Does Technical Analysis Deliver Alpha? A Study of the Dutch Stock Market

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Abstract

This paper finds that applying the moving average (MA) timing strategy on volatility portfolios in the Dutch stock market increases the anomaly on average by 5.77 percent per year. This result holds for MA signals with alternative lag lengths and in other Western European stock markets. In addition, the MA timing strategy improves the volatility anomaly in the bear market but reduces it in the bull market.

Contents

1 Introduction

Many consider technical analysis as the original form of investment analysis. The oldest technique is traced back to the late 1800s and can be attributed to Charles Dow, who published his work in different editorials in the '*The Wall Street Journal*', which was also founded by him during that period (Brock, Lakonishok, & LeBaron, 1992). Technical analysis is defined as study of past market prices by which technical analysts or 'technicians' attempt to forecast future price patterns (Murphy, 1999). Different instruments of technical analysis, also known as 'trading rules', are built into a system that seeks to understand the movements in supply and demand. Over time this system has developed from a purely visual analysis to more quantitative techniques (Scott, Carr, & Cremonie, 2016).

Nowadays technical analysis has a widespread use by many practitioners in the speculative markets (Park & Irwin, 2007). In 2015, the Market Technicians Association, a global professional organization of technical analysts, conducted a comprehensive survey of technical analysis used in practice. The outcome of the survey showed that practitioners have integrated technical analysis with other skills and knowledge (e.g., fundamental analysis or behavioral finance) (Scott et al., 2016). However, the long ongoing debate in the academic world on the effectiveness and profitability of technical analysis has yet to be resolved. In recent years though, an increasing amount of studies have found results in favor of technical analysis. For example, Neely, Rapach, Tu, and Zhou (2014) find strong evidence that technical indicators display statistical and economical significant forecasting power, matching or exceeding that of macroeconomic variables. Goh, Jiang, Tu, and Zhou (2013) match these results but also show that the predictive power of implemented technical analysis in the bond market is comparable to that of the equity market. In addition, Neely et al. (2014) provide multiple theoretical arguments that are in line with the rationale for technical analysis. A paper by Zhu and Zhou (2009) proves that, when stock returns are predictable, technical analysis adds value under uncertain market conditions. In line with this, a more recent paper by the same authors (Zhou & Zhu, 2013) argues that in an equilibrium model with rational informed investors and technical investors, moving average can forecast the future price. Nevertheless, most of the research was conducted based on the American stock returns or other asset classes, leaving a gap in literature of European studies on technical analysis.

To reduce this particular knowledge gap, this study will analyze the profitability of technical analysis in the Dutch stock market. Although technical analysis consists of a variety of forecasting techniques (Park & Irwin, 2007), this paper focuses specifically on the moving average technique, since the moving average (MA) is the most popular and widely used technical trading strategy (Yu, Nartea, Gan, & Yao, 2013). Additionally and in contrast to most other studies, this paper applies the MA technique to volatility-sorted portfolios, which reflects information uncertainty (Zhang, 2006). The use of volatility-sorted portfolios allows for a thorough analysis on the effect of new information. To assess the profitability of technical analysis within these modeled scenarios, this research aims to answer the following question: Do volatility-sorted portfolios yield positive abnormal returns using a moving average strategy? In doing so, two hypotheses are examined. The main hypothesis is based on Han, Yang, and Zhou (2013) finding positive abnormal returns for all volatility portfolios in the US stock market. It is hypothesized that the same holds true for the Dutch stock market. Furthermore, French, Schwert, and Stambaugh (1987) prove the existence of a positive correlation between information uncertainty and related stock return. Accordingly, high-information-uncertain stocks are expected to yield a larger abnormal return than low-information-uncertain stocks.

In order to test these hypotheses the following methodology will be employed. Following the rationale of Han et al. (2013), this paper uses ten volatility decile portfolios. Each portfolio is composed of different stocks, all sorted based on the annual standard deviation of the stock's daily returns of the prior year. To conduct the MA timing strategy, a 10-day MA for each portfolio is computed. An investor ought to buy, or continue to hold, a given portfolio when yesterdays portfolio price exceeds the 10-day MA price. When this trend is broken, the investor invests in the risk-free asset (30-day T-bill). For an optimal assessment, this study examines the return of the MA timing strategy relative to the corresponding return under the buy-and-hold strategy. The difference in performance is defined as the return on the MA portfolios (MAPs) and is structured as a zero-cost arbitrage portfolio. The sample period used for this research covers January 1990 until December 2016, analogue to the Fama and French (2015) European factors.

This paper finds positive results for nine out of ten portfolios and a clear visible relation between volatility and portfolio return. Disregarding the highest-volatility portfolio, for which the average return is negative, the returns range from 1.62% per year to 10.02% per year. Furthermore, the capital asset pricing model as well as the Fama and French (1992) three-factor model both report positive abnormal returns for the first nine portfolios and similar correlations between volatility and return. Moreover, the results are substantiated in several dimensions. Alternative lag lengths of the MA timing strategy are considered. The process is repeated using a 20-, 50-, 100- and 200-day MA strategy. The findings are similar, although the MAPs display smaller returns with increasing lag lengths. Additionally, the abnormal returns are exposed to bull and bear market conditions. The results show an opposite behavior of the MAPs to both dummy variables, which suggests that larger returns are generated during recessionary periods. On average, the MA timing strategy increases the volatility anomaly by 3.40 percentage points in the bear market and decreases it by 5.21 percentage points in the bull market. Furthermore, the trading behavior of the MA timing strategy is addressed. Application of the method of break-even transaction costs demonstrates that the strategy trades more efficiently using longer lags and shows that the higher-volatility portfolios are more resistant to transaction costs. Overall, the break-even level is reasonably high, suggesting the positive abnormal returns will likely persist after considering transaction costs.

To provide a better understanding of the applicability of the MA timing strategy, the MA timing strategy is applied on a country sample that proxies Western Europe. Average returns range from 1.21% per year to 16.98% per year with in this case the highest-volatility portfolio showing a positive average annual return of 5.28%. Interestingly, returns present a perfect monotonic increase from the lowest-volatility portfolio to the 9th portfolio. Likewise, when the countries are analyzed separately, all show a similar pattern and behaviour as is documented for the Netherlands. Finally, this studies shows the results are robust to the Carhart (1997) four-factor model as well as to the Fama and French (2015) five-factor model.

This study contributes to the finance and investment literature in several ways. First, this paper reveals evidence in support of the profitability of technical analysis. Although the profitability has been proven long since in previous research (e.g., Neely et al. (2014), Goh et al. (2013), Han et al. (2013)), this paper adds to the literature by providing a comprehensive study of technical analysis in the Dutch stock market and by applying the same strategy in a cross-country analysis of other Western European stock markets, which to my knowledge has not been performed to date. In particular, this study presents new insights in the effect of bull and bear market conditions on technical analysis in the Dutch stock market. Secondly, this study applies the MA timing strategy on volatility-sorted portfolios. The monotonic increase of return with volatility confirms the theory by French et al. (1987) on the relation between information uncertainty and stock return. Overall, it is the combination of technical analysis on volatility-sorted portfolios in the Dutch stock market that makes this a valuable contribution to current literature.

The remainder of this paper is structured as follows. Section 2 gives an extensive analysis of existing literature. Section 3 provides a theoretical framework for the MA timing strategy and elaborates on the testing procedure and hypotheses. Section 4 discusses the profitability of the MA timing strategy. Section 5 gives a further understanding of the strategy's performance. Section 6 elaborates on the applicability of the MA timing strategy other Western European countries. Section 7 examines the robustness of the results and to summarize Section 8 gives some final and concluding remarks.

2 Literature Review

There are two basic and distinctly different ways to analyze stocks: technical analysis and fundamental analysis (Bodie, Kane, & Marcus, 2011). Fundamental analysts believe the market price of a stock does not always match the true value of the company that that stock represents. Based on public information of the company, the fundamental analyst will buy a stock that he or she considers underpriced and therefore will do better in the future (Edwards, Magee, & Bassetti, 2012). On the other hand, technical analysts believe that the fundamental elements of a stock's value are already accounted for in a stock's price. Moreover, they assume that prices move in trends and that historical patterns in the market as well as in stock prices tend to repeat itself (Murphy, 1999). Technical analysts will buy a stock when they detect a certain pattern or trend in the stock's price change. In research by Han et al. (2013), technical analysis is described as a forecasting method that uses past prices to predict future market movements. Pring (2002), a leading technical analyst, provides a more specific definition:

"The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed" (p. 2).

2.1 The Evolution of Technical Analysis

Ever since the introduction of the Dow theory by Charles Dow in the late 1800s, technical analysis is used partially, or extensively, by many top traders and investors in the financial industry (Lo & Hasanhodzic, 2009). In early stages the methods primarily involved creating charts. The first charting techniques were just what is now known as "point and figure" charts, but later on the more familiar bar charts were developed (Murphy, 1999). The introduction of the bar chart led to pattern analysis becoming more popular. All charts were aimed to outline periods with a high possibility of price consolidation or price reversal (Scott et al., 2016).

By the midst of the 20$^{\text{th}}$ century, charts were commonly applied in the financial industry. Automated trend lines, like moving averages, were added to the charts (Edwards et al., 2012). In recent years, increased access to computer technology and advances in processing power have led to the development of more sophisticated indicators. Nevertheless, under quantitative testing, many of these indicators did not resolve the problems of high trading costs and delayed signals, while some have been shown to add value to the investment selection process (Scott et al., 2016).

2.2 Principles of Technical Analysis

In his book *A Random Walk Down Wallstreet*, Burton Malkiel (2011) presents two basic principles of technical analysis. The first principle states that all available information is automatically reflected in the company's past market prices. Fundamental information is, according to him, "either of inconsequential importance for the pricing of the stock or, if it is important, it has already been reflected in the market days, weeks, or even months before the news has become public" (Malkiel, 2011, p. 113). The second principle Malkiel presents is that prices tend to move in trends. This means, for example, that rising stocks keep on rising, whereas falling stocks keep on falling. In what many consider the bible of technical analysis *Technical Analysis of Stock Trends*, John Magee wrote: "Prices move in trends, and trends tend to continue until something happens to change the supply-demand balance" (Edwards et al., 2012, p. 05). Besides these two principles, John Murphy (1999) adds a third principle; history repeats itself. Or to quote Murphy directly "the key to understanding the future lies in a study of the past, or that the future is just a repetition of the past" (p. 05). He argues that part of the rationale behind technical analysis has to do with the study of human psychology. Following these principles, a true technical analyst does not care what business or industry a company is in, as long as stock prices are publicly available so that possible patterns can be studied (Malkiel, 2011).

2.2.1 The Rationale for Technical Analysis

The question that researchers, as well as practitioners, have been trying to answer ever since the Dow theory was introduced is: Why does technical analysis actually work? Malkiel (2011) gives the following three possible explanations. First, he argues that the crowd instinct of mass psychology makes trends perpetuate themselves, implicating that when investors see a stock price rise and rise, they want to jump on the 'bandwagon' to also profit from the climb. However, by doing so they will create a self-fulfilling prophecy, because by increasing the demand for the stock the price will keep on climbing. Secondly, there may be unequal access to fundamental information about a company. When, for example, a listed mining company has discovered a rich mineral deposit, insiders will trade on this first, causing the price of the stock to rise. After the insiders have told their friends, they will start trading next. Then the news reaches the professionals and blocks of shares are put in the portfolios of the large institutions. In the end, the general public finds out and buys some stocks, driving the price up even further. This is supposed to result in a rather gradual process and technicians are convinced that by observing these price changes they are able to pick up the scent of the 'smart money', which allows them to get in before the general public. The third explanation notes that investors often underreact initially to new information. After, for example, an announcement of earnings that beats the Wall Street estimates, the stock price will increase. Since some investors react later to this new information, it results in a period of price momentum, which the technician can profit from.

Under academics, the ongoing argument on the profitability of technical analysis caused an explosion of literature on the subject. In the extensive survey of Park and Irwin (2007) on the profitability of technical analysis, the empirical literature was categorized into two groups, 'early' studies (1960-1987) and 'modern' studies (1988-2004). In the category of modern studies they reviewed a remarkable amount of 95 papers, 56 of which found positive results regarding technical analysis. They made a distinction between theoretical and empirical explanations. According to Park and Irwin (2007, p. 805): "In theoretical models, technical trading profits may arise because of market 'frictions', such as noise in current equilibrium prices, traders' sentiments, herding behaviour, market power or chaos. Empirical explanations focus on technical trading profits as a consequence of central bank interventions (particularly, in foreign exchange markets), order flow, temporary market inefficiencies, risk premiums, market microstructure deficiencies or data snooping". Moreover, in research of Han et al. (2013) it is stated that "from a theoretical point of view, incomplete information on the fundamentals is a key for investors to use technical analysis" (p. 1442). This is in line with Malkiel's second explanation and is further substantiated by research of Brown and Jennings (1989), Cespa and Vives (2012) and Blume, Easley, and O'Hara (1994). Furthermore, Malkiel's third explanation, based on the market underreaction theory, is for example supported by research of Barberis, Shleifer, and Vishny (1998).

2.2.2 Why Technical Analysis Might Fail

On the other hand, the survey by Park and Irwin (2007) also shows that among the 95 modern studies, 20 studies report no additional benefit when implementing technical analysis compared to the buy-and-hold strategy. Malkiel (2011) argues there are various logical reasons against technical analysis, for which he addresses the following arguments. First, he indicates that a reversal of the price trends might occur quite unexpectedly, consequently the technician often misses the boat. Theoretically technicians only react when a trend has been established. However, by the time an uptrend has been signalled, the event may already have occurred. Secondly, as more investors trade on signals given by technical analysis techniques, the value of the technique may depreciate, in other words "such techniques must ultimately be self-defeating" (Malkiel, 2011, p. 119). Third, technicians tend to anticipate on trading signals. If they, for example, expect a price reversal, they aim to buy before this happens. That said, one can assume that there will be others who try to trade even sooner. However, the sooner technicians start trading before the actual event has happened, the more uncertain the trade will become. Finally and possibly the strongest argument against technical analysis is that the market may well be a most efficient mechanism. The rationale for this comes from the logical implication of profit-maximizing behavior. When, for instance, fundamental traders acquire information about an undervalued stock, they react instantly. Shortly afterwards, other investors and financial institutions will follow, increasing the stock's price to its fundamental value, which all could have taken less than a few minutes. Prices sometimes change so quickly that the whole play is already over before a technical analyst even has established an upward trend. If some traders believe a stock price will hit 50 tomorrow, it will hit 50 today.

2.3 The Efficient Market Hypothesis

Before going to elaborate on the application of technical analysis, it is useful to briefly review the efficient market hypothesis (EMH). The EMH was developed by Eugene Fama, who argued that stocks always trade at their fair value. In his article *Efficient capital markets: a review of theory and empirical work*, Fama (1970) provides the textbook definition of a efficient market: "A market in which prices always 'fully reflect' available information is called efficient" (p. 383). At the end of the 1970s, Michael Jensen (1978) improved Fama's definition and stated: "A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t" (p. 96). Hence, this implies that in an efficient market the expected return of technical trading based only on past prices is zero. This makes any attempt to make profits by exploiting currently available information futile, since the market price already reflects all available information (Park & Irwin, 2007). The EMH implicates that prices are adjusted instantaneously to new information under the assumption that market participants are rational and have homogeneous beliefs about information, hence, current equilibrium prices fully reflect all available information (Park & Irwin, 2004).

2.4 The Concept of Noise

Opponents of the EMH believe the market is not always as efficient as it should be. From their point of view, there will always be some noise (unobserved supply of risky assets or information quality) in the market (Park & Irwin, 2007). The concept of noise was formally introduced by Black (1986), where he defined noise as "information that hasn't arrived yet. It is simply uncertainty about future demand and supply conditions within and across sectors" (p. 529). In contrast to the EMH, noisy rational expectations models assume that not all available information is incorporated into the current price. Therefore prices tend to adjust more slowly to new information (Park & Irwin, 2004).

Working (1958) was the first to develop a model on the basis of asymmetric information. Later, Brown and Jennings (1989) improved Working's model and presented a two-period dynamic model to demonstrate that rational investors use historical prices in forming their demands. They concluded that "noise in the current prices makes it impossible for prices to reveal perfectly private information from earlier periods. As a result, historical prices together with current prices allow more accurate inferences about past en present signals than do current prices alone" (p. 527). Furthermore, Grundy and McNichols (1989) analyzed trade volumes instead of prices and introduced their own multi-period noisy rational expectations model. Unlike previous models, which assumed the source of noise came from the aggregate supply of risky assets, Blume et al. (1994) considered the quality of information as the source of noise. They concluded that the quality of the information explains and coincides with the value of technical analysis.

2.5 Information Uncertainty and Stock Prices

Jiang, Lee, and Zhang (2005) defined information uncertainty as "the degree to which a firm's value cannot be reasonably estimated by even the most knowledgeable investors" (p. 185). Within the framework of stock prices a simple and accurate proxy for information uncertainty is the stock price volatility. The more uncertainty the future holds, the more volatile the stock price is (Han et al., 2013). Likewise, Black (1986) argued that "the volatility of the value of a firm is affected by things like the rate of arrival of information about a firm and the firm leverage" (p. 533), in which the arrival rate of information can be regarded as information uncertainty. Moreover, French et al. (1987) find evidence of a positive correlation between stock returns and the related volatility.

At the start of this section it was stated that there are two distinctly different ways to analyze a stock, technical analysis and fundamental analysis. When the information about stocks is very uncertain, it is plausible that fundamental signals, such as earnings and economic outlook, are inaccurate (Han et al., 2013). Since fundamental signals are inaccurate, investors tend to confide more heavily on technical signals. Consequently, if technical analysis is truly profitable, abnormal returns will more firmly be visible for high-information-uncertain stocks in comparison to low-information-uncertain stocks.

3 Moving Average Timing Strategy

Technical analysis consists of a variety of forecasting techniques, such as chart analysis, pattern recognition analysis, seasonality and cycle analysis, and computerized technical trading systems (Park & Irwin, 2007). In contrast, academic research focuses mainly on technical trading systems, since these can be expressed in quantitative forms. The most popular and widely used technical trading strategy is the moving average technique (Yu et al., 2013). A MA indicates the average value of the stock price over period of time and generates trading signals (buy or sell) for investors to trade on (Park & Irwin, 2007). This section provides a theoretical framework for the MA timing strategy and explains how these tradings signals are generated. Furthermore, it addresses the empirical strategy that will be applied to evaluate the portfolio performance and describes the hypothesis.

3.1 Theoretical Framework

The main focus of this paper will be on the MA strategy. Before the MA strategy can be applied, volatility portfolios need to be constructed first. Volatility level is referred to as the annual standard deviation of the stock's daily return. Based on the volatility levels of the prior year, stocks are sorted into ten decile portfolios and will be rebalanced each year at the end of the previous year. Once stocks are assigned to portfolios, portfolio returns are calculated via equal weighting, to coincide with the Han et al. (2013) portfolios. Each portfolio is indexed from January 1990 (base = 100) using the portfolio returns, which is needed to calculate the MAs later on and will hereafter be referred to as the portfolio price.

Following Han et al. (2013), the returns on the volatility decile portfolios are denoted by R_{jt} (j = 1,...,10) as well as the corresponding portfolio prices (index levels) by P_{jt} (j = 1,...,10). The MA of portfolio j, at day t, with lag L is defined as,

$$A_{jt,L} = \frac{P_{jt-(L-1)} + P_{jt-(L-2)} + ... + P_{jt-1} + P_{jt}}{L} \tag{1}$$

which is the average price of the past L days including day t. This paper considers 10-, 20-, 50-, 100- and 200-day MAs (Eun & Shim, 1989) (Yu et al., 2013). Using the MAs, the strategy is as follows. At the start of trading day t a trading signal will be generated, if the last closing price $P_{jt\text{-}1}$ is above the MA price $A_{jt\text{-}1,L}$, the signal will be BUY. Otherwise, if the closing price $P_{jt\text{-}1}$ is below the MA price $A_{jt\text{-}1,L}$, the signal will be SELL. When the signal on day t is BUY, one should invest in the corresponding decile portfolio j for trading day t. When the signal on day t is SELL, one should invest in the 30-day T-bill. This paper uses a 30-day German government bond, since the investment will be over a short horizon and Germany has the most stable bonds of the European Union (Buttonwood, 2017). The basic idea is that an investor should hold the portfolio in an uninterrupted upward trend and should sell when the trend is broken (Han et al., 2013). Generally, the MA timing strategy delivers an investment signal with one day delay.

From a mathematical point of view, the returns on the MA timing strategy are as follows,

$$\tilde{R}_{jt,L} \quad = \quad \begin{cases} R_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L} \\ r_{ft}, & \text{otherwise} \end{cases} \tag{2}$$

where R_{jt} is the return on the jth volatility decile portfolio on day t and r_{ft} is the return on the 30-day T-bill. Following the study of Han et al. (2013), this paper focusses on the cross-sectional profitability of the MA timing strategy relative to the buy-and-hold strategy of the volatility decile portfolios. Put differently, this research focusses on how $\tilde{R}_{jt,L}$ outperforms R_{jt}, hence, $\tilde{R}_{jt,L}$ - R_{jt} and is called the return on the MA portfolio (MAP). The performance of the MAPs all depends on the effectiveness of the MA signal. With ten decile portfolios, ten MAPs are obtained,

$$MAP_{jt,L} \quad = \quad \tilde{R}_{jt,L} - R_{jt}, \qquad\qquad j = 1, \ldots, 10 \tag{3}$$

Given the mathematical construction of this formula, a MAP can also be taken as a zero-cost arbitrage portfolio. An investor purchases a long position in the MA timing portfolio ($\tilde{R}_{jt,L}$) and acquires a short position in the underlying volatility decile portfolio (R_{jt}) (Han et al., 2013). Hence, the return of the MAPs give a better understanding of the profitability of the MA timing strategy.

3.2 Empirical Strategy

Modern portfolio theory was first introduced by Harry Markowitz in the 1950s. In his article *Portfolio Selection*, Markowitz (1952) presented a theory of 'portfolio choice', which allowed investors to analyze risk relative to their expected return. William Sharpe (1963) contributed to the modern portfolio theory by developing the market model, which explains the relationship between the portfolio and the market (Fabozzi, Gupta, & Markowitz, 2002).

3.2.1 Factor Models

As part of the modern portfolio theory the mean-variance portfolio theory was developed to enable investors to find the optimal portfolio composition. In order to find the optimum, investors are assumed to estimate the mean and variance of the return for each stock considered for the portfolio, as well as the covariances (correlations) between all pairs of stocks (Elton & Gruber, 1997). The principal tool used to estimate the covariances is an index model, which can also be referred to as a factor model. The market model, by Sharpe (1963), was the first single-factor model and became known as the capital asset pricing model (CAPM),

$$\mathrm{E}(r_i) \quad = \quad r_f + \beta_i[\mathrm{E}(r_M) - r_f] \tag{4}$$

$\mathrm{E}(r_i)$ denotes the expected return on stock i, r_f the risk-free rate and $[\mathrm{E}(r_M) - r_f]$ represents the excess return on the market and is specified as the market index. The model is formulated in the following regression,

$$R_{it} = \alpha_i + \beta_i R_{MKT,t} + \epsilon_{it} \tag{5}$$

where R_{it} is the expected excess return, $[\mathrm{E}(r_i) - r_f]$, of stock i at time t, regressed on the market risk factor, $R_{MKT,t}$. The intercept, α_i, is the stock's expected excess return given the market excess return is zero. Furthermore, β_i denotes the asset's sensitivity to the market index, a market beta of 1 implies that the asset will move with the market. Finally, ϵ_{it} represents firm-specific risk, also called the residual (Bodie et al., 2011).

Shortly after the introduction of the market model, researchers started to explore multi-factor models, by adding, other economic risk factors that could explain some of the excess return next to the market index. In general a multi-factor model is as follows,

$$R_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} R_{kt} + \epsilon_{it} \tag{6}$$

here β_{ik} is the sensitivity of stock i to the return of factor k, K the total number of factors employed and R_{kt} the excess return of factor k. Multi-factor models give an even better understanding in the risk-return relationship of the portfolio than the single-factor model (Elton & Gruber, 1997). Furthermore, a multi-factor model is also an useful tool to evaluate portfolio performance, which will be elaborated on at the end of this subsection.

In the years that followed the introduction of the multi-factor model, researchers explored numerous possible factors. The first major improvement to the CAPM that became popular was the three-factor model developed by Fama and French (1992). Fama and French (FF) added two new factors to the already existing market factor of the CAPM. Besides the excess return on the market, FF added (i) the difference between the return of small stocks and the return of big stocks (SMB, small minus big) and (ii) the difference between the return of high-book-to-market stocks and the return of low-book-to-market stocks (HML, high minus low) (Fama & French, 1996). These factors are expressed in the following time-series regression,

$$\begin{aligned} R_{it} = {} & \alpha_i + \beta_{i,MKT} R_{MKT,t} + \beta_{i,SMB} R_{SMB,t} \\ & + \beta_{i,HML} R_{HML,t} + \epsilon_{it} \end{aligned} \tag{7}$$

Moreover, FF upgraded their model by the end of 2014 with two more factors to the FF five-factor model. They included a factor on profitability (RMW, robus minus weak) and a factor for the level of investments (CMA, conservative minus aggressive) (Fama & French, 2015).

Over time, FF were not the only researchers that came up with new improvements to the CAPM. Mark Carhart (1997) argued that persistence in stock performance (momentum) should also be incorporated as a risk factor. In his paper, he demonstrated that the four-factor model substantially improved the average pricing errors of the

CAPM and the FF three-factor model. He showed that, based on yearly performance, last year's winners will continue to do well and last year's losers will continue to perform poorly. With these results he constructed the momentum factor (UMD, up minus down) and added this to the FF three-factor model,

$$\begin{aligned} R_{it} &= \alpha_i + \beta_{i,MKT} R_{MKT,t} + \beta_{i,SMB} R_{SMB,t} \\ &\quad + \beta_{i,HML} R_{HML,t} + \beta_{i,UMDD} R_{UMD,t} + \epsilon_{it} \end{aligned} \tag{8}$$

3.2.2 Portfolio Evaluation

A factor model is also an useful tool for the evaluation of a portfolio. The alpha from the regression can be defined as the abnormal return an investor realizes by outperforming the model (Elton & Gruber, 1997). To evaluate the ten volatility portfolios, the current study includes the following empirical analyses. It employs a time-series regression of the MAPs on the CAPM and the FF three-factor model to enable an evaluation of the portfolio performance by examining the alphas. In addition, the portfolios are evaluated using alternative lag lengths to assess the most profitable strategy. Different business cycles are considered to estimate the impact of bull and bear market conditions. To judge the applicability of the MA timing strategy the strategy is applied in other Western European countries. Ultimately, the MAPs are exposed to the FF five-factor model and Carhart's four-factor model as robustness tests to strengthen the results.

3.3 Hypothesis

The previous section gave a thorough analysis of the exiting literature on technical analysis. Technical analysis, that builds on the explanatory power of past prices, is a trading strategy that has been used from the start of the previous century. Over the years, the strategy is applied by many practitioners in numerous different ways and across various asset markets. The moving average technique has been the most popular and widely used strategy within technical analysis (Yu et al., 2013).

This study aims to answer the following research question: Do volatility sorted portfolios yield abnormal returns (positive alphas) using a moving average strategy in the Dutch stock market? In answering this question two hypotheses are examined. The first hypothesis tests the profitability of the volatility decile portfolios individually. Han et al. (2013) found, in a similar study using volatility decile portfolios for testing the moving average technique, that all portfolios yielded positive abnormal returns in the US stock market. In their research they conducted several regression analyses applying the CAPM and the Fama and French (1992) three-factor model. Their results showed that, after the regression analyses, the MA timing strategy still yielded positive alphas. Although there are differences between the Dutch and the US stock market, history has has shown us that stocks always will follow some sort of trend. Therefore the first hypothesis, all volatility decile portfolios yield positive alphas, is expected to also hold when Dutch stocks are used.

The second hypothesis further explores the relation between information uncertainty and the stock returns. The hypothesis is based on several theories. First, as was shown by

Scott et al. (2016), technical analysis is integrated in the skill set of practitioners together with other skills and knowledge. When information uncertainty is high, fundamental signals, such as earnings or an economic outlook, are more likely to be inaccurate, leading to investors putting more trust into technical signals (Han et al., 2013). Second, French et al. (1987) proved the existence of a positive correlation between volatility levels and corresponding stock returns. Third, research by Zhang (2006) shows that trends in stock prices are attributable to underreaction to new information by investors and that the underreaction moves monotonically to the level of information uncertainty. Because of these reasons, one might argue that if technical analysis is truly profitable, abnormal returns will more firmly be visible for high-information-uncertain stocks in comparison to stocks with low information uncertainty. Hence, return is expected to increase from the lowest-volatility portfolio to the highest-volatility portfolio.

4 Profitability of the MA Timing Strategy

To assess the profitability of the MA timing strategy on the Dutch stock market, this paper analyzes ten volatility decile portfolios combined with a 10-day moving average strategy. This research uses a cross-sectional regression analysis in the Dutch stock market. The following section provides a summary statistics of the volatility decile portfolios and examines the alphas (abnormal returns) of the MAPs.

4.1 Data Selection

For the analysis a dataset is created compiling daily returns of all Dutch stocks traded at the Euronext Amsterdam. All stock data is extracted from Thomson Reuters Datastream. The risk-free rate is a 30-day German Treasury bill from Bloomberg. A 30-day Treasury bill is used since the MA timing strategy operates at a short horizon. Daily European factors are obtained from Kenneth French's Web site on MKT, SMB, HML, UMD, RMW and CMA. The first three are the original factors from the Fama and French (1992) three-factor model, while the latter two, a profitability and an investments factor respectively, are used in the Fama and French (2015) five-factor model. UMD represents the momentum factor from Carhart's four-factor model, which goes long in past winners and short in past losers (Carhart, 1997).

The sample period used for the analysis spans form January 1990 until December 2016, to coincide with the Fama and French (2015) European factors. Following Zhang (2006), stocks with a price below $5 for less than ten days in a row are excluded from the dataset to make sure the results are not driven by small and illiquid stocks or by a bid-ask bounce. Furthermore, the return of the stocks is winsorized to control for any outliers. The resulting number of stocks included in the sample is 480, taken over the whole time frame. The stocks are sorted equally over the 10 volatility decile portfolios, the average number of stocks varies across years between 11.4 to 28.8 stocks per decile portfolio. Daily results are annualized by using an average of 250 trading days per year.

4.2 Summary Statistics

The previous section described the utilization of the MA timings strategy. The strategy compares the return of the MA timing portfolios to the return of the benchmark portfolios, which are constructed using a buy-and-hold strategy. The difference in return is referred to as the MAPs and can be interpreted as a zero-cost arbitrage portfolio. Table 1 provides a summary statistics for the variables of interest. The characteristics of the following variables are presented: the return on the buy-and-hold portfolios, R_{jt} (Panel A), the return on the 10-day MA timing portfolios, $\tilde{R}_{jt,10}$ (Panel B), and the return on the related MAPs, $MAP_{jt,10}$ (Panel C).

Consider Panel A, the buy-and-hold portfolios. The average return, the standard deviation, the skewness and the Sharpe ratio, are given across the ten volatility portfolios. The average returns range from 0.40% per year for the lowest decile to 39.27% per year for the highest decile. Although the returns do not increase strictly monotonically, a medium form of positive correlation is perceptible between the average return and increasing volatility. Note that the last row indicates the difference between the highest and the lowest decile. Most average returns are statistically significant with a hypotheses test of the average return being positive. Panel B provides the 10-day MA timing strategy. The average returns range from 2.16% per year to 17.80% per year and besides from portfolio 9 and 10 we could see the average return as an increasing function of the deciles. The average return of the MA timing strategy (except for the highest-volatility decile) is not only larger across portfolios than the buy-and-hold strategy, the standard deviation is also considerably smaller. For instance, the difference in standard deviation of the lowest decile is 1.53% versus 0.93%, while decile 9 shows a difference of 22.03% versus 14.08%. Naturally, a larger return and a smaller standard deviation result in a higher Sharpe Ratio. Additionally, the MA timing portfolios also display either less negative or more positive skewness compared to the buy-and-hold portfolios. Positive skewness is preferred over negative skewness, since negative skewness implies more downside risk, as is explained by Kraus and Litzenberger (1976). The results of the MAPs are reported in Panel C. Overall, the average return across all deciles accumulates to a return of 2.42% per year. Interestingly, when disregarding portfolio 10 results, the average changes to 5.77% on annual basis. In line with Panel A and B, a medium strong relation between average return and volatility is visible. Furthermore, by combining the buy-and-hold strategy and the MA timing strategy, the deviations from the mean showed a subtle increase. This resulted in a standard deviation for the MAPs that is slightly larger than those documented for the MA timing strategy, though they remain smaller than the standard deviations of the buy-and-hold strategy alone. Moreover, examining the skewness of the MAPs, half of the portfolios show an even smaller negative or more positive skewness compared to the MA timing strategy, further lowering the implication of downside risk. Lastly, Panel C also presents the success rate, which is defined as the fraction of trading days that the return of the MAPs are equal or exceed the risk-free rate. The success rate ranges between 44% and 49%, indicating a moderate timing ability of the MA timing strategy.

Table 1

Summary Statistics

All local stocks traded at Euronext Amsterdam are sorted into 10 decile portfolios. The portfolios are constructed based on the annual standard deviation of daily stock returns within the prior year. Portfolios are weighted equally and rebalanced at the end of each year. Moving average (MA) prices are calculated each day using portfolio returns of the last 10 days including the current day. Comparing portfolio prices to the MA prices generates a trading signal that instructs to BUY the portfolio if the portfolio price exceeds the MA price and to SELL the portfolio otherwise. When the signal is BUY, the underlying decile portfolio is held from the next day until the upward trend is broken. If yesterday's signal is SELL, money is invested into a 30-day risk-free T-bill. Each panel reports the average return (Avg Ret), the standard deviation (Std Dev), and the skewness (Skew) for all 10 decile portfolios. Panel A presents the buy-and-hold benchmark portfolios, where as Panel B reports the MA timing decile portfolios. In Panel C the MA portfolios (MAPs) are given, which is the difference between the MA timing portfolios and the buy-and-hold portfolios. Furthermore, the table reports the annualized Sharpe ratio (SRatio) for the buy-and-hold strategy and the MA timing strategy, as well as the success rate for the MAPs. The sample period spans form January 1990 until December 2016. All results apart from the skewness are annualized. Returns are in percentages, *t*-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	Panel A. Buy-and-Hold Portfolio				Panel B. MA(10) Timing Portfolio				Panel C. MAP			
Rank	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
1 (Low)	0.40	1.53	−0.31	−1.41	2.40***	0.93	4.48	−0.15	2.00***	1.23	3.04	0.46
	(1.39)				(13.64)				(8.61)			
2	0.54	2.44	−0.89	−0.82	2.16***	1.64	−3.99	−0.23	1.62***	1.81	−0.54	0.45
	(1.18)				(6.98)				(4.74)			
3	3.96***	7.75	−0.31	0.18	5.77***	4.65	−1.03	0.70	1.81	6.21	0.05	0.48
	(2.70)				(6.58)				(1.54)			
4	5.80***	10.60	−0.43	0.31	8.50***	6.53	−0.21	0.91	2.70*	8.35	0.66	0.49
	(2.89)				(6.88)				(1.71)			
5	6.33***	12.01	−0.39	0.32	13.07***	7.30	−0.22	1.44	6.74***	9.51	0.54	0.45
	(2.79)				(9.47)				(3.75)			
6	7.01***	13.52	−0.38	0.33	14.84***	8.36	−0.21	1.47	7.82***	10.59	0.55	0.45
	(2.75)				(9.39)				(3.91)			
7	7.33***	16.90	−0.15	0.28	16.88***	10.52	0.34	1.36	9.54***	13.19	0.36	0.45
	(2.30)				(8.49)				(3.83)			
8	8.08**	17.97	−0.06	0.28	17.80***	11.67	0.72	1.31	9.72***	13.62	0.47	0.45
	(2.38)				(8.07)				(3.78)			
9	4.84	22.03	0.17	0.10	14.85***	14.08	0.56	0.87	10.02***	16.92	−0.12	0.45
	(1.16)				(5.58)				(3.13)			
10 (High)	39.27***	38.32	1.45	0.96	11.53**	27.72	1.51	0.32	−27.74***	26.50	−2.93	0.44
	(5.42)				(2.20)				(−5.54)			
High - Low	38.87***	38.37	1.44	0.95	9.13*	27.73	1.52	0.24	−29.73***	26.54	−2.93	0.38
	(5.36)				(1.74)				(−5.93)			

4.3 Alphas from CAPM and Fama & French Factors

A simple summary statistics shows that the MA timing strategy outperforms the buy-and-hold strategy in all but last the last portfolio. Larger average returns combined with smaller standard deviations resulted in higher Sharpe ratios. In line with this result, skewness is either less negative or more positive and a success rate of around 45% suggesting that the MA timing strategy generates an abnormal return almost half of the time. To evaluate whether the portfolio return differences still hold in a risk based model, the MAPs will be exposed to several different risk factors. Note, all of the following regression results are adjusted for heteroscedasticity as well as serial correlation.

First the returns of the zero-cost portfolios are regressed on the CAPM and the Fama and French (1992) three-factor model,

$$MAP_{jt,L} = \alpha_j + \beta_{j,MKT} R_{MKT,t} + \epsilon_{jt}, \qquad j = 1, \ldots, 10 \tag{9}$$

$$\begin{aligned} MAP_{jt,L} = {} & \alpha_j + \beta_{j,MKT} R_{MKT,t} + \beta_{j,SMB} R_{SMB,t} \\ & + \beta_{j,HML} R_{HML,t} + \epsilon_{jt}, \qquad j = 1, \ldots, 10 \end{aligned} \tag{10}$$

where Equation (9) represents the CAPM including only the market factor (*MKT*) and Equation (10) indicates the FF three-factor model adding the size (*SMB*) and value factor (*HML*) as described in the previous section. The results of both regressions are reported in Table 2, Panel A and Panel B respectively.

The alphas or risk-adjusted returns documented for the CAPM even exceed the unadjusted ones, the average returns of the MAPs as reported in Table 1. Neglecting the highest decile portfolio, alphas range from 1.67% to 12.28% per year and all are highly statistically significant. Additionally, a monotonic increase in the risk-adjusted returns from the lowest-volatility decile to higher-volatility deciles is clearly visible, disregarding the first and the tenth decile. Examining the market betas for the MAPs, it is evident the betas decrease across deciles from 0.00 to -0.39. As was mentioned in the previous section, a market beta of 1 implies that the portfolio will move in parralel with the market. Pointed out by Han et al. (2013), the reason for the market factor being negative and decreasing across deciles is as follows: "The MA timing strategy is designed to avoid the negative portfolio returns" (p. 1440). More specifically, the successful timing ability induces that if portfolio returns are negative, the return on the market will most likely be negative as well. On the other hand, if portfolio returns go up, the market is most likely increasing too. In the case of positive returns, the MA indicators do not turn to BUY immediately, they are restrained to some extent due the strategy's design. Therefore, the MA timing portfolios move less in line with the market than the buy-and-hold portfolios. Consequently, market betas for the MA timing strategy are smaller than those of the buy-and-hold strategy, resulting in negative market betas for the MAPs. Overall, the returns of the MA timing strategy are substantially larger than the returns of the buy-and-hold strategy, so that the MAPs still generate positive alphas under the CAPM.

Panel B of Table 2 reports the regression results of the MAPs on the FF three-factor model. Compared to the average returns of the MAPs, the results of the FF three-factor model still display larger alphas, though slightly smaller than those of the CAPM. The general pattern of increasing returns across portfolios is present nonetheless. Furthermore, analyzing the risk factors, it appears the market betas are even more negative than was the case for the CAPM. The size betas also demonstrate a negative relation to abnormal returns, however, results are only statistically significant for the top half of the table. The negative betas of the market factor and the size factor is again the effect of less exposure of the MA timing portfolios to these two factors. For the value factor the output

Table 2

Alphas CAPM and Fama & French 3-factor model

Alphas, betas and adjusted R^2 are reported for a factor model regression of the MAPs on either the CAPM (Panel A) or the Fama and French (1992) three-factor model (Panel B). The analysis uses a 10-day moving average timing strategy and European risk factors. The sample period spans form January 1990 until December 2016. Alphas are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	Panel A. CAPM			Panel B. FF 3-factor model				
Rank	α	β_{MKT}	Adj. R^2 (%)	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2 (%)
1 (Low)	2.00***	0.00*	0.01	2.00***	0.00***	−0.01***	0.01***	0.36
	(8.63)	(−1.67)		(8.62)	(−4.44)	(−3.36)	(4.61)	
2	1.67***	−0.01***	0.72	1.60***	−0.02***	−0.02***	0.04***	3.20
	(4.96)	(−3.59)		(4.88)	(−5.57)	(−4.79)	(5.50)	
3	2.63**	−0.14***	16.75	2.55**	−0.15***	−0.03*	0.04***	16.98
	(2.42)	(−9.00)		(2.33)	(−8.32)	(−1.69)	(2.53)	
4	4.02***	−0.23***	24.52	3.98***	−0.25***	−0.04**	0.04	24.72
	(2.89)	(−16.35)		(2.84)	(−13.80)	(−1.92)	(1.53)	
5	8.33***	−0.27***	27.41	8.55***	−0.30***	−0.07***	−0.02	27.69
	(5.07)	(−17.33)		(5.16)	(−14.12)	(−2.56)	(−0.81)	
6	9.64***	−0.31***	28.80	9.86***	−0.32***	−0.03	−0.05**	28.91
	(5.36)	(−21.21)		(5.45)	(−16.19)	(−1.00)	(−1.85)	
7	11.71***	−0.37***	26.23	11.40***	−0.38***	0.00	0.09***	26.43
	(5.26)	(−19.47)		(5.09)	(−15.22)	(−0.09)	(2.55)	
8	11.95***	−0.39***	26.26	12.16***	−0.39***	−0.03	−0.04	26.31
	(5.36)	(−22.43)		(5.41)	(−17.87)	(−1.03)	(−1.13)	
9	12.28***	−0.39***	17.43	11.88***	−0.40***	−0.01	0.12***	17.65
	(4.28)	(−18.60)		(4.13)	(−14.16)	(−0.19)	(2.59)	
10 (High)	−26.22***	−0.26***	3.17	−26.84***	−0.29***	−0.05	0.21***	3.44
	(−5.58)	(−8.44)		(−5.70)	(−8.10)	(−0.98)	(3.23)	
High - Low	−28.23***	−0.26***	3.13	−28.85***	−0.28***	−0.04	0.21***	3.38
	(−6.00)	(−8.40)		(−6.11)	(−7.96)	(−0.79)	(3.14)	

shows mainly positive betas. This implies that the MA timing strategy is more exposed to value stocks (high book/market ratio) than growth stocks (low book/market ratio) compared to the buy-and-hold strategy. In general it seems some of the abnormal return is explained by the size and value factor, since alphas are slightly lower than in the CAPM case. In contrast, the increase in adjusted R^2 is almost negligible, it appears the FF three-factor does not have much additional explanatory power over the CAPM.

4.4 Interpreting the Abnormal Returns

In the previous subsection the profitability of the MA timing strategy was verified by exposing MAPs to the CAPM and the FF three-factor model. The alphas, or abnormal returns, that resulted from these regressions are consistent with the prior determined hypotheses. Apart from the highest-volatility portfolio, all the zero-cost portfolios showed positive average returns. These average returns persisted when controlled for different risk factors, by employing multiple regression analyses. Remarkably, controlling for the different risk areas even increased the abnormal returns. The resulting positive alphas are in support of the first hypothesis. Moreover, visible trough out all the results, a general pattern of increasing returns from the lowest-volatility decile to higher-volatility deciles. This increasing pattern confirms the second hypothesis on finding a positive correlation between volatility and portfolio returns. Accordingly this supports the positive relationship between information uncertainty and portfolio returns. In other words, high-information-uncertain stocks generate larger abnormal returns than low-information-uncertain stocks.

However, this research cannot ignore the fact that the highest-volatility MAP showed a negative return, implicating that to buy and hold the portfolio is more profitable than applying the MA timing strategy. One possible explanation could be that the incorporation of new information happens too fast for the MA timing strategy to profit from this. The trading signal changes to BUY when the moving average exceeds the portfolio price, but the technical analyst is only able to buy the portfolio after the closing price is established at the end of the day. When, for example, positive information is published first thing in the morning, the stock price starts rising during the rest of the day. The technical analyst however, only detects the rise when he acquires the closing price. It could be that this new information is already incorporated and the stock has reached its new price level. This is especially the case for high volatile stocks. Table A1 in the Appendix substantiates this notion. The table is a precise replica of Table 1 in all but one important thing. In this analysis Equation (2) is altered by using $t-0$ instead of $t-1$. In other words, the portfolio is bought the day at which the trading signal will change to BUY and not the day after. It should acknowledged that this modelled scenario is not realistic in real-life stock trading; no one can foretell the future in reallife. Yet, interestingly, this one day changes everything. The average return of the highest-volatility decile using the fictional 10-day MA timing strategy has now increased to around 138% per year. This is twelve times the average return that was documented for the same decile in Table 1, 11.53% per year. Naturally, the difference is also visible in the other deciles, but fades away with decreasing volatility. Note again this is purely fictional and is only done to give a better understanding in the matter at hand. All in all, this confirms that for high-volatility-stocks new information is incorporated too fast for the MA timing strategy to profit from this.

In a general comparison of the performance of the MA timing strategy, similar results were found by research of Han, Yang, and Zhou (2013). They applied the same MA timing strategy combined with volatility-decile portfolios on the US stock market. However, there are also some differences to report. First of all and in line with this research, the average returns of the MAPs found in the US are positive and display a smooth monotonic increase across deciles. Moreover, employing multiple regression analyses on US stock markets, resulted in even higher abnormal returns. However, for a small stock market such as the Netherlands it is sometimes hard to compete with the stronger players like the US. The MA timing strategy yielded significantly larger abnormal returns for the US stock market than for the Dutch's. Where the MAPs in the Dutch stock market only generated an average return across deciles of 2.42% on annual basis, the US stock market generated an average of 12.28% per year. Looking at the results of the FF three-factor model in the US, the MAPs show a similar negative statistical relation to the market and size factor. On the other hand, the sensitivity of the value factor is negative, compared to a positive sensitivity documented for the Dutch stock market. This implies the MA timing strategy in the Netherlands is more exposed to value stocks than in the US. Nevertheless, in both studies the MA timing strategy yielded positive and statistically significant alphas. Furthermore, both studies displayed a monotonic increase in abnormal return from the lowest-volatility decile to the higher-deciles. Yet, the economic significance and the robustness of the results from the Dutch stock market need further elaboration.

5 Understanding the profitability of MA Timing

In this section, the profitability of the MAPs is substantiated by examining the abnormal returns in several dimensions. First, alternative lag lengths of the MA strategy are considered. Second, this study addresses different business cycles to correct for bull and bear market periods. Third, average holding days, trading frequency and break even transaction costs are examined to analyze the trading behavior of the MA timing strategy.

5.1 Alternative Lag Lengths

Up to now the analysis of the profitability of the MAPs was solely based on the 10-day MA timing strategy. This was done because of two reasons: (i) to coincide the paper by Han et al. (2013), which confirmed the 10-day MA timing strategy was the most profitable strategy for the US stock market and (ii) because on average the this is also true for the European sample, which will be elaborated on in the following section. Consider now an analysis of various lag lengths (L) for the Dutch stock market by altering Equation (1).

Table 3 provides both the average returns of the MAPs and the Fama and French (1992) alphas using 20-, 50-, 100- and 200-day MA strategy. Comparing the various lag lengths, it appears in the first instance that using a 10-day MA is not the most profitable strategy in the case of the Dutch stock market. Although, using a 10-day MA strategy is the most profitable on average in the US and the European stock market, for the Dutch stock market using a 50-day MA strategy yields on average the largest return. Combing the results of Table 1, the average return across deciles using a 10-day MA yields 2.42% on annual basis. The average annual return across deciles using a 50-day MA strategy yields 4.06%. However, when disregarding portfolio 10 due to negative returns, the average return across deciles for MAP(10) is 5.77% annually, whereas MAP(50) generates an average of 4.86% per year. In general, it follows that using longer lag lengths in the analysis reduces the average returns. The average return across deciles for MAP(200) is 2.16%. Increasing the number of lags only reduces return by a small amount for portfolio

Table 3

Alternative Moving Average Lag Lengths

Average returns (Avg Ret) and Fama and French (1992) alphas (FF α) of the MAPs are reported using a 20-, 50-, 100- and a 200-day moving average timing strategy. The analysis uses European risk factors. All results are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively. The sample period spans form January 1990 until December 2016.

	MAP(20)		MAP(50)		MAP(100)		MAP(200)	
Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
1 (Low)	1.92***	1.92***	1.87***	1.87***	1.75***	1.75***	1.70***	1.70***
	(8.50)	(8.50)	(9.15)	(9.00)	(8.99)	(8.93)	(9.15)	(9.06)
2	1.65***	1.63***	1.76***	1.74***	1.54***	1.52***	1.24***	1.22***
	(4.74)	(4.85)	(5.13)	(5.24)	(4.70)	(4.90)	(3.94)	(3.97)
3	2.11*	2.88***	2.74**	3.54***	2.21**	2.97***	1.72	2.38**
	(1.86)	(2.74)	(2.34)	(3.29)	(1.95)	(2.82)	(1.62)	(2.35)
4	3.44**	4.63***	3.33**	4.53***	2.40	3.55***	2.46*	3.50***
	(2.17)	(3.33)	(2.10)	(3.22)	(1.55)	(2.58)	(1.70)	(2.63)
5	6.38***	8.14***	4.98***	6.68***	6.06***	7.71***	3.35**	4.87***
	(3.56)	(4.84)	(2.81)	(3.93)	(3.41)	(4.48)	(1.96)	(2.86)
6	6.88***	8.90***	4.79**	6.88***	4.65**	6.62***	1.28	3.11*
	(3.42)	(4.80)	(2.38)	(3.75)	(2.38)	(3.67)	(0.67)	(1.70)
7	8.43***	10.18***	6.13***	7.88***	6.78***	8.53***	3.94	5.49**
	(3.40)	(4.46)	(2.46)	(3.39)	(2.66)	(3.56)	(1.58)	(2.27)
8	8.51***	10.87***	8.67***	10.92***	7.85***	10.11***	3.02	5.42**
	(3.30)	(4.73)	(3.36)	(4.65)	(3.00)	(4.19)	(1.13)	(2.21)
9	11.53***	13.43***	9.46***	11.35***	8.24***	10.17***	4.30	5.81**
	(3.57)	(4.72)	(2.89)	(3.94)	(2.52)	(3.54)	(1.32)	(1.95)
10 (High)	−11.73***	−10.85***	−3.06	−2.04	−2.00	−1.23	−1.33	−0.86
	(−2.58)	(−2.58)	(−0.70)	(−0.52)	(−0.48)	(−0.32)	(−0.33)	(−0.23)
High - Low	−11.31***	−10.43***	−3.43	−2.39	−1.42	−0.66	−1.32	−0.85
	(−2.48)	(−2.47)	(−0.79)	(−0.60)	(−0.34)	(−0.17)	(−0.33)	(−0.23)

1 to 9. Remarkable is however, that for portfolio 10 using longer lag lengths also increases the average return. Where portfolio 10 yields a negative return of -11.73% using a 20-day MA strategy, this negative return increases to -1.33% if a 200-day MA is applied. One possible explanation could be that, as was put forward in the previous section, most of the profit in the highest-volatility decile is made in the same day the trading signal changes to BUY. By design the MA timing strategy is too slow to detect this. However, by using longer lag lengths, the portfolio is held over a broader horizon and captures a longer trend. The MA timing strategy benefits in a way that return is generated because the portfolio was already acquired.

Analyzing the table vertically, we detect a weak monotonic increase of returns across deciles for all the different MA timing strategies. This relation is weakest for the 200-day MA strategy. However, disregarding the highest and the lowest deciles the relation is quite clear for the MAP(20, 50, 100). These results are similar to what was already reported for the 10-day MA strategy. Moreover, this strengthens the notion of the second hypothesis, which stated that high-information-uncertain stocks are expected to yield larger alpha's than low-information-uncertain stocks due to a positive correlation between volatility levels and corresponding stock returns.

5.2 Business Cycles

In the following subsection the MA timing strategy is exposed to both bull and bear market conditions, to control for possible market trends. In two separate analyses the MAPs from the Dutch stock market are regressed on Fama and French (1992) three-factor model together with either a bull market dummy variable (BULL) or a bear market dummy variable (BEAR). The latter is yearly data directly retrieved from the OECD Composite Leading Indicators, whereas the former is specified as a yearly dummy with a positive return in the previous year (Han et al., 2013). The estimated regression model is as follows,

$$\begin{aligned} MAP_{jt,L} \quad &= \quad \alpha_j + \beta_{j,MKT} R_{MKT,t} + \beta_{j,SMB} R_{SMB,t} + \beta_{j,HML} R_{HML,t} \\ &\quad + \beta_{j,x} Dummy_{x,t} + \epsilon_{jt}, \qquad\qquad j = 1, \ldots, 10 \end{aligned} \tag{11}$$

where x denotes either the bull or bear market dummy variable. The alphas, dummy coefficients and adjusted R^2 from the regression results are reported in Table 4.

In this analysis the alpha is neglected and only the dummy coefficients are examined, since the alpha is interpreted as the benchmark effect of the dummy variable. Panel A represents the bear market condition. Considering the dummy coefficients it is evident that the effect increases across deciles, as was found previously. Although only half of them are statistically significant, the difference is quite big. Where the lowest two volatility deciles show a negative coefficient, the betas turn more positive with increasing volatility. The positive betas indicate that the MAPs are more exposed to recessionary periods than to expansionary periods, implying that the MA timing strategy generates larger abnormal returns under bear market conditions. Panel B under bull market conditions, confirms this. It demonstrates an opposite pattern to the one documented in Panel A, with most of the dummy coefficients being negative. The table suggests that on average the MA timing strategy increases the volatility anomaly by 3.40 percentage points in the bear market and decreases it by 5.21 percentage points in the bull market. It can be concluded that the MAP effect found previously is largely dominated by the bear market periods. Based on this it can be proposed an investor applies, if possible, the MA timing strategy only during recessionary periods and tries to avoid expansionary periods.

Table 4

Bull and Bear Market conditions

Panel A of Table 4 presents the regression output of the MAPs from the Dutch stock market based on the Fama and French (1992) three-factor model included with an OECD based bear market dummy variable for the Netherlands. Hence, the model estimated is; $MAP_{jt,L} = \alpha_j + \beta_{j,MKT}R_{MKT,t} + \beta_{j,SMB}R_{SMB,t} + \beta_{j,HML}R_{HML,t} + \beta_{j,x}Dummy_{x,t} + \epsilon_{jt}$, where x represents the bear market in case of Panel A. Reported are the alphas, dummy coefficients (β_{BEAR}) and adjusted R^2. In Panel B, using the same regression model, x represents the bull market dummy variable, which denotes 1 when last years average return was positive. Reported are the alphas, regression coefficients (β_{BULL}) and adjusted R^2. In both panels a 10-day moving average timing strategy and European risk factors are applied. The sample period spans form January 1990 until December 2016. Both the alphas and the dummy betas are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	Panel A. With Bear Market Dummy			Panel B. With Bull Market Dummy		
Rank	α	β_{BEAR}	Adj. R^2 (%)	α	β_{BULL}	Adj. R^2 (%)
1 (Low)	2.93***	−1.77***	0.66	1.07***	1.36***	0.56
	(7.78)	(−3.79)		(3.32)	(3.07)	
2	2.14***	−1.05*	3.26	0.61	1.44*	3.28
	(6.07)	(−1.64)		(0.81)	(1.76)	
3	0.53	3.86*	17.02	3.57**	−1.49	16.99
	(0.39)	(1.84)		(2.42)	(−0.74)	
4	3.88**	0.19	24.99	5.94***	−2.88	25.00
	(2.28)	(0.07)		(2.53)	(−1.00)	
5	6.66***	3.63	27.84	9.24***	−1.00	27.83
	(3.45)	(1.15)		(3.30)	(−0.29)	
6	10.26***	−0.77	29.16	11.78***	−2.81	29.16
	(4.44)	(−0.22)		(3.86)	(−0.75)	
7	7.05***	8.33**	27.70	19.48***	−11.82**	27.73
	(2.84)	(1.94)		(4.31)	(−2.31)	
8	8.18***	7.62*	27.49	20.23***	−11.81**	27.52
	(2.84)	(1.75)		(4.89)	(−2.43)	
9	7.77***	7.87	18.93	16.46***	−6.70	18.92
	(2.48)	(1.41)		(2.53)	(−0.94)	
10 (High)	−23.83***	−5.77	3.65	−17.11**	−14.24	3.66
	(−4.19)	(−0.62)		(−1.98)	(−1.39)	

5.3 Trading Behavior and Transaction Costs

This subsection addresses the trading behavior of the MA timing strategy and evaluates the abnormal return in consideration with transaction costs. Given that the strategy uses trading signals on daily basis, it is important to examine the trading frequency of the strategy. For this assessment the average holding days, trading frequency and the break-even transaction costs are analyzed. Table 5 reports the results using a 10-, 20-, 50-, 100- and a 200-day MA timing strategy.

Considering the average holding days it appears decile 5 to 7 have the longest average holding period across deciles. The average holding days increases with longer lag lengths.

Table 5

Trading Behavior and Transaction Costs

Table 5 presents the trading behavior of the moving average (MA) timing strategy. Reported are the average holding days per trade (Holding), trading frequency defined as the number of trades relative to total number of observations (Trading) and the break-even transaction costs (BETC). The BETC is defined as the average return divided by the number of trades, so that it equalizes the average return of the MAPs to zero. The BETC is reported in basis points and for the analyses a 10-, 20-, 50-, 100- and a 200-day MA strategy is applied. The sample period spans form January 1990 until December 2016.

	MA(10)			MA(20)			MA(50)			MA(100)			MA(200)		
Rank	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC
1 (Low)	3.28	0.02	33.27	6.37	0.02	40.87	16.94	0.01	78.31	33.24	0.01	119.90	66.55	0.00	200.70
2	3.56	0.04	15.91	6.32	0.03	20.67	11.93	0.02	30.90	27.09	0.01	49.35	48.64	0.01	57.71
3	4.89	0.08	8.53	9.15	0.05	15.70	19.58	0.03	38.05	34.95	0.02	48.69	70.72	0.01	68.68
4	5.20	0.09	11.55	10.97	0.05	26.83	21.25	0.03	46.76	30.92	0.02	47.54	55.09	0.01	81.05
5	6.41	0.08	30.46	13.60	0.04	56.60	27.76	0.02	84.09	53.71	0.01	196.94	65.32	0.01	126.25
6	6.50	0.08	35.18	13.24	0.04	59.27	24.48	0.03	71.20	38.48	0.02	105.05	51.33	0.01	37.41
7	6.61	0.08	43.08	14.19	0.04	76.37	22.80	0.03	86.68	41.65	0.01	169.41	61.08	0.01	138.53
8	6.25	0.08	42.61	12.79	0.04	72.81	25.26	0.02	140.03	42.48	0.01	210.41	55.01	0.01	103.15
9	5.66	0.09	41.61	11.75	0.05	93.36	20.60	0.03	133.74	36.04	0.02	192.90	47.58	0.01	122.88
10 (High)	4.75	0.11	−95.64	9.20	0.06	−73.64	18.46	0.03	−36.89	28.66	0.02	−35.78	50.46	0.01	−38.97

For example, applying a 10-day MA timing strategy results in an average holding period ranging from 3 to 7 days, whereas using a 200-day MA timing strategy renders an average holding period of about 48 to 67 days. Not surprisingly, since longer lag lengths operate at a broader horizon and therefore capture longer trends. Furthermore, trading frequency is defined as the fraction of trades relative to the total number of trading days in the sample. Analyzing the trading frequency, it is as expected that the higher-volatility deciles trade more often than the lower-volatility deciles. Using the same line of reasoning as for the average holding days it is evident that longer lag lengths result in a smaller fraction of trades. With a 10-day MA timing strategy trading frequency ranges between 2% and 11% compared to a 200-day MA timing strategy that only trades 1% of the days.

Incorporating transaction costs into the model is a difficult task, since it is hard to estimate the appropriate level of costs. It is common knowledge that transaction costs consist of different elements e.g., broker commission, exchange fees, settlement fees. However, these fees and commissions vary considerably across brokers. According to the most recent trading fee guide of Euronext, they charge their members €0.15 per executive order and 0.45 to 0.95 basis points (bps) depending on the order volume. For bonds there is only a fixed fee of €2.00 per order. For the sake of simplicity, it is assumed no transaction costs are incurred for trading the risk-free asset. Hence, transaction costs are only relevant regarding the decile portfolios. Furthermore, since the prices mentioned are still without a broker commission, which can vary significantly, this study applies the break-even transaction costs (BETC). The BETC is defined as the amount of basis points per trade that equalizes the average return of the MAPs to zero. The results are reported in every third column of Table 5. Contrary to what would be expected based on trading frequency, the BETC increases across deciles. This is remarkable, since it suggests that larger average returns are generated on the higher-volatility portfolios even though the these portfolios are traded more often than the lower-volatility portfolios. Comparing the BETC across the different lags it is evident MA(100) has the highest BETC, about 210 bps for decile 8. The lowest BETC is documented for decile 3 under MA(10) with 8.53 bps. In general, a pattern is visible of higher BETC with the use of longer lag lengths, implying that the MA timing strategy operates more efficiently when longer lags are used. Overall, the break-even levels are reasonably high, suggesting the abnormal returns will likely persist after considering transaction costs.

6 Applicability of the MA Timing Strategy

In order to further fill the gap in the literature of European studies on technical analysis, the following section explores the applicability of the MA timing strategy in other Western European countries. First, these countries are examined together as a proxy for Western Europe (WE), which enables a more accurate comparison with the US stock market. Thereafter, they are studied separately to put beside the results of the MAPs from the Netherlands. For the analysis the following countries are considered: Belgium, France, Germany, Italy, the Netherlands, Spain and Sweden. All these countries have a sufficient number of stocks available during the sample period (January 1990 - December 2016) and are therefore selected for this sample.

6.1 Western Europe

Together these countries form an proxy for the Western European stock market. Table 6 reports all the essential results and is presented in the same structure as Table 1. It includes the buy-and-hold strategy, the MA timing strategy using a 10-day MA as well as the MAPs. Additionally, the alphas of the Fama and French (1992) three-factor model are also added to the table. In total 9,853 stocks are used in this analysis, during the complete sample period from January 1990 until December 2016. The average number of stocks per decile varies across years between 400 stocks at the end op 2008 and 209 stocks at the start of the sample period in 1990.

Examining the buy-and-hold strategy and the MA timing strategy it is evident the latter strategy is substantially more profitable. The best example is portfolio 9, where the average return increased almost by 17 percentage points. This is noticeably more than what was reported for the Dutch stock market, where the greatest difference was 10 percentage points. Overall, the average return across deciles for the MA timing strategy (Panel B) is nearly double the average return compared to that of the Netherlands, 19.36% versus 10.78% per year. Together with a larger return, the MA timing strategy also considerably reduces the standard deviation. Aside from the first two deciles, the standard deviations from the European sample are even smaller related to those presented in Table 1, though returns are larger. Naturally, larger returns and smaller standard deviations result in higher Sharpe ratios, as is confirmed by the table. From the lowest-decile to the highest-decile a strong increase in Sharpe ratios is visible, ranging from

-0.43 to 5.38. Remarkably, the Sharpe ratios are substantially higher than those for MA timing strategy in the Dutch market, where the highest reported was 1.47. Exploring the return of the MAPs, shows an annual average return across deciles of precisely 9%. This is almost four times the return documented for the Netherlands, 2.42% per year. Apparently the increase in return is not due an improvement of the strategy, since the success rate, which was defined as the fraction of trading days that the return of the MAP exceeds the risk-free rate, did not change by much. The accumulation of the stocks made the monotonic increase of return across deciles significantly more visible, only the highest-decile alters a little from the general pattern.

Table 6

An Western European country sample

Table 6 uses all local traded stocks from a sample of Western European countries, which includes: Belgium, France, Germany, Italy, the Netherlands, Spain and Sweden. Panel A to C report the average return (Avg Ret) and the standard deviation (Std Dev) for all 10 decile portfolios. Panel A presents the buy-and-hold benchmark portfolios, where as Panel B reports the moving average (MA) timing decile portfolios using a 10-day MA. In Panel C the MA portfolios (MAPs) are given, which is the difference between the MA timing portfolios and the buy-and-hold portfolios. Furthermore, the table reports the annualized Sharpe ratio (SRatio) for the buy-and-hold strategy and the MA timing strategy, as well as the success rate for the MAPs. Lastly, Panel D provides the alphas (FF α) and the adjusted R^2 of the Fama and French (1992) three-factor model using European risk factors. The sample period spans form January 1990 until December 2016. All results are annualized and returns are in percentages. Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	Panel A. Buy-and-Hold Strategy			Panel B. MA Timing Strategy			Panel C. MAP			Panel D. 3-factor model	
Rank	Avg Ret	Std Dev	SRatio	Avg Ret	Std Dev	SRatio	Avg Ret	Std Dev	Succeess	FF α	Adj. R^2 (%)
1 (Low)	0.13	4.54	−0.53	1.34***	2.77	−0.43	1.21*	3.61	0.49	1.38**	6.00
	(0.15)			(2.56)			(1.77)			(2.14)	
2	−0.38	4.85	−0.60	2.22***	2.87	−0.11	2.60***	3.92	0.47	2.92***	7.60
	(−0.42)			(4.09)			(3.52)			(4.01)	
3	2.98***	6.05	0.07	8.54***	3.36	1.78	5.56***	5.01	0.46	6.42***	28.96
	(2.61)			(13.44)			(5.87)			(7.02)	
4	5.52***	7.63	0.39	13.66***	4.30	2.59	8.14***	6.25	0.46	9.47***	36.56
	(3.83)			(16.81)			(6.89)			(8.67)	
5	6.54***	9.12	0.44	16.36***	5.30	2.61	9.82***	7.35	0.46	11.43***	38.99
	(3.80)			(16.35)			(7.06)			(9.08)	
6	7.32***	9.76	0.49	18.27***	5.77	2.73	10.95***	7.79	0.46	12.54***	38.17
	(3.97)			(16.76)			(7.44)			(9.43)	
7	7.04***	10.59	0.42	20.36***	6.27	2.84	13.32***	8.43	0.47	14.86***	38.62
	(3.52)			(17.19)			(8.36)			(10.31)	
8	7.10***	11.29	0.40	23.19***	6.90	2.99	16.09***	8.80	0.47	17.34***	36.64
	(3.32)			(17.80)			(9.68)			(11.05)	
9	10.24***	12.13	0.63	27.21***	7.76	3.18	16.98***	9.15	0.48	17.55***	33.03
	(4.47)			(18.57)			(9.81)			(10.65)	
10 (High)	57.16***	14.15	3.86	62.44***	11.14	5.38	5.28***	8.59	0.49	4.92***	21.30
	(21.38)			(29.65)			(3.26)			(3.13)	
High - Low	57.03***	14.00	3.89	61.10***	11.34	5.16	4.07***	8.74	0.48	3.54**	13.85
	(21.56)			(28.51)			(2.47)			(2.14)	

Consider further Panel D, which presents the regression output of the MAPs based on the FF three-factor model. Parallel to previous results, alphas (FF α) documented in Panel D are larger than the average returns. Only the highest-volatility decile shows a slightly smaller abnormal return. Furthermore, Table A2 in the Appendix presents the full regression output of the MAPs under the CAPM and the FF three-factor model. In line with the results of Table 2, which displayed the similar regression model but for the Dutch stock market alone, the betas from the market and size factor indicate a negative exposure of the MAPs towards these factors. The value factor demonstrates mainly positive coefficients and increases with volatility. Similar to what was found earlier, the FF three-factor model does not show much more explanatory power than the CAPM. However, increasing the number of stocks in the sample did increase the adjusted R^2 by about 10 percentage points compared to the Netherlands.

Now, having a proxy for the Western European stock market enables making a better comparison with the US. Not quite unexpected, the results documented by Han et al. (2013) for the US stock market are in most cases superior to those of WE. In the US for example, the average return of the MAPs across deciles is 12.28% per year, whereas WE reports an average of 9.00% per year. Especially in lower-volatility deciles the return in the US is much larger. For instance, the lowest-volatility decile in the US presents an average return of 8.42% per year compared to only 1.21% per year in WE. Similar to the US, the MAPs in WE under the CAPM and the FF three-factor model (Table A2) have larger abnormal returns and show negative exposure to the market and size factor. In contrast to the US, the value factor reports a positive exposure.

6.2 A Cross-Country Analysis

To further verify the applicability of the MA timing strategy in Europe this study examines all the countries separately. Inspecting these countries separately gives a better view of the performance of the MAPs and allows comparing the results to the Dutch stock market.

Table 7 reports the average return and the Fama and French (1992) alphas using a 10-day MA strategy for all the countries in the European sample. The total number of stocks used for this analysis varies across countries between 307 and 2535 stocks, for Spain and Germany respectively. A brief look at the table verifies that all countries experience the same monotonic increase of returns across deciles as was demonstrated for the Dutch stock market. However, in some countries the correlation is stronger than others. Italy, for example, poses the strongest correlation across deciles, while Belgium presents the weakest. Comparing the results to the abnormal returns of the Dutch stock market, it becomes clear most countries perform considerably better than the Netherlands. The average return across deciles for the Dutch stock market yielded 2.42% on annual basis. Only Belgium scores below this level with an average return of 2.02% per year. Italy performs the best within the sample followed by Germany, respectively 16.59% and 9.71% per year. The largest difference in average return between the Netherlands and Italy is found in the highest decile, with -27.74% versus 27.27% per year. Spain and Sweden also show a positive average return for portfolio 10, this in contrast to the Netherlands and

Table 7

Alternative Countries

Average returns (Avg Ret) and Fama and French (1992) alphas (FF α) of the MAPs are reported for a sample of Western European countries. The country sample includes: Belgium, France, Germany, Italy, Spain and Sweden. A 10-day moving average timing strategy and European risk factors are applied for this analysis. All results are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively. The sample period spans form January 1990 until December 2016.

	Belgium		France		Germany		Italy		Spain		Sweden	
Rank	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α	Avg Ret	FF α
1 (Low)	0.75	1.19	3.09***	3.62***	1.73***	2.23***	6.38***	7.24***	3.35***	3.62***	1.16	1.34
	(0.83)	(1.33)	(4.42)	(4.86)	(2.42)	(3.11)	(6.63)	(7.53)	(4.87)	(5.20)	(1.14)	(1.36)
2	1.37	2.15**	5.01***	6.00***	4.52***	5.62***	9.03***	10.64***	5.02***	5.71***	1.36	1.53
	(1.30)	(2.13)	(5.07)	(6.01)	(3.86)	(5.04)	(6.11)	(7.35)	(4.95)	(5.58)	(1.33)	(1.54)
3	3.34***	4.20***	7.95***	9.18***	6.32***	7.62***	12.44***	14.60***	4.25***	5.50***	2.67***	2.88***
	(2.76)	(3.55)	(6.78)	(7.89)	(4.57)	(5.76)	(6.48)	(7.78)	(2.90)	(3.83)	(2.54)	(2.74)
4	1.56	2.56**	8.78***	10.22***	8.23***	9.57***	15.49***	17.92***	5.24***	6.99***	4.12***	4.34***
	(1.15)	(1.92)	(6.54)	(7.88)	(5.42)	(6.83)	(6.98)	(8.58)	(2.74)	(3.78)	(3.67)	(3.74)
5	3.45***	4.53***	9.17***	10.69***	11.45***	12.81***	15.11***	17.82***	6.29***	8.21***	3.48***	3.71***
	(2.46)	(3.23)	(6.66)	(8.13)	(6.94)	(8.07)	(6.33)	(8.22)	(3.29)	(4.62)	(3.05)	(3.21)
6	1.73	2.84*	10.46***	11.98***	14.05***	15.23***	19.34***	22.33***	10.45***	12.88***	3.21***	3.46***
	(1.07)	(1.78)	(7.19)	(8.64)	(7.71)	(8.86)	(7.41)	(9.22)	(4.82)	(6.70)	(2.73)	(2.90)
7	7.21***	8.80***	10.55***	11.82***	17.50***	18.54***	18.81***	21.66***	7.51***	9.80***	3.71***	3.95***
	(3.93)	(4.81)	(7.23)	(8.12)	(8.22)	(9.15)	(7.12)	(8.93)	(3.10)	(4.34)	(3.08)	(3.36)
8	6.19***	7.49***	10.29***	11.26***	19.39***	20.10***	20.37***	23.56***	15.12***	18.13***	7.53***	8.47***
	(3.34)	(4.08)	(6.90)	(7.36)	(9.04)	(9.64)	(6.96)	(8.84)	(5.36)	(6.89)	(4.13)	(4.99)
9	6.38***	7.67***	6.72***	7.00***	14.33***	14.37***	21.70***	24.33***	15.77***	18.46***	14.24***	15.92***
	(3.04)	(3.66)	(4.35)	(4.48)	(6.36)	(6.38)	(7.47)	(8.82)	(5.48)	(6.80)	(5.23)	(6.52)
10 (High)	−11.73***	−11.19***	−5.85***	−5.85***	−0.45	−1.25	27.27***	29.69***	14.71***	17.17***	8.50***	9.50***
	(−3.35)	(−3.28)	(−3.45)	(−3.42)	(−0.18)	(−0.50)	(8.22)	(9.30)	(4.33)	(5.34)	(2.73)	(3.31)
High - Low	−12.48***	−12.38***	−8.94***	−9.47***	−2.18	−3.48	20.89***	22.45***	11.35***	13.55***	7.34***	8.16***
	(−3.53)	(−3.61)	(−5.07)	(−5.30)	(−0.84)	(−1.33)	(6.79)	(7.43)	(3.36)	(4.24)	(2.52)	(2.96)

the other countries. Examining the alphas of the FF three-factor model, it follows that for all countries applying the model increases the abnormal return. Overall, it is evident all countries within this sample show the same general pattern and similar effects as was documented for the Netherlands. It can be concluded that the MA timing strategy is profitable not only in the Netherlands, but also in other Western European countries.

7 Robustness

Together Section 4 and 5 presented the results for the MA timing strategy in the Dutch stock market. This section provides various robustness checks to these results. First, the MAPs are exposed to the momentum factor of the Carhart (1997) four-factor model. Second, the MAPs are exposed to the profitability and the investment factor of the Fama and French (2015) five-factor model.

7.1 The Four-Factor Model

The Carhart (1997) four-factor model is applied to assess whether the abnormal return of the MAPs can in some way be explained by the momentum effect. The momentum factor is based on the concept of going long in past winners and short in past losers, as is explained previously. Both the momentum factor (*UMD*) as well as the MAPs are trend-following and zero-cost portfolios (Han et al., 2013). Therefore, correlations between the momentum factor and the MAPs are computed first. Across deciles the correlations range from -0.01 to 0.15, which are low and would suggest a weak sensitivity of the MAPs towards the momentum factor. To verify this and examine the exposure of the MAPs to the momentum effect, the following regression model is applied,

$$\begin{aligned} MAP_{jt,L} \quad = \quad & \alpha_j + \beta_{j,MKT} R_{MKT,t} + \beta_{j,SMB} R_{SMB,t} + \beta_{j,HML} R_{HML,t} \\ & + \beta_{j,UMD} R_{UMD,t} + \epsilon_{jt}, \qquad\qquad j = 1, \ldots, 10 \end{aligned} \tag{12}$$

the output is documented in Table 8. The alphas are the largest that are documented so far, ranging from 1.55% to 12.36% per year. The average across deciles is 4.05% anunally, almost twice the average return across deciles reported for the MAPs. Similar to the CAPM and the FF three-factor model, Table 8 shows a clear increase in abnormal return from decile 2 to decile 8, with decile 9 being slightly smaller. The larger abnormal returns are due to the integration of the momentum factor, which strengthened the sensitivity of the market, size and value factors. Market and size betas became more negative, whereas the value betas more positive. The momentum factor itself shows mostly positive betas, though all but one are statistically insignificant. The insignificance confirms the implication of a low correlation between the MAPs and the momentum factor. Interesting is however, when the number of lags used in the MA timing strategy is increased this also increases the sensitivity of the MAPs towards the momentum factor. Table A3 in the Appendix substantiates this. The table presents the regression output of the MAPs based on the Carhart (1997) four-factor model, similar to Table 8. However, the analysis uses various lag lengths for the MA timing strategy (L = 20, 50, 100, 200).

Table 8

Four-Factor Model Results

Table 8 presents the regression output of the MAPs under the Carhart (1997) four-factor model. Reported are the alphas, betas from the four risk factors and adjusted R^2. The analysis uses a 10-day moving average timing strategy and European risk factors. The sample period spans form January 1991 until July 2016. Alphas are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

Rank	α	β_{MKT}	β_{SML}	β_{HML}	β_{UMD}	Adj. R^2 (%)
1 (Low)	2.05***	0.00***	−0.01***	0.01***	0.00	0.32
	(8.64)	(−4.39)	(−2.74)	(3.99)	(−0.04)	
2	1.55***	−0.02***	−0.02***	0.04***	0.01	3.35
	(4.66)	(−5.46)	(−4.88)	(5.54)	(1.42)	
3	2.55**	−0.15***	−0.04**	0.05***	0.03***	17.56
	(2.28)	(−8.31)	(−2.18)	(3.27)	(2.61)	
4	3.59***	−0.25***	−0.06***	0.05	0.02	25.09
	(2.46)	(−13.67)	(−2.48)	(1.62)	(0.87)	
5	8.50***	−0.30***	−0.08***	−0.03	0.00	27.97
	(4.93)	(−14.04)	(−2.80)	(−0.69)	(0.17)	
6	10.28***	−0.33***	−0.03	−0.06**	−0.02	29.33
	(5.45)	(−16.22)	(−0.94)	(−2.03)	(−1.02)	
7	11.74***	−0.38***	−0.01	0.10***	0.01	26.47
	(5.08)	(−15.00)	(−0.36)	(2.57)	(0.30)	
8	12.36***	−0.40***	−0.04	−0.04	0.00	26.53
	(5.27)	(−17.60)	(−1.42)	(−0.89)	(0.11)	
9	11.95***	−0.40***	−0.03	0.16***	0.04	17.60
	(4.01)	(−13.84)	(−0.66)	(2.96)	(1.28)	
10 (High)	−24.11***	−0.30***	−0.06	0.22***	−0.01	3.73
	(−5.02)	(−8.19)	(−1.28)	(3.20)	(−0.25)	
High - Low	−26.15***	−0.29***	−0.06	0.21***	−0.01	3.66
	(−5.44)	(−8.06)	(−1.10)	(3.12)	(−0.25)	

Reported are only the alphas and the momentum betas. First of all note the improvement in statistical significance by expanding the number of lagged days. It is clear that the MAPs are positively correlated to the momentum factor. Not only do the momentum betas increase with increasing volatility, they also increase with the use of longer lags. In general, a positive coefficient for the momentum factor implies that the MA timing strategy is more exposed to recent winners than the buy-and-hold strategy. The positive relationship between the MA timing strategy and the momentum factor is realistic, since both are trend-following portfolios (Han et al., 2013). Increasing the number of days at which the MA timing strategy operates appears to even strengthen the relationship. Nevertheless, adding the momentum factor did not alter the explanatory power of the model by much. The increase of the adjusted R^2 compared to the FF three-factor model is is almost negligible, which is also the case with the alternative lag lengths.

7.2 The Five-Factor Model

Table 9 further exploits the exposure of return of the MAPs to other risk factors of the Fama and French (2015) five-factor model. Applying the FF five-factor model this study

Table 9

Five-Factor Model Results

Table 9 presents the regression output of the MAPs under the Fama and French (2015) five-factor model. Reported are the alphas, betas from the five risk factors and adjusted R^2. The analysis uses a 10-day moving average timing strategy and European risk factors. The sample period spans form January 1990 until December 2016. Alphas are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

Rank	α	β_{MKT}	β_{SML}	β_{HML}	β_{RMW}	β_{CMA}	Adj. R^2 (%)
1 (Low)	2.05***	−0.01***	−0.01***	0.01***	−0.01	−0.01***	0.48
	(8.89)	(−5.20)	(−3.57)	(3.84)	(−1.67)	(−4.37)	
2	1.54***	−0.02***	−0.02***	0.04***	0.01	0.01	3.24
	(4.84)	(−5.01)	(−4.61)	(4.44)	(0.78)	(1.14)	
3	2.37**	−0.15***	−0.02	0.04**	0.02	0.02	17.00
	(2.17)	(−8.22)	(−1.62)	(2.18)	(0.81)	(0.85)	
4	3.28**	−0.24***	−0.04*	0.08**	0.12***	−0.01	25.01
	(2.34)	(−13.61)	(−1.85)	(2.23)	(2.53)	(−0.33)	
5	8.12***	−0.29***	−0.06***	−0.04	0.05	0.08**	27.84
	(4.76)	(−13.97)	(−2.45)	(−0.64)	(0.53)	(2.26)	
6	9.66***	−0.31***	−0.02	−0.09**	−0.01	0.12***	29.17
	(5.35)	(−16.01)	(−0.80)	(−2.41)	(−0.17)	(3.38)	
7	9.41***	−0.34***	0.01	0.08*	0.24***	0.26***	27.69
	(4.29)	(−14.73)	(0.41)	(1.81)	(3.57)	(5.74)	
8	10.51***	−0.36***	−0.02	−0.08*	0.17***	0.30***	27.48
	(4.70)	(−16.92)	(−0.49)	(−1.77)	(3.23)	(6.28)	
9	9.74***	−0.35***	0.01	0.07	0.23***	0.38***	18.92
	(3.44)	(−11.77)	(0.32)	(1.23)	(3.30)	(5.97)	
10 (High)	−27.72***	−0.25***	−0.04	0.13*	0.05	0.29***	3.65
	(−5.89)	(−6.75)	(−0.71)	(1.80)	(0.51)	(3.45)	
High - Low	−29.78***	−0.25***	−0.03	0.13*	0.05	0.30***	3.61
	(−6.32)	(−6.59)	(−0.51)	(1.71)	(0.56)	(3.56)	

analyzes whether the return of the zero-cost portfolios can be explained to either the profitability (RMW) or investments (CMA) factor. The following regression model is used,

$$\begin{aligned} MAP_{jt,L} \quad = \quad & \alpha_j + \beta_{j,MKT} R_{MKT,t} + \beta_{j,SMB} R_{SMB,t} \\ & + \beta_{j,HML} R_{HML,t} + \beta_{i,RMW} R_{RMW,t} \\ & + \beta_{i,CMA} R_{CMA,t} + \epsilon_{jt}, \qquad\qquad j = 1, \ldots, 10 \end{aligned} \tag{13}$$

the results are presented in the table above. The abnormal returns are still slightly larger under the five-factor model than the average return of the MAPs. Only portfolios 2, 7 and 9 show smaller alphas. Compared to the FF three-factor model they are all smaller though. The average across deciles is 2.89% per year for the alphas versus 2.42% per year for the average return of the MAPs. The correlation between the alphas and the level of volatility weakened somewhat, but remains visible across deciles. Examining the market, size and value betas, show the effect that was documented for the FF three-factor model became weaker. The betas from the market and size factor increased to a small degree, while the value betas decreased. However, the signs in front of the betas stayed the same. Turning to the effect of the profitability and investment factor, it is evident that most betas are positive, though not all statistically significant. The positive betas of the profitability factor imply that the MA timing strategy is more exposed to stocks with robust profitability (high risk) than is the buy-and-hold strategy. The same can be said for the investment factor, positive betas indicate that the MA timing portfolios puts more weight to stocks with a conservative investment strategy (high risk) compared to the underlying buy-and-hold portfolios. The correlation between risk and volatility is further evidenced by a small increase in betas from the lowest-decile portfolio to higher-deciles for both factors. On model fitting, the FF five-factor model does not seem to have any additional explanatory power than the three-factor model or even the CAPM. This is substantiated by the lack in increase of the adjusted R^2 and the little change in the risk factors.

8 Concluding Remarks

The aim of this paper has been to shed light on the profitability of technical analysis in the Dutch stock market. By using a standard moving average (MA) timing strategy applied to volatility sorted portfolios, this study shows positive abnormal returns for nine out of ten portfolios. Substantially outperforming the buy-and-hold portfolios, the MA timing strategy has proved to be a profitable zero-cost investment strategy. The abnormal returns sustained after regressing the differences in return (MAPs) on the Fama and French (1992) three-factor model. The MAPs showed negative exposure towards the market and size factor, whereas the value factor only displayed little positive exposure. Exposing the MAPs to bull and bear market conditions revealed that the MA timing strategy improves the volatility anomaly in the bear market but reduces it in the bull market. Furthermore, the results held for MA signals with alternative lag lengths and lasted after considering transaction costs. Applying this MA timing strategy to various Western European countries provided similar results. Although the alphas reported for the Netherlands were among the smallest of considered European countries, the general findings showed equal patterns and effects. In conclusion, the answer to the research question: 'do volatility sorted portfolios yield positive abnormal returns using a moving average strategy in the Dutch stock market?' is yes. In turn, this justifies the application and profitability of technical analysis in the Dutch stock market.

The limitations of this paper provide several important topics for further research. This study encountered multiple problems that could be addressed. For practical reasons only local traded stocks from the Euronext Amsterdam stock exchange were used in the analysis. To improve the statistical significance of the results and the explanatory power of the different models, the dataset could be expanded with the foreign stocks traded at the Euronext Amsterdam. Furthermore, this paper has used equal-weighted portfolios, in which the stocks with a small market capitalization are more heavily represented. According to literature (Fama and French (1992)), small capitalization stocks capture higher risks and hence, have a higher expected return. Therefore, future research should also focus on value-weighted portfolios, to control for these differences in market capitalization.

References

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics*, *49*(3), 307–343.

Black, F. (1986). Noise. *The journal of finance*, *41*(3), 528–543.

Blume, L., Easley, D., & O'Hara, M. (1994). Market statistics and technical analysis: The role of volume. *The Journal of Finance*, *49*(1), 153–181.

Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investment and portfolio management.* McGraw-Hill Irwin.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of finance*, *47*(5), 1731–1764.

Brown, D. P., & Jennings, R. H. (1989). On technical analysis. *Review of Financial Studies*, *2*(4), 527–551.

Buttonwood. (2017, May 27). *Why are american bond yields higher than europe's?* Retrieved from www.economist.com/blogs/economist-explains/2017/03/economist-explains-21

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57–82.

Cespa, G., & Vives, X. (2012). Dynamic trading and asset prices: Keynes vs. hayek. *The Review of Economic Studies*, *79*(2), 539–580.

Edwards, R. D., Magee, J., & Bassetti, W. C. (2012). *Technical analysis of stock trends.* CRC Press.

Elton, E. J., & Gruber, M. J. (1997). Modern portfolio theory, 1950 to date. *Journal of Banking & Finance*, *21*(11), 1743–1759.

Eun, C. S., & Shim, S. (1989). International transmission of stock market movements. *Journal of financial and quantitative Analysis*, *24*(2), 241–256.

Fabozzi, F. J., Gupta, F., & Markowitz, H. M. (2002). The legacy of modern portfolio theory. *The Journal of Investing*, *11*(3), 7–22.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383–417.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427–465.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), 55–84.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of financial Economics*, *19*(1), 3–29.

Goh, J., Jiang, F., Tu, J., & Zhou, G. (2013). Forecasting government bond risk premia using technical indicators.

Grundy, B. D., & McNichols, M. (1989). Trade and the revelation of information through prices and direct disclosure. *Review of financial Studies*, *2*(4), 495–526.

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.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of financial economics*, *6*(2-3), 95–101.

Jiang, G., Lee, C. M., & Zhang, Y. (2005). Information uncertainty and expected returns. *Review of Accounting Studies*, *10*(2), 185–221.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance*, *31*(4), 1085–1100.

Lo, A. W., & Hasanhodzic, J. (2009). *The heretics of finance: Conversations with leading practitioners of technical analysis*. New York, NY: Bloomberg Press.

Malkiel, B. G. (2011). *A random walk down wall street: The time-tested strategy for successful investing (tenth edition)*. W. W. Norton.

Markowitz, H. (1952). Portfolio selection. *The journal of finance*, *7*(1), 77–91.

Murphy, J. J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. Penguin.

Neely, C., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: the role of technical indicators. *Management Science*, *60*(7), 1772–1791.

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777–787.

Park, C.-H., & Irwin, S. H. (2004). The profitability of technical analysis: A review. *AgMAS Project Research Report*(2004-04).

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

Pring, M. J. (2002). *Technical analysis explained: The successful investor's guide to spotting investment trends and turning points.* McGraw-Hill Professional.

Scott, G., Carr, M., & Cremonie, M. (2016). Technical analysis: Modern perspectives. *Research Foundation Reviews*, *11*(1), 1–36.

Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management science*, *9*(2), 277–293.

Working, H. (1958). A theory of anticipatory prices. *The American Economic Review*, *48*(2), 188–199.

Yu, H., Nartea, G. V., Gan, C., & Yao, L. J. (2013). Predictive ability and profitability of simple technical trading rules: Recent evidence from southeast asian stock markets. *International Review of Economics & Finance*, *25*, 356–371.

Zhang, X. (2006). Information uncertainty and stock returns. *The Journal of Finance*, *61*(1), 105–137.

Zhou, G., & Zhu, Y. (2013). An equilibrium model of moving-average predictability and time-series momentum. *Unpublished working paper, Washington University in St. Louis*.

Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, *92*(3), 519–544.

Appendices

Additional Tables

Table A1

Summary Statistics from fictional MA timing strategy

Table A1 presents the same summary statistics and uses the same dataset as reported for Table 1. However, this analysis applied a fictional 10-day moving average timing strategy. Note that this is not realistic and is only done to confirm the notion that in the highest-volatility decile most of the profit is made in the first day and the design of the MA timing strategy is therefore too slow to detect this. The sample period spans form January 1990 until December 2016. All results apart from the skewness are annualized. Returns are in percentages, t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	Panel A. Volatility Decile Portfolio				Panel B. MA(10) Timing Portfolio				Panel C. MAP			
Rank	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
1 (Low)	0.40 (1.39)	1.53	−0.31	−1.40	3.67*** (16.91)	1.15	10.57	0.98	3.27*** (16.98)	1.02	17.13	0.54
2	0.54 (1.18)	2.44	−0.89	−0.82	6.42*** (20.70)	1.64	4.72	2.36	5.87*** (17.61)	1.77	6.35	0.54
3	3.96*** (2.70)	7.75	−0.31	0.18	23.22*** (25.17)	4.88	4.15	4.24	19.26*** (17.73)	5.75	3.02	0.53
4	5.80*** (2.89)	10.60	−0.43	0.31	34.88*** (28.27)	6.53	2.62	4.95	29.08*** (19.52)	7.88	2.20	0.54
5	6.33*** (2.79)	12.01	−0.39	0.32	41.73*** (30.19)	7.31	1.96	5.36	35.40*** (21.02)	8.91	1.69	0.52
6	7.01*** (2.75)	13.52	−0.38	0.33	48.45*** (30.71)	8.35	2.26	5.50	41.43*** (22.17)	9.89	2.00	0.52
7	7.33** (2.30)	16.90	−0.15	0.28	57.68*** (28.51)	10.71	2.77	5.15	50.35*** (21.86)	12.19	2.01	0.52
8	8.08** (2.38)	17.97	−0.06	0.31	62.99*** (28.56)	11.67	2.35	5.18	54.91*** (22.97)	12.65	1.80	0.52
9	4.84 (1.16)	22.03	0.17	0.10	73.66*** (27.04)	14.42	2.86	4.93	68.83*** (23.60)	15.43	1.69	0.53
10 (High)	39.27*** (5.42)	38.32	1.45	0.96	138.09*** (23.72)	30.80	3.12	4.40	98.82*** (25.75)	20.31	1.97	0.54
High - Low	38.87*** (5.36)	38.37	1.44	0.95	62.74*** (10.49)	31.65	2.39	1.90	23.87*** (5.89)	21.43	−0.68	0.47

Table A2

Alphas under CAPM and Fama & French Three-Factor Model for Western Europe

Table A2 presents the regression output of the MAPs from the European sample under both the CAPM as well as the Fama and French (1992) three-factor model. The sample includes the following Western European countries: Belgium, France, Germany, Italy, the Netherlands, Spain and Sweden. Reported are the alphas, betas and adjusted R^2. The analysis uses a 10-day moving average timing strategy and daily European risk factors. The sample period spans form January 1990 until December 2016. Alphas are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	Panel A. CAPM			Panel B. FF 3-factor model				
Rank	α	β_{MKT}	Adj. R^2 (%)	α	β_{MKT}	β_{SMB}	β_{HML}	Adj. R^2 (%)
1 (Low)	1.48**	−0.05***	5.41	1.38**	−0.05***	0.00	0.03***	5.65
	(2.30)	(−10.72)		(2.14)	(−9.95)	(−0.02)	(3.09)	
2	2.94***	−0.06***	7.30	2.92***	−0.06***	0.00	0.01	7.31
	(4.07)	(−14.13)		(4.01)	(−11.72)	(−0.42)	(1.15)	
3	6.42***	−0.15***	28.71	6.42***	−0.15***	−0.01	0.01	28.74
	(7.07)	(−14.76)		(7.02)	(−11.93)	(−1.06)	(0.47)	
4	9.33***	−0.21***	35.78	9.47***	−0.22***	−0.05***	−0.01	36.10
	(8.56)	(−18.41)		(8.67)	(−15.00)	(−2.95)	(−0.60)	
5	11.27***	−0.25***	38.11	11.43***	−0.27***	−0.05***	−0.02	38.34
	(9.01)	(−19.94)		(9.08)	(−15.67)	(−2.44)	(−0.87)	
6	12.47***	−0.26***	36.81	12.54***	−0.28***	−0.06***	0.02	37.11
	(9.40)	(−19.81)		(9.43)	(−15.88)	(−2.80)	(0.78)	
7	14.95***	−0.28***	36.24	14.86***	−0.30***	−0.05**	0.06***	36.60
	(10.35)	(−21.40)		(10.31)	(−16.98)	(−2.28)	(2.58)	
8	17.68***	−0.27***	31.50	17.34***	−0.31***	−0.08***	0.15***	33.14
	(10.99)	(−20.48)		(11.05)	(−17.56)	(−3.45)	(4.94)	
9	18.38***	−0.24***	23.03	17.55***	−0.28***	−0.06***	0.28***	27.54
	(10.51)	(−18.31)		(10.65)	(−16.49)	(−2.63)	(7.26)	
10 (High)	6.08***	−0.14***	8.34	4.92***	−0.17***	−0.03	0.36***	16.24
	(3.54)	(−11.69)		(3.13)	(−10.76)	(−1.38)	(7.56)	
High - Low	4.60***	−0.09***	3.51	3.54***	−0.12***	−0.03	0.33***	10.00
	(2.58)	(−7.13)		(2.14)	(−7.44)	(−1.36)	(6.92)	

Table A3

Four-Factor Model with Alternative MA Lag Lengths

Table A3 presents the regression output of the MAPs from the Dutch stock market under the Carhart (1997) four-factor model. The analysis uses various lag lengths for moving average timing strategy. Reported are only the alphas and the momentum betas. Daily European risk factors are applied and the sample period spans form January 1991 until July 2016. Alphas are annualized and in percentages, Newey and West (1987) robust t-statistics are given in parentheses and ***, **, * indicate significance at a 1%, 5% and 10% level respectively.

	MA(20)		MA(50)		MA(100)		MA(200)	
Rank	α	β_{UMD}	α	β_{UMD}	α	β_{UMD}	α	β_{UMD}
1 (Low)	2.00***	0.00	1.92***	0.00	1.79***	0.00	1.73***	0.00
	(8.69)	(−0.26)	(9.23)	(0.27)	(9.17)	(0.78)	(9.33)	(0.89)
2	1.65***	0.00	1.68***	0.01***	1.40***	0.01***	1.09***	0.01***
	(4.77)	(0.87)	(4.96)	(2.61)	(4.49)	(3.72)	(3.53)	(3.79)
3	2.68***	0.04***	2.91***	0.07***	2.16**	0.08***	1.23	0.11***
	(2.49)	(3.13)	(2.65)	(5.22)	(2.03)	(6.53)	(1.23)	(8.96)
4	3.77***	0.05***	3.29**	0.08***	2.11	0.11***	1.43	0.17***
	(2.60)	(2.22)	(2.28)	(4.03)	(1.51)	(5.74)	(1.10)	(10.25)
5	7.77***	0.02	5.59***	0.07***	5.80***	0.13***	2.00	0.20***
	(4.43)	(0.94)	(3.16)	(2.79)	(3.30)	(5.56)	(1.17)	(9.67)
6	8.95***	−0.01	5.84***	0.06**	4.91***	0.11***	0.21	0.19***
	(4.62)	(−0.56)	(3.04)	(2.42)	(2.63)	(5.19)	(0.11)	(9.88)
7	9.89***	0.03	6.45***	0.12***	5.85**	0.22***	1.28	0.32***
	(4.18)	(1.11)	(2.68)	(4.01)	(2.41)	8.09)	(0.54)	(12.88)
8	10.60***	0.02	9.65***	0.09***	7.68***	0.20***	1.45	0.30***
	(4.39)	(0.84)	(3.89)	(3.29)	(3.04)	(7.08)	(0.58)	(11.80)
9	12.67***	0.08***	9.68***	0.14***	7.22**	0.23***	0.69	0.37***
	(4.25)	(2.42)	(3.21)	(3.82)	(2.41)	(6.75)	(0.23)	(11.26)
10 (High)	−11.13***	−0.02	−2.97	0.02	−3.09	0.06*	−3.72	0.14***
	(−2.51)	(−0.62)	(−0.71)	(0.58)	(−0.77)	(1.75)	(−0.96)	(4.16)
High - Low	−10.80***	−0.02	−3.44	0.02	−2.60	0.07*	−3.82	0.15***
	(−2.42)	(−0.59)	(−0.81)	(0.68)	(−0.64)	(1.86)	(−0.99)	(4.32)