the post-BLL period.

Overall, these results demonstrate that changes in predictive power of MA rules following the BLL paper were not simple continuations of trends which originated before 1987. Rather, there was a structural break in the time-series behaviour of profits from MA rules around ~~year~~ 1987. This supports the notion that market participants started to utilise the MA rules to a greater extent (maybe as a result of learning from the BLL study), which led to erosion of the predictive power of those rules. However, as discussed before, abrupt changes in other variables coinciding with publication of BLL results might have also caused the observed weakening of predictive power of MA rules post-1987.

6.3. How did the markets adapt?

To give an anatomy of the markets' adaptation in the post 1986 period, we examine the returns to MA strategies on days around new buy/sell signals for the pre- and post-BLL samples. [14] We look at the ~~one~~ day before a new signal (t=-*1*), the day of the new signal (t=*0*) and the ten days subsequent to the new signal, as returns cumulated over the first five or ten days. Panels A and B of Table 5 reports the returns around new buy and sell signals from different MA rules for the DJIA. All t=-*1* returns are significant and positive (negative) prior to a buy (sell) signal, and the post-BLL returns are higher in magnitude than their pre-BLL counterparts. This indicates stronger price reactions post-BLL, in line with the hypothesis that trading based on anticipation of new signals intensified from 1987 onwards. This reasoning is further supported by the fact that t=*0* returns are significant pre- but not post-BLL in all but one case, again in line with the notion of trading taking part in anticipation of the signal (at t=-*1*) rather than on the day of the signal in the post-BLL era, whereas pre-BLL significant price reactions at t=*0* indicate that not all price adjustment took place at t=-*1*. In addition, for the MA(1,50) rule, returns in days 1-5 and/or 1-10 are significant and positive (negative for sells) only in the pre-BLL era, further suggesting that the entire price adjustment post-1986 was taking place in anticipation of the signal rather than following it.

[14] A new buy signal is a buy signal that is preceded by a sell or neutral signal, that is, it is the movement from a sell/neutral signal to a buy signal.

As for the FT30, returns on days prior to the signal are all significant and positive (negative) for new buys (sells), with those observed post-BLL higher in magnitude than their pre-BLL counterparts, with one exception. As for the US, this result is in line with stronger anticipation of and trading on new signals following BLL. The $t=0$ returns for all sells and MA(1,50) buys are significant pre-BLL but insignificant thereafter, again suggesting a shift of trading from the signal day to the preceding one, in anticipation of the signal. The cumulated returns for~~in~~ five or ten days after the signal are significant only in the pre-BLL era (for MA(1,50) buys and MA(1,150) and MA(1,200) sells), again suggesting that the price adjustment process driven by trades continues after the signal in the pre-BLL period but takes place entirely in $t=-1$ post-BLL.

The results for the TOPIX are broadly consistent with those for the US and UK. All $t=-1$ returns are significant and positive (negative) for buys (sells) pre- and post-BLL, with the later higher in magnitude than the former, suggesting stronger price reactions post-BLL at $t=-1$. The signal day returns appear to have diminished in the post-BLL era: buy returns are all lower and in two cases turn insignificant post-BLL, sell returns for MA(1,150) and MA(1,200) rules even turn positive post-BLL. These results further evidence an erosion of signalling power of MA rules post-BLL. In addition, in two out of three cases the cumulated returns following buy signals are positive and significant prior to but not after the BLL period, again supporting the notion that trades-driven price reactions to buy/sell signals mostly moved into day $t=-1$, in line with our hypothesis 4 that investors increasingly anticipated new signals in the post-BLL period.

[Table 5 about here]

Overall, the results are consistent across all three markets: price reactions at $t=-1$ became stronger and those at $t=0$ and following days weaker in the period after the BLL results became publically known. This finding is in line with our hypothesis 4, stating that investors anticipation new signals migrated their trades to day $t=-1$, to timely capitalise on their expectations. We do not find any evidence for hypothesis 2 or 3, however, i.e., there are no systematic over- or under-reactions to new MA signals post-1986. Given those findings, we further investigate whether investors can realise superior profits by predicting the signal in the post-BLL period. If the answer is positive, this will strongly support our interpretation of anticipatory trades. If not, it would be more difficult to argue that the observed price behaviour is generated by investors acting on their predictions of new signals: if they are losing money, they are less likely to exert sustained impact on prices (although some price impact might result from investors timing long term trades they were intending to make in any event). The ability to realise profits by anticipating buy/sell signals will be examined in more detail next.

6.4. Perfectly anticipated MA rules

Since the original MA rule is less predictive post-1986, we examine the perfectly anticipated MA rules to determine whether these rules have predictive power in these three markets. Table 6 presents the results for the perfectly anticipated MA rule for the DJIA, FT30 and TOPIX for the sample period 1987-2013. We assume that investors can predict future trading signals from the rules perfectly and trade accordingly. It should be repeatedly stressed that we are not postulating that perfect predictions are possible in reality; rather, results from perfectly anticipated rules can be regarded as a benchmark for the maximum benefits obtainable from predicting signals. Panel A reports that the number of buy signals for each rule for the DJIA is greater than the number of sell signals. Also for each rule, the one-day buy returns are all positive and statistically significant, while the one-day sell returns are all negative and statistically significant. Unlike the results from original rules for the same period, these buy-sell differences are all positive and significant, suggesting that if investors had perfectly anticipated the following days' signals, there was a significant predictive power from technical trading in 1987-2013. Panel B documents the results for the perfectly anticipated MA rule of the FT30 for the sample period 1987-2013. The number of buy signals exceeds the number of sell signals for each rule and the one-day buy returns are all positive, while the one-day sell returns are all negative and also significant. The buy-sell differences are all positive and all statistically significant. These buy-sell differences are greater than the original rules' buy-sell differences for the same sample period, indicating that predicting the following day's signal would be more successful than the original MA rule. Panel C documents the results for the perfectly anticipated MA rule for the TOPIX and shows that the number of buy and sell signals are quite similar and vary between rules as to which one is greater. The one-day buy returns are all positive and significant, while the one-day sell returns are all negative and significant. The buy-sell differences are all positive and statistically significant at the 1% level. Three of the rules produce buy-sell differences that are greater than the corresponding buy-sell differences under the original rules, indicating that predicting the following days signal does not always produce returns greater than the original rules for the TOPIX.

[Table 6 about here]

Overall, these results show that the perfectly anticipated MA rules have high predictive power for the 1987-2013 period and that they tend to be more successful than the original MA rule, supporting our Hypothesis 4. In reality, investors would not be able to predict future trading signals perfectly. Rather, their realised profits would depend on individual investor's forecasting ability, would probably vary over time and with market conditions, and be certainly lower than those obtainable under the assumption of perfect foresight.

6.5. Trading on anticipated buy and sell signals

From the literature and our own results, we know that the predictive power of MA rules prevailed in the pre-1987 period but deteriorated thereafter. Tables 7-10 document the results of using the "double or out" trading strategy on the post-BLL data for the original and the perfectly anticipated MA rule. Tables 7 shows that the original MA rule fails to generate positive roundtrip breakeven costs indicating no economic significance from the trading rule from 1987-2013. The FT30 and TOPIX results both show that roundtrip breakeven costs are very low indicating that the original moving average rule marginally outperforms the two markets over the 1987-2013 period. Table 8 shows the anticipated moving average rule results for the 1987-2013 period and shows that roundtrip breakeven costs are substantially higher (up to six times higher) than for the original moving average rule. This suggests that anticipating signals yields superior returns and supports the notion that investors could have taken advantage of this fact and consequently influenced prices in anticipation of new signals, thus supporting our Hypothesis 4. [15]

[Tables 7-8 about here]

Overall, these results show that both the anticipated MA rules have high predictive power for the 1987-2013 period and that they tend to be more successful than the original MA rule,

[15] The results for the simple strategy are qualitatively similar and not reported to conserve space but available upon request.

supporting our Hypothesis 4. In reality, investors would not be able to predict future trading signals perfectly. Rather, their realised profits would depend on individual investor's forecasting ability, would probably vary over time and with market conditions, and be certainly lower than those obtainable under the assumption of perfect foresight.

7. Summary and Conclusions

This paper has studied the MA rule using very long historical data for the US, UK and Japanese stock markets which includes a substantial amount of post BLL data. An examination of post-BLL data reveals that in the DJIA the MA rule has failed to generate any predictive power, and the FT30 and TOPIX results show its predictive power to have diminished. Further analysis shows that there was a structural break in the time-series behaviour of the profits from the MA rules in about 1987.

When we look into the price behaviour process around days when new buy/sell signals are generated in the post BLL period, we find that, unlike in the pre-1987 era, prices react to those signals in advance, a day before they are generated by closing index values. In addition, prices in the US and the UK change less on days following signal emergence. Taken together, this evidence supports the notion that investors have learned when new buy/sell signals are generated. This supports our hypothesis 4 that investors may be anticipating signals.

This interpretation is further tested by analysing the profits from anticipated trades in the post-BLL era: if those profits are low, one should not expect investors to engage in anticipatory trades, hence the anticipation of next days' new signals would not offer a good explanation for the observed price patterns. To analyse potentially achievable profits from trading on anticipated signals, this paper suggests a modified MA rule, namely the perfectly anticipated rule, whereby the investor predicts the following days signal today. The results show that ~~both~~ the perfectly anticipated MA rule has a significant predictive power in all three markets over the post-BLL period, indicating that if investors can fairly accurately forecast the MA rule signal, the rule is still highly predictive. After accounting for reasonable transaction costs, we find that anticipating rules produce net profits higher than the buy-and-hold strategy in the post-BLL era, and higher than what the profits from the original rules in this subperiod would have been. This result indicates that investors would have had incentives to engage in trading based on anticipated signals in the post-BLL period, which would give rise to significant price reactions prior to, and not on, the days new signals are generated by the MA rules.

The results in this paper suggest that investors may have become generally familiar with the MA rule in the post-1986 period, and/or it became less costly to implement those rules. Given this, as one would expect given the EMH, the predictive power declined. However, our results show that when investors realised that the returns from the rule were limited by the fact it was well known, some of them began adapting the rule by forecasting future signals. Hence, this finding is in line with predictions of the AMH (hypothesis 5), as a previously successful trading strategy no longer has predictive power but a more sophisticated rule is predictive, representing the evolution of the market.

References

Atanasova, C.V. and Hudson, R.S. (2010). Technical trading rules and calendar anomalies - Are they the same phenomena? *Economics Letters*, 106(2), 128-130.

Bajgrowicz, P., and Scaillet, O. (2012). Technical trading revisited: False discoveries, persistence tests, and transaction costs'. *Journal of Financial Economics*, 106(3), 473-491.

Bessembinder, H. and Chan, K. (1995). The profitability of technical trading rules in the Asian stock markets. *Pacific-Basin Finance Journal*, 3(2-3), 257-284.

Bessembinder, H. and Chan, K. (1998). Market efficiency and the returns to technical analysis. *Financial Management*, 27(2), 5-27.

Brock, W., Lakonishok, J. and LeBaron, B. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance*, 47(5), 1731-1764.

Chen, C.-W., Huang, C.-S. and Lai, H.-W. (2009). The impact of data snooping on the testing of technical analysis: An empirical study of Asian stock markets. *Journal of Asian Economics*, 20(5), 580-591.

Chong, T.T. and Ng, W. (2008). Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30. *Applied Economics Letters*, 15(14), 1111-1114.

Cootner, P.H. (1962). Stock prices: random vs. systematic changes. *Industrial Management Review*, (3), 24-45.

Day, T.E. and Wang, P. (2002). Dividends, nonsynchronous prices, and the returns from trading the Dow Jones Industrial Average. *Journal of Empirical Finance*, 9(4), 431-454.

Fama, E.F. (1970). Efficient Capital Markets: A Review of the Theory and Empirical Work. *Journal of Finance*, 25(2), 383-417.

Fama, E.F. and Blume, M.E. (1966). Filter Rules and Stock-Market Trading. *The Journal of Business*, 39(1), 226-241.

Fang, J., Jacobsen, B., Qin, Y. (2013). Predictability of the simple technical trading rules: An out-of-sample test. *Review of Financial Economic*, 23, 30-45.

Fifield, S.G.M., Power, D.M. and Sinclair (2005). An analysis of trading strategies in eleven European stock markets. *The European Journal of Finance*, 11(6), 531-548.

Han, Y., Yang, K., Zhou, G. (2013). A New Anomaly: The Cross-Sectional Profitability of Technical Analysis. *Journal of Financial and Quantitative Analysis*, 48(5), 1433-1461.

Hudson, R., Dempsey, M. and Keasey, K. (1996). A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices - 1935 to 1994. *Journal of Banking & Finance*, 20(6), 1121-1132.

Hull, M., McGroarty, F. (2014). Do emerging markets become more efficient as they develop? Long memory persistence in equity indices. *Emerging Markets Review*, 18, 45-61.

Ito, A. (1999). Profits on technical trading rules and time-varying expected returns: evidence from Pacific-Basin equity markets. *Pacific-Basin Finance Journal*, 7(3-4), pp. 283-330.

Ito, M., Sugiyama, S. (2009). Measuring the degree of time varying market inefficiency. *Economics Letters* 103(1), 62-64.

James, F.E., Jr. (1968). Monthly Moving Averages--An Effective Investment Tool? *The Journal of Financial and Quantitative Analysis*, 3(3), 315-326.

Jensen, M.C. and Benington, G.A. (1970). Random Walks and Technical Theories: Some Additional Evidence. *The Journal of Finance*, 25(2), 469-482.

Kim, J. H., Shamsuddin, A., Lim, K. P. (2011). Stock return predictability and the adaptive markets hypothesis: Evidence from century-long U.S. data. *Journal of Empirical Finance* 18(5), 868-879.

Koenker, R. and Hallock, K.F. (2001). Quantile Regression. *Journal of Economic Perspectives*, *15*, 143–156.

Lebaron, B. (2000). The Stability of Moving Average Technical Trading Rules on the Dow Jones Index. *Derivatives Use, Trading, and Regulation,* 5(4), 324--338.

Lim, K. P., Brooks, R. D. (2006). The Evolving and Relative Efficiencies of Stock Markets: Empirical Evidence from Rolling Bicorrelation Tests Statistics. SSRN Working Paper, available at http://ssrn.com/abstract=931071.

Lim, K. P., Luo, W., Kim, J. H. (2013). Are US stock index returns predictable? Evidence from automatic autocorrelation-based tests. *Applied Economics* 45(8), 953-962.

Lo, A.W. (2004). The Adaptive Markets Hypothesis. *Journal of Portfolio Management*, 30, 15-29.

Lo, A.W. and Hasanhodzic, J. (2010). *The Evolution of Technical Analysis: Financial Prediction from Babylonian Tablets to Bloomberg Terminals*. USA: John Wiley and Sons.

Manahov, V., Hudson, R. (2014). A note on the relationship between market efficiency and adaptability – New evidence from artificial stock markets. *Expert Systems with Applications*, 41(16), 7436-7454.

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance*, 34(11), 2573-2586.

Metghalchi, M., Marcucci, J. and Chang, Y.-H. (2012). Are moving average trading rules profitable? Evidence from the European stock markets. *Applied Economics*, 44(12), 1239-1559.

Park, C. and Irwin, S.H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, 21(4), 786-826.

Ready, M. (2002). Profits from technical trading rules. *Financial Management*, 31(3), 43-61.

Schulmeister, S. (2009). Profitability of Technical Stock Trading: Has it moved from daily to intraday data? *Review of Financial Economics*, 18(4), 190-201.

Shynkevich, A. (2012). Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking & Finance*, 36, 193-208.

Smith, G. (2012). The changing and relative efficiency of European emerging stock markets. *European Journal of Finance*, 18(8), 689-708.

Sullivan, R., Timmermann, A. and White, H. (1999). Data-Snooping, Technical Trading Rule Performance, and the Bootstrap. *The Journal of Finance*, 54(5), 1647-1691.

Taylor, N. (2014). The rise and fall of technical trading rule success. *Journal of Banking and Finance*, 40, 286-302.

Todea, A., Zoicas-Ienciu, A., and Filip, A. (2009). Profitability of the Moving Average Strategy and the Episodic Dependencies: Empirical Evidence from European Stock Markets. *European Research Studies*, XII(1), 63-72.

Urquhart, A. and Hudson, R. (2013). Efficient or adaptive markets? Evidence from major stock markets using very long run historic data. *International Review of Financial Analysis*, 28, 130-142.

Urquhart, A., and McGroarty, F. (2014). Calendar effects, market conditions and the Adaptive Market Hypothesis: Evidence from long-run U.S. data. *International Review of Financial Analysis*, 35, 154-166.

Van Horne, J.C. and Parker, G.G.C. (1967). The Random-Walk Theory: An Empirical Test. *Financial Analysts Journal*, 23(6), 87-92.

Van Horne, J.C. and Parker, G.G.C. (1968). Technical Trading Rules: A Comment. *Financial Analysts Journal*, 24(4), 128-132.

Zhou, J., Lee, J. M. (2013). Adaptive market hypothesis: evidence from the REIT market. *Applied Financial Economics*, 23(21), 1649-1662.

Table 1: Descriptive Statistics of daily returns of each market. ***, **, * indicate significance at 1%, 5% and 10% respectively of the Jarque-Bera statistic.

		Obs	Mean	S.D.	Max	Min	Skewness	Kurtosis	JB
DJIA	Full sample	31881	0.000198	0.010876	0.14	-0.26	-0.54	23.93	583421.9***
	Pre-Brock	25039	0.000166	0.010673	0.14	-0.14	-0.12	15.68	167915.7***
	Post-Brock	6842	0.000317	0.011587	0.11	-0.26	-1.74	45.30	513494.4***
FT30	Full sample	20198	0.000165	0.010616	0.11	-0.12	-0.20	12.22	71702.33***
	Pre-Brock	13157	0.000194	0.009979	0.11	-0.10	0.08	13.15	56438.51***
	Post-Brock	7041	0.000110	0.011715	0.09	-0.12	-0.52	10.70	17727.79***
TOPIX	Full sample	16433	0.000287	0.128646	0.13	-0.16	-0.52	15.41	106266.0***
	Pre-Brock	9389	0.000522	0.007798	0.06	-0.09	-0.78	12.74	38046.0***
	Post-Brock	7044	-0.000026	0.013077	0.12	-0.16	-0.35	12.21	25012.25***

Table 2: Test Results for the Moving Average Rules full sample**.** N(Buys) and N(Sells) are the number of buy and sell signals. No. Buy > 0 and No. Sell > 0 are the number of buy and sell returns. ***, **, * indicate significance at 1%, 5% and 10%.

	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Panel A: DJIA							
(1,50,0)	18851	12981	0.000445**	-0.000161***	0.54	0.50	0.000606***
			(2.47)	(-3.17)			(4.53)
(1,50,1)	15494	9890	0.000525***	-0.000199***	0.54	0.50	0.000724***
			(3.07)	(-3.17)			(4.45)
(1,150,0)	19803	11929	0.000386*	-0.000117***	0.53	0.50	0.000503***
			(1.92)	(-2.68)			(3.58)
(1,150,1)	18078	10240	0.000408**	-0.000161***	0.54	0.50	0.000570***
			(2.36)	(-2.62)			(3.63)
(1,200,0)	20291	11391	0.000381*	-0.000148***	0.53	0.50	0.000529***
			(1.94)	(-2.85)			(3.66)
(1,200,1)	18833	10072	0.000394**	-0.000172***	0.54	0.50	0.000566***
			(2.13)	(-2.84)			(3.59)
Panel B: FT30							
(1,50,0)	11879	8269	0.000557	-0.000399***	0.51	0.48	0.000956***
			(3.19)	(3.19)			(5.96)
(1,50,1)	9762	6452	0.000597***	-0.000526***	0.52	0.48	0.00112***
			(3.30)	(-4.54)			(5.88)
(1,150,0)	12239	7810	0.000386*	-0.000193**	0.51	0.48	0.000580***
			(1.85)	(-2.49)			(3.49)
(1,150,1)	11045	6760	0.000451**	-0.000262***	0.51	0.48	0.000714***
			(1.99)	(-3.07)			(3.87)
(1,200,0)	12352	7647	0.000413**	-0.000249***	0.51	0.48	0.000662***
			(2.08)	(-2.85)			(3.94)
(1,200,1)	11523	6881	0.000419**	-0.000240***	0.51	0.48	0.000659***
			(2.14)	(-2.64)			(3.64)
Panel C: TOPIX							
(1,50,0)	9621	6763	0.000786***	-0.000455***	0.53	0.45	0.001241***
			(3.84)	(-4.85)			(7.02)
(1,50,1)	8148	5366	0.000902***	-0.000517***	0.54	0.45	0.001420***
			(4.46)	(-4.84)			(6.86)
(1,150,0)	9458	5783	0.000626***	-0.000309***	0.53	0.45	0.000936***
			(2.65)	(-3.67)			(4.98)
(1,150,1)	8798	5146	0.000692***	-0.000298***	0.53	0.44	0.000989***
			(3.06)	(-3.44)			(4.89)
(1,200,0)	9598	5593	0.000540**	-0.000210***	0.53	0.45	0.000750***
			(2.07)	(-2.96)			(3.92)
(1,200,1)	9063	5107	0.000575**	-0.000256***	0.53	0.44	0.000831***
			(2.28)	(-3.13)			(4.07)

Table 3: Test Results for the Moving Average Rules 1987-2013. N(Buys) and N(Sells) are the number of buy and sell signals. No. Buy > 0 and No. Sell > 0 are the number of buy and sell returns greater than zero. ***, **, * indicate significance at 1%, 5% and 10%.

	N(Buy)	**N(Sell)**	**Buy**	**Sell**	**Buy > 0**	**Sell > 0**	**Buy-Sell**
Panel A: DJIA							
(1,50,0)	4420	2372	0.000239 (0.24)	0.000395 (0.37)	0.52	0.54	-0.000156 (-0.45)
(1,50,1)	3649	1720	0.000138 (0.65)	0.000467 (0.55)	0.52	0.54	-0.000329 (-0.74)
(1,150,0)	4659	2033	0.000326 (0.06)	0.000279 (0.11)	0.52	0.54	0.000047 (0.14)
(1,150,1)	4244	1630	0.000373 (0.26)	0.000306 (-0.04)	0.52	0.54	0.000067 (0.21)
(1,200,0)	4783	1859	0.000288 (0.08)	0.000352 (0.15)	0.38	0.53	-0.000065 (-0.21)
(1,200,1)	4403	1541	0.000302 (0.14)	0.000406 (0.41)	0.38	0.53	-0.000105 (-0.32)
Panel B: FT30							
(1,50,0)	4112	2878	0.000318 (1.03)	-0.000259 (-1.31)	0.50	0.51	0.000577* (1.87)
(1,50,1)	3418	2226	0.000336 (1.04)	-0.000401* (-1.69)	0.50	0.51	0.000737** (1.98)
(1,150,0)	4124	2766	0.000262 (0.88)	-0.000246 (-1.15)	0.51	0.49	0.000508 (1.58)
(1,150,1)	3726	2421	0.000345 (1.20)	-0.000283 (-1.23)	0.51	0.49	0.000628* (1.76)
(1,200,0)	4077	2763	0.000328 (1.16)	-0.000340 (-1.50)	0.51	0.49	0.000668** (2.07)
(1,200,1)	3842	2495	0.000329 (1.14)	-0.000280 (-1.23)	0.51	0.49	0.000609* (1.75)
Panel C: TOPIX							
(1,50,0)	3478	3516	0.000453* (1.85)	-0.000545* (-1.83)	0.49	0.45	0.000998*** (3.19)
(1,50,1)	2936	2913	0.000563** (2.25)	-0.000494 (-1.64)	0.50	0.45	0.001057*** (2.99)
(1,150,0)	3341	3553	0.000366 (1.56)	-0.000468 (-1.50)	0.50	0.44	0.000834*** (2.67)
(1,150,1)	3104	3295	0.000485** (2.01)	-0.000397 (-1.24)	0.50	0.45	0.000882*** (2.72)
(1,200,0)	3263	3581	0.000263 (1.20)	-0.000376 (-1.13)	0.50	0.45	0.000640** (2.05)
(1,200,1)	3054	3355	0.000275 (1.23)	-0.000331 (-0.96)	0.50	0.45	0.000607* (1.85)

Table 4: Trends in MA returns. The table presents results from estimations of the following models: $MW\_MAR_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + (\beta_0 + \beta_1 t + \beta_2 t^2)POST_t + \epsilon_t$, where MW_MAR_t stands for average daily returns from a MA strategy, calculated in 5 year windows moving by three months in each step; t denotes the time trend, and $POST_t$ is a dummy equal to one in the post BLL period (starting 01/01/1987) and zero before that date. Parameter values in the table are multiplied by 100,000. Estimates obtained by means of quantile regression technique. 'F-stat (p-val)' refer to results of a test with the Null of: $\beta_0 = \beta_1 = \beta_2 = 0$.

	MA(1,50) Buys		MA(1,50) Sells		MA(1,150) Buys		MA(1,150) Sells		MA(1,200) Buys		MA(1,200) Sells	
	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value
Panel A: DJIA												
α_0	42.9000	8.90	-25.0700	-3.67	63.8700	12.22	-26.9500	-3.17	42.6200	8.71	-25.7600	-3.53
α_1	0.1080	2.36	-0.0370	-0.57	-0.1890	-3.81	0.1550	1.92	0.0313	0.67	0.1540	2.22
α_2	-0.0003	-2.85	0.0001	1.00	0.0003	3.44	-0.0003	-1.86	-0.0001	-1.40	-0.0003	-2.19
β_0	2572.54	4.91	-2723.87	-3.67	3237.30	5.70	-6664.46	-7.20	3379.52	6.35	-13083.21	-16.50
β_1	-9.1500	-4.89	10.6500	4.01	-11.1900	-5.52	24.1800	7.32	-11.8500	-6.24	47.3400	16.72
β_2	0.0081	4.86	-0.0101	-4.28	0.0095	5.25	-0.0215	-7.32	0.0103	6.12	-0.0423	-16.79
F stat (p-val)	13.5	(<0.01)	21.76	(<0.01)	20.38	(<0.01)	20.84	(<0.01)	19.48	(<0.01)	103.48	(<0.01)
Panel B: FT30												
α_0	60.2500	7.76	-69.1800	-5.63	-3.5700	-0.54	-7.4100	-0.50	-2.8400	-0.38	-2.2600	-0.16
α_1	-0.0922	-0.70	0.1640	0.78	0.7260	6.49	-0.5810	-2.30	0.6820	5.40	-0.7370	-2.98
α_2	0.0004	0.94	0.0004	0.53	-0.0024	-6.03	0.0035	3.83	-0.0021	-4.74	0.0041	4.62
β_0	475.23	1.98	946.94	2.49	850.34	4.19	-1072.48	-2.34	817.42	3.57	-555.46	-1.24
β_1	-2.3800	-1.69	-4.8200	-2.16	-5.1100	-4.29	7.2400	2.70	-5.1700	-3.85	4.8000	1.82
β_2	0.0025	1.19	0.0055	1.66	0.0082	4.67	-0.0136	-3.44	0.0085	4.30	-0.0112	-2.88
F stat (p-val)	11.21	(<0.01)	14.99	(<0.01)	29.17	(<0.01)	13.97	(<0.01)	12.57	(<0.01)	27.45	(<0.01)
Panel C: TOPIX												
α_0	124.6300	15.22	-47.2400	-3.04	100.5500	7.42	-6.3800	-0.49	104.5200	7.62	3.9400	0.26
α_1	-0.9240	-4.47	-0.3720	-0.95	-0.7200	-2.11	-0.7380	-2.26	-1.0100	-2.91	-0.8470	-2.23
α_2	0.0035	3.24	0.0044	2.11	0.0026	1.42	0.0060	3.48	0.0038	2.05	0.0082	4.05
β_0	759.92	6.72	782.44	3.65	-4.57	-0.02	1743.63	9.75	667.10	3.52	1637.40	7.86
β_1	-5.0800	-5.56	-5.6600	-3.26	0.7750	0.51	-12.2800	-8.50	-4.5700	-2.98	-11.2600	-6.69
β_2	0.0069	3.37	0.0070	1.82	-0.0037	-1.10	0.0174	5.40	0.0063	1.85	0.0134	3.57
F stat (p-val)	21.5	(<0.01)	9.71	(<0.01)	2.09	(0.101)	58.97	(<0.01)	5.53	(<0.01)	56.4	(<0.01)

Table 5: The average returns the day before and various days after a new buy/sell signal in the DJIA, FT30 and TOPIX. T-values in parentheses. ***, **, * indicate significance at 1%, 5% and 10% respectively.

		Days Relative to New Signal Day (*t=0*)					Days Relative to New Signal Day (*t=0*)					Days Relative to New Signal Day (*t=0*)				
		-1st	**0**	**1st**	**Cum 1st-5th**	**Cum 1st-10th**	**-1st**	**0**	**1st**	**Cum 1st-5th**	**Cum 1st-10th**	**-1st**	**0**	**1st**	**Cum 1st-5th**	**Cum 1st-10th**
		Panel A: DJIA New Buys					**Panel C: FT30 New Buys**					**Panel A: DJIA New Buys**				
Pre-Brock Average	1,50,0	0.01108***	0.00116***	-0.00018	0.00153*	0.00277**	0.01048***	0.00163***	0.00091*	0.00191	0.00396*	0.00962***	0.00223***	0.0011**	0.00235*	0.00343
		(29.35)	(3.14)	(-0.51)	(1.82)	(2.10)	(17.83)	(3.02)	(1.66)	(1.48)	(1.82)	(19.18)	(4.13)	(2.38)	(1.67)	(1.60)
Post-Brock Average		0.01275***	0.000764	0.00020	-0.00004	0.00228	0.01224***	0.00073	0.00090	0.00071	0.00140	0.01443***	0.00077	-0.00003	0.00109	-0.00010
		(21.81)	(1.19)	(0.34)	(-0.03)	(0.24)	(19.04)	(1.05)	(1.46)	(0.49)	(0.71)	(20.08)	(1.11)	(-0.04)	(-0.58)	(0.04)
Pre-Brock Average	1,150,0	0.01115***	0.00175***	-0.00014	0.00133	0.00245	0.01161***	0.00052	0.00061	-0.00004	0.00248	0.00871***	0.00289***	0.00083	0.00144	0.0029
		(22.60)	(3.59)	(-0.32)	(1.16)	(1.35)	(13.78)	(0.70)	(0.85)	(-0.03)	(0.97)	(13.01)	(4.02)	(1.05)	(0.84)	(1.11)
Post-Brock Average		0.01274***	-0.00064	0.00022	0.00038	0.00231	0.01267***	-0.00077	0.00037	0.00101	0.00216	0.01325***	0.00091	0.00107	0.00095	0.00544
		(17.11)	(-0.91)	(0.30)	(0.23)	(1.00)	(14.67)	(-0.94)	(0.44)	(0.50)	(0.79)	(12.08)	(0.80)	(1.00)	(0.39)	(1.43)
Pre-Brock Average	1,200,0	0.01175***	0.0021***	0.00021	0.0009	0.00153	0.01074***	0.00043	0.00132	0.00149	0.00308	0.01024***	0.00156	0.00072	0.00298	0.00517*
		(14.59)	(3.76)	(0.39)	(0.64)	(0.85)	(13.71)	(0.47)	(1.60)	(0.81)	(1.04)	(10.46)	(1.57)	(1.12)	(1.57)	(1.91)
Post-Brock Average		0.01286***	0.00059	0.00019	0.00058	0.00019	0.01195***	-0.00003	0.00034	0.00130	0.00175	0.01311***	0.00083	0.00088	-0.00095	-0.00060
		(16.53)	(0.71)	(0.24)	(0.32)	(0.07)	(11.31)	(-0.03)	(0.34)	(0.55)	(0.35)	(11.39)	(0.76)	(0.84)	(-0.38)	(-0.16)
		Panel B:DJIA New Sells					**Panel D: FT30 New Sells**					**Panel A: DJIA New Sells**				
Pre-Brock Average	1,50,0	-0.01162***	-0.0015***	-0.00012	-0.00171*	-0.00092	-0.01151***	-0.00203***	-0.00044	-0.00051	-0.00213	-0.01017***	-0.00098*	0.00015	-0.00228	-0.00205
		(-31.82)	(-3.76)	(-0.29)	(-1.91)	(-0.67)	(-18.80)	(-2.98)	(-0.79)	(-0.40)	(-1.19)	(-13.75)	(-1.71)	(0.24)	(-1.41)	(-0.92)
Post-Brock Average		-0.01349***	-0.00035	0.00037	0.00129	0.00476	-0.01258***	-0.00101	0.00083	-0.00007	-0.00161	-0.01310***	-0.00187*	-0.00166	-0.00320*	-0.00493*
		(-20.19)	(0.59)	(0.62)	(0.41)	(0.03)	(-18.28)	(-1.23)	(1.13)	(-0.05)	(-0.79)	(-21.43)	(-1.79)	(-1.60)	(-1.74)	(-1.95)
Pre-Brock Average	1,150,0	-0.01175***	-0.00113*	0.00048	0.00017	-0.00048	-0.01247***	-0.00169**	-0.00044	-0.00209	-0.0041	-0.00983***	-0.00148	-0.0016	0.00064	0.00169
		(-23.82)	(-1.90)	(0.82)	(0.13)	(-0.23)	(-18.55)	(-2.33)	(-0.54)	(-1.28)	(-1.76)	(-8.73)	(-1.56)	(-1.18)	(0.32)	(0.55)
Post-Brock Average		-0.01359***	-0.00027	0.00098	-0.00006	0.00145	-0.01277***	-0.00075	0.00054	-0.00046	0.00105	-0.01621***	0.00149	0.00012	-0.00189	-0.00352
		(-14.87)	(-0.26)	(1.09)	(-0.03)	(0.54)	(-11.98)	(-0.54)	(0.48)	(-0.20)	(0.36)	(-7.51)	(0.77)	(0.09)	(-0.60)	(-0.78)
Pre-Brock Average	1,200,0	-0.01178***	-0.00051	0.001	0.00024	-0.00258	-0.01211***	-0.00177**	-0.00109	-0.0032	-0.00501*	-0.01193***	-0.00003	0.00066	0.00229	0.00376
		(-19.39)	(-0.80)	(1.48)	(0.17)	(-1.08)	(-15.29)	(-2.17)	(-1.28)	(-1.41)	(-1.67)	(-7.24)	(-0.03)	(0.56)	(1.01)	(1.18)
Post-Brock Average		-0.01387***	-0.00007	-0.00184	-0.00215	0.00212	-0.01296***	-0.00137	0.00071	-0.00206	0.00009	-0.01768***	0.00012	0.00035	-0.00190	-0.00301
		(-14.35)	(-0.06)	(-0.79)	(-0.89)	(0.81)	(-8.70)	(-0.70)	(0.52)	(-0.72)	(0.03)	(-7.60)	(0.06)	(0.23)	(-0.60)	(-0.75)

Table 6: Test Results for the perfectly anticipated moving average rule from 1987 – 2013. N(Buys) and N(Sells) are the number of buy and sell signals reported during the sample. Buy >0 and Sell >0 are the fraction of buy and sell returns greater than zero. ***, **, * indicate significance at 1%, 5% and 10%.

	N(Buy)	N(Sell)	Buy	Sell	Buy > 0	Sell > 0	Buy-Sell
Panel A: DJIA							
(1,50,0)	4419	2372	0.001679*** (6.18)	-0.002290*** (-9.33)	0.52	0.54	0.003969*** (11.44)
(1,50,1)	3648	1720	0.001932*** (6.39)	-0.002885*** (-10.51)	0.52	0.54	0.004817*** (10.94)
(1,150,0)	4340	2351	0.001670*** (6.14)	-0.002292*** (-9.23)	0.52	0.54	0.003962*** (11.35)
(1,150,1)	3578	1709	0.001919*** (6.32)	-0.002873*** (-10.37)	0.51	0.54	0.004791*** (10.82)
(1,200,0)	4783	1858	0.000940 (1.26)	-0.001372** (-2.34)	0.53	0.53	0.002312*** (3.93)
(1,200,1)	4403	1541	0.000925 (1.33)	-0.001562** (-2.33)	0.52	0.53	0.002487*** (3.76)
Panel B: FT30							
(1,50,0)	4112	2878	0.001715*** (7.09)	-0.002254*** (-8.99)	0.50	0.51	0.003969*** (13.01)
(1,50,1)	3418	2226	0.001995*** (7.67)	-0.002846*** (-10.35)	0.50	0.51	0.004841*** (13.22)
(1,150,0)	4124	2766	0.001011*** (4.12)	-0.001366*** (-5.38)	0.51	0.49	0.002377*** (7.39)
(1,150,1)	3726	2421	0.001048*** (4.13)	-0.001558*** (-5.84)	0.51	0.49	0.002607*** (7.34)
(1,200,0)	4077	2763	0.000838*** (3.34)	-0.001090*** (-4.33)	0.51	0.49	0.001928*** (5.97)
(1,200,1)	3842	2495	0.000866*** (3.76)	-0.001326*** (-4.71)	0.51	0.49	0.002192*** (6.29)
Panel C: TOPIX							
(1,50,0)	3477	3516	0.002112*** (7.95)	-0.002185*** (-7.89)	0.49	0.45	0.004297*** (13.93)
(1,50,1)	2935	2913	0.002349*** (8.86)	-0.002709*** (-8.55)	0.50	0.45	0.005058*** (14.43)
(1,150,0)	3340	3553	0.001120*** (4.29)	-0.001177 (-4.12)***	0.50	0.44	0.002297*** (7.40)
(1,150,1)	3103	3295	0.001201*** (4.88)	-0.001346*** (-4.10)	0.50	0.45	0.002547*** (7.78)
(1,200,0)	3262	3581	0.001005*** (3.86)	-0.001052*** (-3.63)	0.50	0.45	0.002057*** (6.63)
(1,200,1)	3053	3355	0.001043*** (4.14)	-0.001158*** (-3.72)	0.50	0.45	0.002201*** (6.77)

Table 7: Test results for the moving average rule using the double or out trading strategy on the 1987-2013 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns (rule profit/B&H profit). The annualised % difference in profit between the trading rules and the buy-and-hold strategies, while the breakeven costs represent the percentage roundtrip trading costs that would eliminate the difference between the rule profits and the B&H strategy.

Rule	No. of Buy	No. of Sell	Rule Profit	B&H Profit	Difference	Annualised % Difference	Breakeven Costs (%)
				Panel A: DJIA			
(1,50,0)	243	242	8.26	8.60	-0.98	-0.15%	-0.02%
(1,50,1)	280	206	2.73	8.60	-0.32	-4.16%	-0.47%
(1,150,0)	142	141	20.85	8.60	2.42	3.33%	0.62%
(1,150,1)	154	133	23.70	8.60	2.76	3.83%	0.71%
(1,200,0)	123	123	15.67	8.60	1.82	2.25%	0.49%
(1,200,1)	115	116	14.26	8.60	1.66	1.89%	0.44%
				Panel B: FT30			
(1,50,0)	232	231	13.71	2.10	6.54	7.20%	0.81%
(1,50,1)	241	206	9.93	2.10	4.73	5.93%	0.69%
(1,150,0)	122	121	8.67	2.10	4.13	5.39%	1.16%
(1,150,1)	115	117	13.10	2.10	6.24	7.02%	1.57%
(1,200,0)	84	84	14.49	2.10	6.91	7.42%	2.30%
(1,200,1)	74	101	12.54	2.10	5.97	6.84%	2.03%
				Panel C: TOPIX			
(1,50,0)	210	209	23.38	0.83	28.06	13.14%	1.59%
(1,50,1)	197	221	27.26	0.83	332.71	13.79%	1.66%
(1,150,0)	86	85	11.52	0.83	13.82	10.22%	3.05%
(1,150,1)	80	101	20.33	0.83	24.39	12.56%	3.50%
(1,200,0)	79	78	5.58	0.83	6.69	7.29%	2.41%
(1,200,1)	80	90	5.38	0.83	6.46	7.15%	2.18%

Table 8: Test results for the perfectly anticipated moving average rule using the double or out trading strategy on the 1987-2013 data for each market. The number of new trades (No. of buy/sell) is shown with the profit from trading on the rule (Rule Profit) and the buy-and-hold strategy as well as the difference between the rule returns and the buy-and-hold strategy returns (rule profit/B&H profit). The annualised % difference in profit between the trading rules and the buy-and-hold strategies, while the breakeven costs represent the percentage roundtrip trading costs that would eliminate the difference between the rule profits and the B&H strategy.

Rule	No. of Buy	No. of Sell	Rule Profit	B&H Profit	Difference	Annualised % Difference	Breakeven Costs (%)
				Panel A: DJIA			
(1,50,0)	242	242	2790643.58	8.60	324458.32	60.00%	5.18%
(1,50,1)	279	206	1325180.09	8.60	154074.03	55.65%	4.87%
(1,150,0)	238	237	1978000.22	8.60	229975.13	57.97%	5.13%
(1,150,1)	276	203	918739.45	8.60	106818.61	53.55%	4.78%
(1,200,0)	123	122	8040.03	8.60	934.79	28.83%	5.51%
(1,200,1)	115	116	3435.61	8.60	399.45	24.84%	5.12%
				Panel B: FT30			
(1,50,0)	231	231	1339199.34	2.10	637029.25	64.05%	5.70%
(1,50,1)	240	206	837290.89	2.10	398281.85	61.22%	5.70%
(1,150,0)	99	121	4180.43	2.10	1988.54	32.49%	6.79%
(1,150,1)	90	117	2471.08	2.10	1175.44	29.93%	6.72%
(1,200,0)	83	83	924.45	2.10	439.74	25.28%	7.20%
(1,200,1)	73	101	776.64	2.10	369.43	24.48%	6.68%
				Panel C: TOPIX			
(1,50,0)	209	209	2386038.47	0.83	2862883.39	73.44%	6.99%
(1,50,1)	196	221	973363.54	0.83	1167888.26	67.77%	6.59%
(1,150,0)	85	85	1777.99	0.83	2133.32	32.83%	8.82%
(1,150,1)	79	101	1726.80	0.83	2071.90	32.69%	8.31%
(1,200,0)	78	78	705.12	0.83	846.03	28.36%	8.46%
(1,200,1)	79	90	584.27	0.83	701.04	27.47%	7.61%

Figure 1: Stylised view of market movements in the pre-BLL (solid line) and post-BLL (dashed line) period

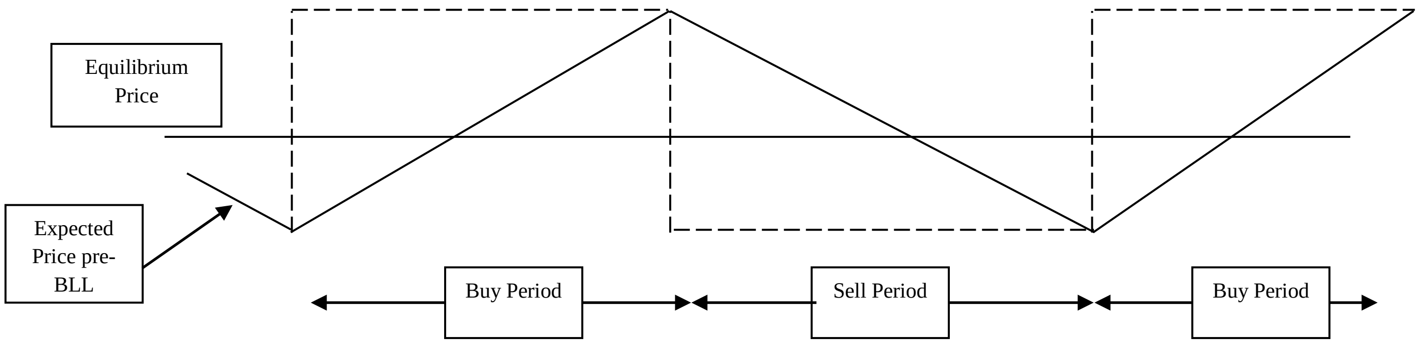
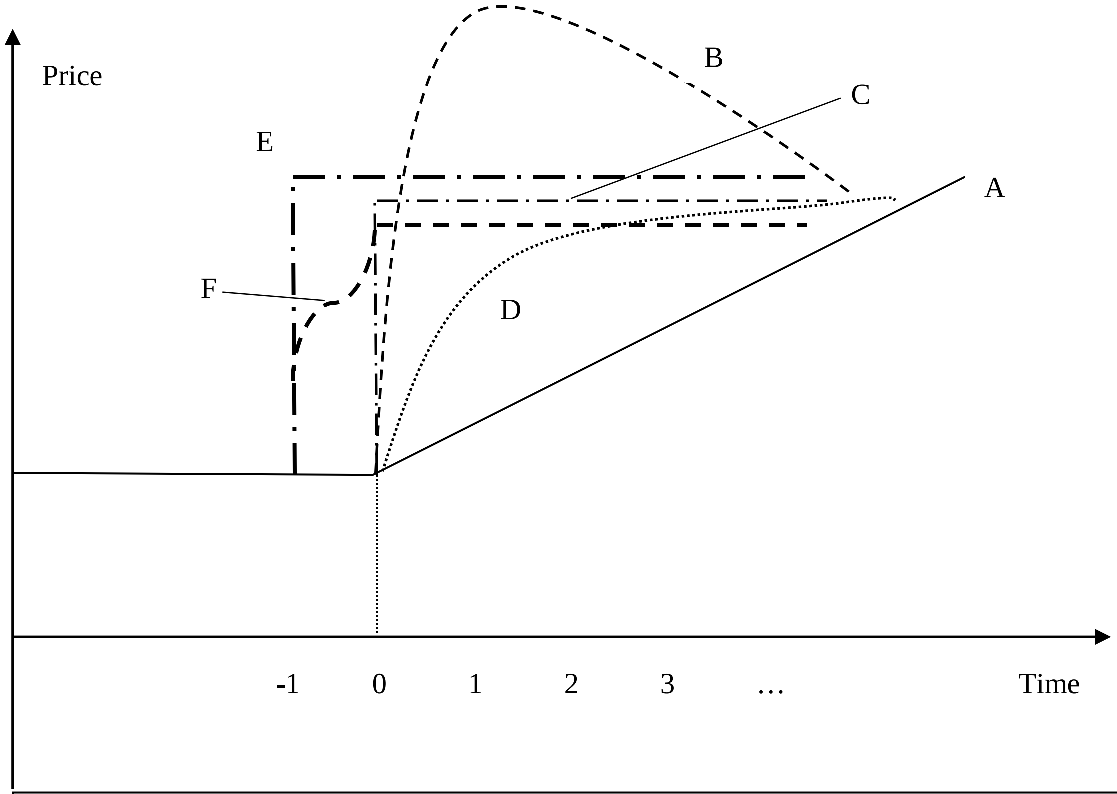


Figure 2: Different price adjustment paths around a new buy signal at t=0.

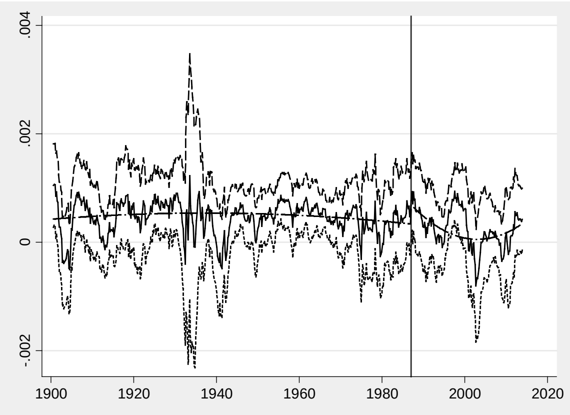


Note: The lines represent stylised price movements under different assumptions: A: pre-BLL period with no significant trading on MA signals, B: overreaction to a buy signal, C: efficient response to a buy signal, D: sluggish/under-reaction to a buy signal, E: full reaction at t=-1to anticipated signal, F: partial reaction at t=-1 to anticipated signal.

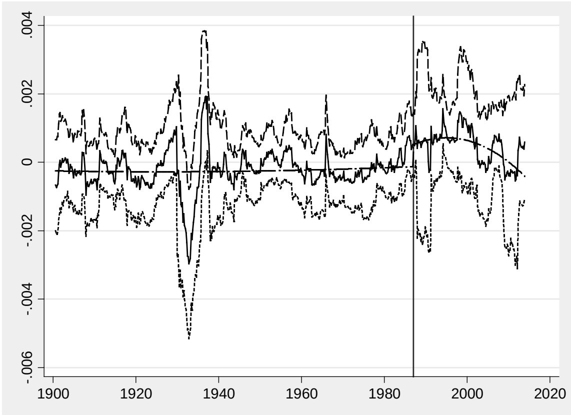
Figure 3: Moving window estimates of average MA daily returns. The solid volatile line represents returns following a buy (left) and sell (right) signals generated by each rule, calculated as mean daily returns in a 5 year window which moves by three months in each step. The dashed (dotted) line represents the upper (lower) bound of the 95% confidence interval for those returns. The solid vertical line denotes the end of the BLL sample (01/01/1987). The solid smooth line represents the fitted regression line (model (3)).

DJIA

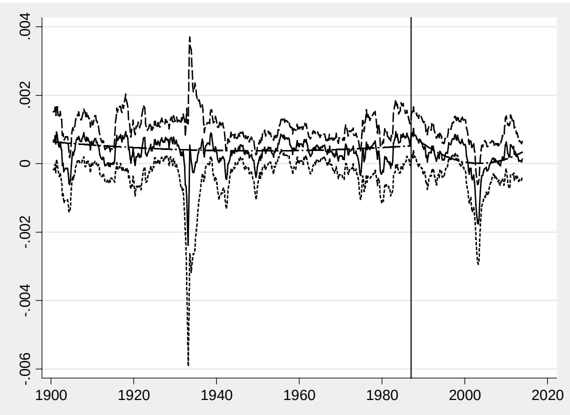
MA(1,50) BUY



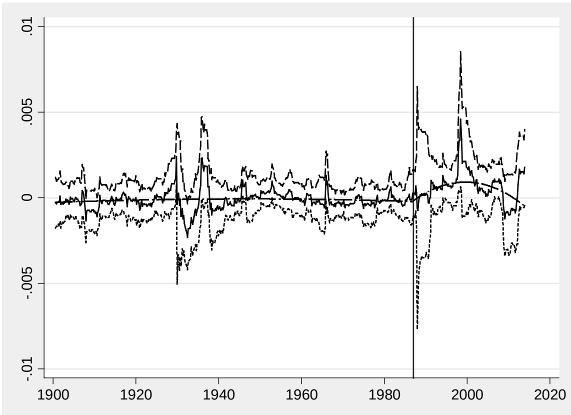
MA(1,50) SELL



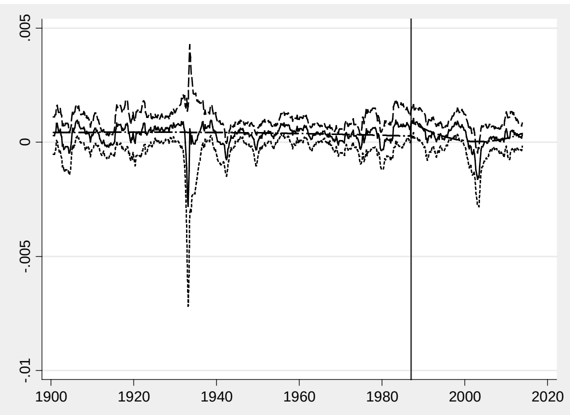
MA(1,150) BUY



MA(1,150) SELL



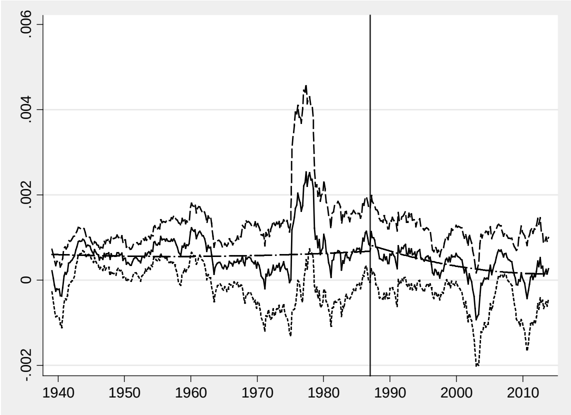
MA(1,200) BUY



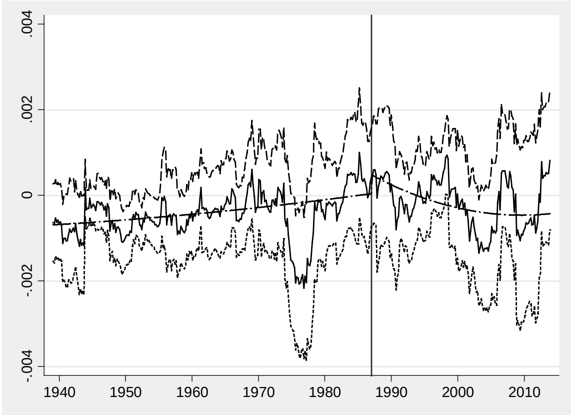
MA(1,200) SELL

FT30

MA(1,50) BUY



MA(1,50) SELL



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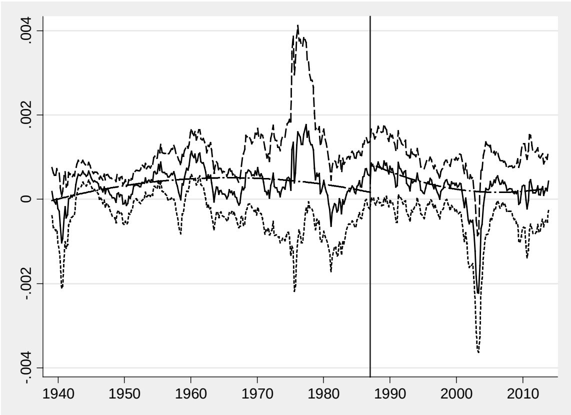

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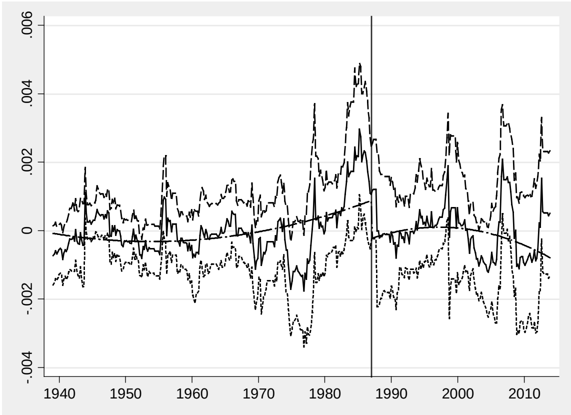

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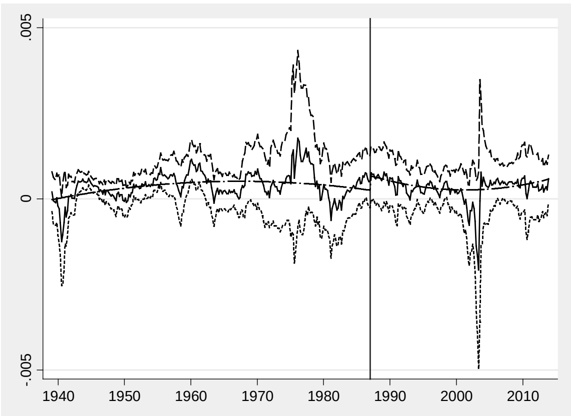
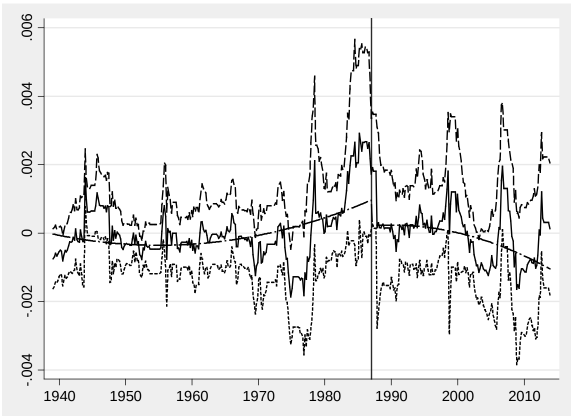
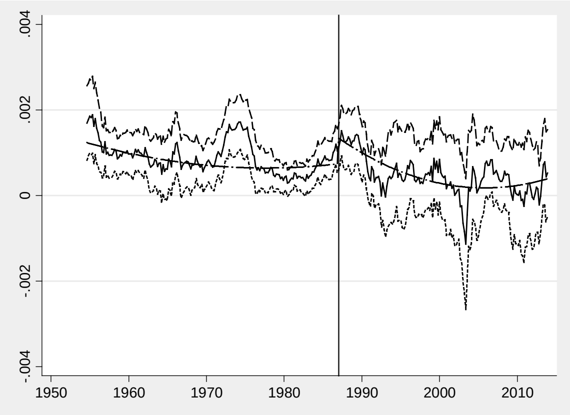


MA(1,200) SELL

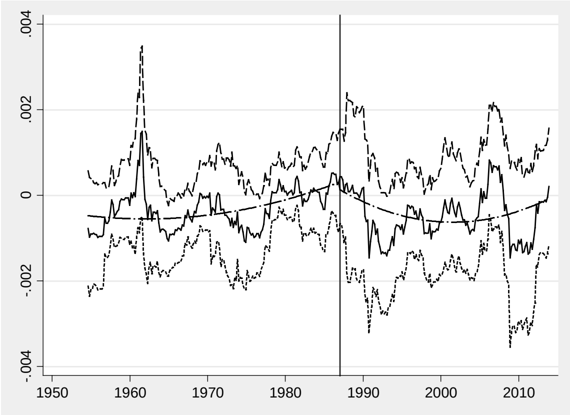


TOPIX

MA(1,50) BUY



MA(1,50) SELL



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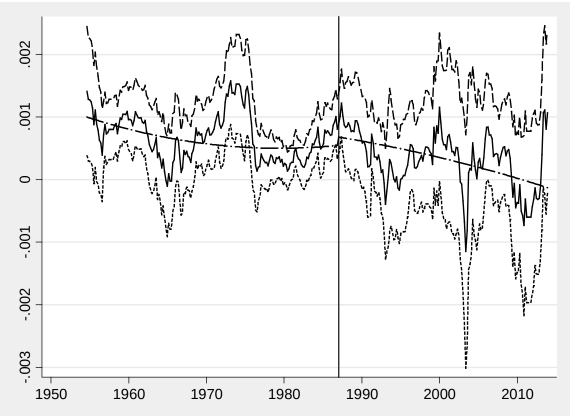
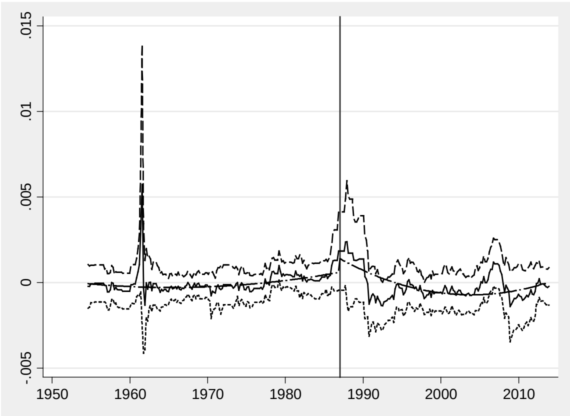
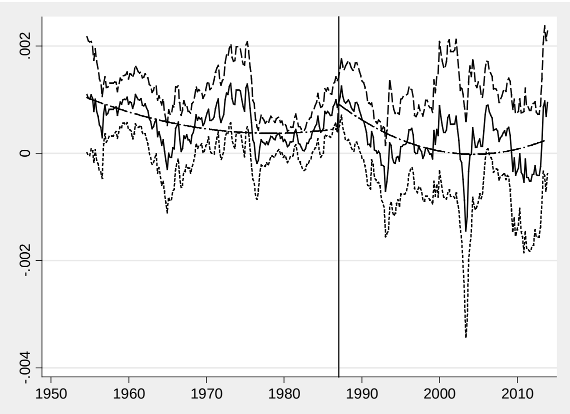


MA(1,150) SELL



MA(1,200) BUY



MA(1,200) SELL