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A comparison of the technical moving average strategy, the momentum strategy and the short term reversal

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Preface

This thesis is not only the result doing research for several months, it is the result of almost two decades of learning and developing, specifically of my five years of studying at the Erasmus University Rotterdam. I am very grateful for all opportunities I have had in all these years to develop myself. I enjoyed my time of being a student, but am glad to finish my study with this thesis. This thesis would not be completed without all the support from friends and roommates, who were always interested in talking about my thesis. Special thanks to my parents who have supported me my entire life, and who will never stop doing this, and gave me confidence which resulted now in finishing my study. I also want to thank my girlfriend for making me happy every day and helping and supporting me in all my choices. My supervisor, Mr Xing, was a great support during the process, his feedback and enthusiasm were of great use during the writing process.

Abstract

This thesis compares three different investment strategies in terms of profitability, correlations and sensitivity to risk factors in the timeframe 1990-2015. The three investment strategies are the technical moving average, momentum and the short term reversal. The first strategy outperforms the latter two strategies both in excess and abnormal returns. The low returns on the momentum and short term reversal portfolios are caused by two prolonged periods of severe negative returns, called momentum-crashes. The bottom decile of the technical moving average outperforms the top decile, while the opposite is documented in earlier research. This could possibly be caused by the construction of the strategy measure, which could measure a reversal in the short run. Different analyses support the statement that the momentum strategy and short term reversal strategy are very different strategies, while the short term reversal is, as expected, the opposite of the momentum strategy.

Keywords:

Technical moving average, momentum, short term reversal, asset-pricing models, abnormal returns

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Section I: Introduction

Anomalies, the phenomenon that portfolios based on certain asset characteristics tend to outperform the market, are a hot topic in the financial literature, which is not surprising there it is an attack on one of the biggest economic theories: the efficient market hypothesis constructed by Fama (1970). The momentum effect is an example of an anomaly, which implies that the previous winners on average outperform the previous losers. The corresponding investment strategy, which also exists in a contrarian form called the short-term reversal, has some similarities with an investment strategy called technical moving average. All three strategies are depending on historical stock prices and have, contrary to many anomalies, no rational or risk-based explanation.

Because of the lack of rational explanations, there is yet no consensus on these investment strategies. The strategies are often tested on their profitability, but it is unknown how these strategies are related in terms of methodology and sources of profit. The research question of this thesis is therefore: "*To what extent are the momentum strategy, the short term reversal and the technical moving average strategy related?*". An answer on this question will provide more insight in the (dis)similarities of the investment strategies. The comparison will be based on profitability, correlations and sensitivity to the factors from the three-, four- and five-factor model.

The literature on the investment strategies will be compared in order to be able to compare the strategies qualitatively, although the focus on this thesis is an empirical comparison. The empirical comparison is based on the time-interval 1990-2015, which is interesting because it includes both bullish markets and bearish markets. The dataset will be divided into deciles for all investment strategies, which are used to create zero-investment portfolios. These portfolios are generally constructed by buying the top decile and shorting the bottom decile. The excess returns on the zero-investment portfolios will be computed for the different strategies, with two formation periods for the technical moving average, abbreviated TMA, and momentum strategies. Subsequently, the three-, four- and five-factor models will be used to look to what extent the excess returns on the zero-investment portfolio can be explained by risk factors, and to what extent the strategies are able to generate abnormal returns. The sensitivities to the risk factors are useful to compare the portfolios of the several tested investment strategies. In the end, several robustness checks will be done in order to test the initial findings. This robustness checks include double sorting, different holding period for the momentum strategy and different construction of the TMA measure.

This research finds that The TMA strategy has average monthly excess and abnormal returns around 1%. The surprising finding here is not the size of the returns, but the fact that the bottom decile consistently outperforms the top decile. The results are similar for both formation periods and the robustness checks. However, these findings are not in line with evidence documented in earlier research, which states that the top decile outperforms the bottom decile. This reversal in sign could be caused by the combination of holding period and the construction of the strategy measure based on which stocks are divided into deciles. Most of the research to the TMA strategy is executed by deciding in every period whether a portfolio should be bought or should be shorted, leaving the possibility that all portfolios are either bought or shorted at the same period. This thesis uses deciles in order to execute this strategy, resulting in long- and short-transactions every period. The combination of the holding period and the used construction could measure a reversal in return on the technical moving average strategy in the first month.

The momentum strategy seems profitable in general, but the annual return of -60% during the financial crisis causes the strategies' profit to be negligible. Many papers documented significant abnormal returns on this strategy, although earlier research shows that the momentum strategy is very sensitive to so-called momentum-crashes. The fact that two prolonged periods of severe negative returns are part of the relatively small time-window could explain the low returns on the momentum-strategy found in this paper. The findings on the profitability for the short term reversal are comparable, while the other findings show that this strategy is the opposite of the general momentum strategy.

The findings in this thesis are consistently suggesting that the TMA strategy and momentum strategy are uncorrelated. The correlation between the monthly return on the zero-investment portfolios is negligible and both strategies have very different factor sensitivities. The TMA strategy has a significant positive sensitivity to the market factor, while the momentum strategy has significant negative sensitivities to the size and value factors. Double sorting also shows that the TMA strategy is able to consistently create returns within the momentum deciles.

This thesis shows that the momentum strategy is generally profitable, but the strategy is very sensitive to crises. Earlier research showed that it would be possible to predict the crises, a strategy which includes this prediction could be more profitable there an opposite position during the crisis would lead to extremely high returns. The findings on the TMA strategy are specifically interesting with regard to the performance of the deciles, certainly because different constructions of this strategy show all the same results. The results could indicate an overreaction in the market to news, which is an often-heard explanation for the short term reversal. Firms that performed better in the last month then they did on average in the previous year, perform less than the firms that performed worse in the last month than in the past year on average. This could indicate that the stock price increases too much after news, which causes the stock to underperform in the subsequent period.

The next section provides a review of the earlier literature, with more attention for the investment strategies. The third section show the hypotheses that are drawn based on the literature review. In Section IV, the process of data gathering and formatting is elaborated along with the methodology. Section V shows the results of the methodology and discusses these results. The last section, Section VI, concludes with a conclusion and tips for further research.

Section II: Literature review

This section gives a summary of the three different strategies. The papers of other researchers to these strategies is used to get better image of the theoretical background and the earlier findings on these strategies. The first subsection looks at the momentum strategy, while the second subsection looks at the technical moving average strategy. The short-term reversal is covered in the first subsection, because it is an application of momentum. The third subsection will connect the first and second subsection in comparing the theoretical background and empirical findings on the strategies. The last subsection briefly covers the different factors that are incorporated in the three-, four-, and five-factor models. These models are used to determine the abnormal returns of the different investment strategies.

Section II.I: The momentum strategy

This subsection, which is again divided into three parts will elaborate on the momentum strategy. The first part will go through literature and findings on the momentum strategy, and the second part contains a view on a diverging form of the momentum strategy which also will be tested in this thesis. The third sub-subsection gives an insight in the behavioral explanations for the momentum strategy.

Section II.I.I: Literature and Empirical Findings

Momentum in stock prices represents the phenomenon that stocks that have been winners in the past months tend to be the winners in the subsequent months, and that previous losers tend to be the new losers. A profitable, self-financing momentum-portfolio can therefore be constructed by shorting the past losers and going long in the past winners. An abnormal return around 1% per month is found for a momentum strategy in the US-market over the time-interval 1965-1989, looking at the past twelve to three months (Jegadeesh & Titman, 1993). Similar results are found for the same market between 1990-1998 (Jegadeesh & Titman, 2001).

The method of shorting the losers and buying the winners is now known as a momentum strategy, but one of the first papers looking at a strategy based on past returns was executed using a complete other approach. De Bondt and Thaler (1985) construct momentum-portfolios by doing the exact opposite, shorting the past winners and buying the past losers. Both the formation period and the holding period used are three to five years. This contrarian investment style leads to positive abnormal returns of 25% over 36 months. The contrarian investment style uses an opposite approach relative to the conventional momentum strategy, but the paper makes a contribution to the discussion about behavioral explanations which follows later.

A conventional momentum strategy was tested by Jegadeesh and Titman (1993), who documented a momentum-effect for the US-market. The same effect with similar magnitude has been found for twelve European countries (Rouwenhorst, 1998). Due to the many indications of a momentum-anomaly, including his own findings, Carhart created a four-factor model, which added a momentum factor to the

three factor-model of Fama and French (Carhart, 1997). He finds that the momentum factor yields a positive abnormal return of 1 percent per month, when shorting the 30 percent worst past performers and buying the 30 percent top past performers.

Recently it is found that the momentum strategy can have periods of pronounced negative returns which are persistent for some time, while the strategy is economically strong in most periods (Daniel & Moskowitz, 2014). These so-called 'momentum-crashes' occur if the market has a strong bearish period with high volatility and are found for different countries, time-periods and asset classes. Using bear market indicators and volatility, it is possible to predict these crashes. The financial crash in 2008-2009 led in their research to a severe momentum-crash, primarily because of the extreme good relative performance of the past losers relative to the past winners.

Another interesting finding with regard to momentum comes from Novy-Marx (2012). He finds that the intermediate past performance seems to better predict stock returns than more recent past performance. The intermediate past performance is computed over the last twelve to seven months, and the holding period equals one month. His finding is robust for different asset classes and markets. The empirical finding that stocks with good performance in the last twelve to seven months outperform stocks with good performance in the last six to two last months, is contradicting the thought that the momentum effect is caused by positive autocorrelation in stock prices (Novy-Marx, 2012).

This thesis looks at the sensitivity to several factors from three asset pricing models. Wu (2002) Did something similar for the momentum strategy on the three factor model. In his predictions, the zero-investment portfolio has a negligible sensitivity to the market factor, a negative sensitivity to the size factor and a negative sensitivity for the value factor.

Li et al (2008) are one of the few to find a risk-based explanation for momentum. The time-varying unsystematic risk for winners would be higher than for losers. Besides, the volatility of winners' prices tents to be higher than for losers. Looking at this two findings of Li et al., the momentum effect also could be a premium for risk. However, there is no consensus about a rational explanation.

Section II.I.II: The short term return reversal

The first use of a momentum strategy was a contrarian strategy which yielded positive returns in the long run, 3-5 years, and a 'conventional' momentum strategy is effective over a year. However, a momentum-based portfolio can also be based only on the return of the last month. The negative serial correlation is highly significant for the first month and can lead to a zero-investment portfolio with a monthly risk-adjusted return of around 2 percent (Jegadeesh, 1990). Returns of this size can hardly be explained by transaction costs (Da, Liu, & Schaumburg, 2014).

Two explanations for this reversal, it is called a reversal because the sign of the returns of the stocks change on average, that received much attention are a behavioral explanation and a liquidity-based explanation. The first is covered in Section II.I.III, the latter is related to a price pressure that sometimes occurs when the short-term demand curve has a negative slope coefficient or when this coefficient is positive for the supply curve. The short term return reversal could be explained by the fact that this strategy profits from its' positions in small and illiquid stocks (Avramov, Chordia, & Goyal, 2006). Da, Liu and Schaumburg (2014) conclude in their paper that the short-term return reversal is greater than previously documented, and that this performance is strongly driven by liquidity shocks and investor sentiment. They find a highly significant positive alpha in the three-factor model of Fama and French of 1.34% per month. The liquidity shocks explain the reversal for the losers, while the investor sentiment, which is consistent with short-sale constraints, explains the reversal for the winners.

Section II.I.III: Behavioral explanations

Fama and French, and others, believe strongly in an efficient, rational market. However, not all academics share this opinion. Several behavioral explanations are discussed in literature, these explanations can be divided into two main groups: underreaction and overreaction (Van der Sar, 2011).

If there is a underreaction to new information, not all information is incorporated in asset prices at once, this will happen gradually over time. When all information is incorporated, no predictions are made over the following price movements. Findings from many different academics support this theory (Van der Sar, 2011). For example, the finding that firms with unexpectedly high earnings tend to perform better than firms with unexpectedly low earnings in the six months after the earnings announcement, suggests an existence of underreaction (Bernard and Thomas 1989). The disposition effect, investors sell winners but hold losers, is also in line with a underreaction because it slows the incorporation of information in prices.

The second group identifies an overreaction to news as the cause of the momentum effect. De Bondt and Thaler (1985) state that several empirical studies provide clear evidence for overreaction to new information. When positive information becomes public, people may mistakenly identify this as permanent good news, causing people to buy stocks based on extrapolation. The theory of overreaction is backed by empirical findings from several papers. For example, Jegadeesh and Titman (2001) find

that the returns of a momentum strategy on average turn negative after the first year. Lee and Swaminathan (2000) also observed a reduction in the profitability in the second, third, fourth and fifth year. The empirical findings of De Bondt and Thaler (1985) show that a contrarian investment is generating positive returns in the long run. All these studies point to an overreaction in the stock market to new information. However, the findings of Novy-Marx (2012) that the profitability of the momentum effect is more dependent on the medium term historical returns than the returns on the past months is contradicting a possible overreaction to new information.

Section II.II: The technical moving average-strategy

The Technical Moving Average- (TMA-) strategy is a part of technical analysis. Technical analysis is an old investing technique; it is already used in the 1800's by Dow, who believed that the market moves with phases that can be predicted (Zhu & Zhou, 2009). In the following centuries, many technical analysts have tried to predict prices by studying historical prices and some other statistics about trading. This kind of investment is completely not in line with the efficient market hypothesis, which suggests that historical prices do not contain predicting power at all. Since the efficient market hypothesis has been fiercely attacked, more and more people start believing that technical analysis could work. The success of technical analysis is backed by the finding that technical indicators are as good forecasters as popular macroeconomic variables (Neely, Rapach, Tu, & Zhou, 2013). In the same year researchers find that technical analysis can yield much better forecasts in the bond market, than those macroeconomic variables can do (Goh, Jiang, Tu, & Zhou, 2013). As a consequence, technical analysis is a key source of information used for modern portfolio management (Chincarini & Kim, 2006).

The TMA strategy is a based on buy and sell signals that are created by the moving average of historical prices. When the short term average of a stock or portfolio is above its the long term average, the stock or portfolio is bought. This part of the TMA strategy is general, but the strategy has been executed and tested in several different ways. Brock, Lakonishok and LeBaron (1992) use a bootstrap methodology to test a range of TMA-strategies. They try different lengths for the moving averages: 50, 150 and 200 days for the long term average and 1 or 2 days for the short term average. Besides, they make use of a band, which is a minimum percentage difference between long and short term average before a buy or sell signal is produced by the model. The returns produced by the different strategies are consistently positive. The documented return after a buy signal is on average 12% annually, while the stocks decrease 7% in value after a sell signal.

The returns on TMA-based portfolio are not fully explained by asset characteristics, because the technical analysis adds value itself (Han, Yang, & Zhou, 2013). They find that all deciles, ranked on historical volatility, experience significant positive abnormal returns with regard to the three-factor model, in the range of 13.27% to 22.06% per annum. They sort portfolios on historical volatility, because volatility is a proxy for uncertainty, portfolios with high historical volatility yield the highest returns.

Instead of shorting the portfolio when a sell-signal is given, they buy treasury bills. This approach is widely used, and is called the '*simple moving* average' (Zakamulin, 2014). The different approaches contribute to the robustness of the findings.

LeBaron (1999) and Neely (2002) find that portfolios based on moving averages outperform the markets substantially. However, the statistical reliability of several papers providing support for technical analysis-based trading seems to be low according to several academics and it is not likely that there will soon be consensus about the effectiveness of technical analysis (Zhu & Zhou, 2009). Data snooping or datamining could be a severe problem in testing the TMA strategy (Zakamulin, 2014). It is not strange that a certain strategy had better returns over the last decades than other strategies. The market timing performance is not consistent over time, with short periods of outperformance and very long periods of underperformance. The success of the TMA strategy is caused by two four-year intervals with superior performance, but generally this strategy is not profitable at all. Sullivan, Timmermann and White (1999) also show that the returns of the TMA strategy is much weaker than often thought, there it underperforms a passive strategy.

Among others, Han, Huang and Zhou (2015) used a different approach. Where aforementioned academics mostly used the closing price of the last day, they compare the average return of the last 50 days with the average return on the long term, 200 days. They call this the Moving Average convergence/divergence (MACD). Their findings are similar. Intuitively, there is a strong correlation between an investment looking at historical returns and an investment looking at historical price fluctuations, because price fluctuations are equal to the returns. However, there are cases in which the two approaches result in different investments, and therefore different returns.

Section II.III: A comparison

The previous subsections gave an insight in the literature on both the momentum- and the TMA strategy. This subsection will compare several components of the strategies. Dependence on historical price movements, expected returns and correlation all will be mentioned briefly.

The dependence on historical price movements can be derived when looking at the construction of the strategies. The momentum strategy is obviously positively correlated with historical price movements, as this strategy buys stocks that have appreciated the most and shorts the stocks that have lost most in value. So, if a stock has a higher value on t=-1 than on t=-12 there is a chance that the stock will be in the top-decile and thus bought, while stocks that depreciated in this time-interval make almost no chance to be bought. This will only happen if at least 90 percent of the stocks lost even more, in general it can be concluded that the momentum strategy is positively correlated with historical price movements. This is different for the short term return reversal, because this is actually a contrarian momentum strategy. This strategy is negatively related to historical price changes.

The link with historical prices is probably not as clear for the TMA strategy. But it is helpful to analyze the moving averages which decide the investments for this strategy. When the short moving average, which is often the closing price of one day, is above the long moving average, which is dependent on historical prices, then a long position is taken in the portfolio. Historical prices being low makes it more likely that the last closing price is above the historical average. This would suggest that the more negative a firm's historical price movements are, the bigger the chance that the long term average is below the short term average, resulting in a buy-signal. However, the current price has to be above the historical moving average which excludes the firms that are still losing. Interestingly, this is in some ways like the short term reversal that is found in research to the momentum strategy, like in De Bondt and Thaler (1985).

Where the momentum and short term reversal strategy use an absolute measure of performance, a stock is bought if its return over the formation period is high (or low in case of the short term reversal), is the technical moving average more a relative measure of performance. If a stock is performing better than it performed on average during the formation period, the stock is bought. This intuitive interpretation of the TMA strategy again illustrates that is neither strictly positive nor strictly negative depending on historical price changes.

Both strategies have an arsenal of researches providing support for the strategies. Han, Yang and Zhou (2013) compared the returns on their moving-average portfolios with the returns on a momentum strategy. They find a positive return of 12% annually for the momentum strategy, but substantially higher returns for the TMA strategy. This strategy outperformed the market 13.27% to 22.06% per annum. These two strategies seem to target different aspects of the markets, because they find a correlation between -0.01 and -0.07. Both strategies yield positive returns, but still are negatively correlated. This finding is in line with the earlier mentioned differences in dependence on historical price movements.

The paper of Wu (2002) gave predictions for the factor loadings of the momentum strategy, however, there is no similar paper found for the technical moving average strategy. It is therefore hard to have concrete expectations based on earlier literature.

Section II.IV: The pricing models

The previous subsections mentioned different findings from earlier research. If is tested whether a certain investment strategy statistically gets a high risk-adjusted return, the returns of the strategy are compared to different versions of a pricing model. Several decades ago, the CAPM of Lintner (1965), Sharpe (1965) and Mossin (1966) functioned as a benchmark. Nowadays, three different models are often used, which are all based on the CAPM: the three-, four- and five-factor models.

The three factor model is the most basic of the three models, both the four- and the five-factor model incorporate the complete three factor model and add one or two new factors to the model. The three-factor model is introduced by Fama and French consists of the risk premium (Market, MKT)), a size-related risk factor (Small-Minus-Big, SMB) and a value factor (High-Minus-Low, HML). The risk premium equals the difference between the market return and the risk free rate, SMB represents the difference between small and big firms in terms of returns and HML is based on the book-to-market value of a firm.

Generally, MKT tends to be positive, with a value of 1 on average. A high sensitivity (MKT>1) for the market-factor means that the return of the firm increases more than 1% if the market return increases with 1%. It is possible to construct portfolios with a market factor of zero or even below. This implies that the return of the portfolio is either uncorrelated, or negatively correlated with the market return. The factor value of SMB increases when small firms outperform the bigger firms. This factor value is used as an independent variable in the different models, but this factor value is not the same as the sensitivity of a portfolio to the SMB factor. If a portfolio has a negative SMB-factor sensitivity, the portfolio primarily consists of big stocks, while it has a positive sensitivity when the portfolio is primarily constructed of small stocks. When a portfolio has a high positive sensitivity for the HML-factor, the portfolio has primarily firms with a high book-to-market value. Firms with a high book value relative to the market value tend to outperform stocks with a relatively low book value.

The four- and five-factor models build upon the three-factor model by including one or two new factors. The four-factor model is introduced by Carhart in 1997. His finding, very related to this thesis, that the momentum-factor (Winner-Minus-Loser, WML) is very profitable moves him to include a momentum-related factor into the pricing model. A portfolio with a high (positive) sensitivity to the momentum-factor consists primarily of firms that had high previous returns.

The five-factor model is introduced by Fama and French (2015) and does not include the WML-factor. This model includes profitability (Robust-Minus-Weak, RMW) and investment (Conservative-Minus-Aggressive, CMA) measures. These measures take the robustness of the profitability and the amount of investments into account.

Section III: Hypotheses

The previous section contained information on the two used strategies, and the information in this section will be used to draw several hypotheses. These hypotheses will be helpful for answering the research question of this thesis, which is*: "To what extent are the momentum strategy, the short-term reversal and the technical moving average strategy related?"* This research question will be answered in the last section, Section VI Conclusion. The three strategies will be compared on profitability, correlations and factor sensitivity.

In Section II it is stated that the strategies generally yield positive (abnormal) returns. According to Han, Yang and Zhou (2013), the TMA strategy will result in higher excess and abnormal returns. The excess return is the difference between the return on a portfolio minus the risk-free rate, while the abnormal return is the part of the excess return that cannot be explained by the market model. The first hypothesis is related to the returns on the strategies.

Hypothesis I

H_0: There is no significant difference between the technical moving average, the short term reversal and the momentum strategy in term of excess and abnormal returns.

H_a: The technical moving average strategy will yield similar excess and abnormal returns than the momentum strategy and the short term reversal.

The dependence on historical price movements is different for the three investment strategies. One has a clear positive link with historical prices, one has a negative link and for the other it is difficult to predict. This difference will lead to different portfolio compositions and because both strategies invest in different stocks, the returns are likely to be depending on other aspects of the market. In order to test to what extent the returns on the strategies are different, the following hypotheses are tested.

Hypothesis II:

H_0: The momentum strategy is not significantly correlated with the technical moving average strategy

H_a: The momentum strategy is significantly correlated with the technical moving average strategy

Hypothesis III:

H_0: The momentum strategy has significant sensitivities to other factors than the technical moving average strategy.

H_a: The momentum strategy has significant sensitivities to the same factors as the technical moving average strategy

These hypotheses will be used to analyze the results, and to get a broad view on the similarities and dissimilarities between the different strategies. The short term return reversal is included in the research and primarily compared with the momentum strategy, there the construction is the opposite of the conventional momentum strategy. The focus will however be more on the conventional momentum strategy than on the short-term reversal. The main reason for this choice is the fact that the time-interval used for testing the momentum- and the TMA strategy are equal, while the time-interval for the short-term reversal is different.

Section IV: Data and Methodology

The previous section contained the hypotheses that will be tested in order to answer the research question of this thesis. The first subsection of this section describes the data that is used to do this. Both a description of the data and the way this data is gathered will be provided. The second subsection will elaborate about the methodology of this thesis.

Section IV.I: Data

This thesis is aimed at the return of several investment strategies in the time-period 1990-2015 for stocks in either the NYSE or the AMEX. The NYSE and AMEX together represent a big part of the US-economy, and the combination of the two is therefore often assumed to be representative for the US-economy. The dataset will probably be of a relatively high quality, because firms in the two aforementioned indices are generally followed closely. Therefore, stock prices and other firm specific characteristics are likely be documented correctly. Besides a practical consideration is this dataset suited for several reasons. First, the time-interval is large enough to have sufficient data points, even when using monthly data. The reason for the choice of monthly data will be elucidated later. Second, the time-interval consists of several bearish and bullish markets. This different states of the market are a good robustness check for the strategies, and can possibly help in identifying differences between different investment strategies. The practical consideration for the time-interval is related to the factor data.

The factor data from the online library of K. French is used, however, one disadvantage of the database is the fact that the data is only available from 1990. The dataset used in this thesis contains data with a monthly frequency. Daily stock data is available, which has its benefits with regard to the amount of observations. However, the return on the different investment strategies is analyzed using the three-, four- and five-factor model. The factor data could also be derived for daily data, but because of time constrains and the lack of strong disadvantages, the factor data from the online library of K. French is used. Because this library only contains monthly factor data, this frequency is also used for the stock data. The factor data is available for several geographical areas, the data related to North America is used there all firms included in this research belong to this geographical area. The factor data consists of the risk free rate and the six aforementioned factors that are used for regressing the portfolio returns on the three-, four-, and five-factor model.

The stock data is queried using the CRSP database. The total-return index for all constituents of the NYSE and AMEX in the used time-interval are downloaded. The advantage of a total return index relative to stock prices, is the fact that the return on a stock is negatively influenced by paid dividends. The stock price will decline with the same amount as the dividend, it is therefore not possible to correctly measure the yield on an investment by only looking at the stock price.

Because the total return index incorporates dividends, this data is more suited to calculate the yield. The used price changes are computed using the logarithms, there these price changes can be added while this is not the case otherwise. The result is a database consisting of 4710 firms. However, not all firm-years are included in the final dataset. If the price of a stock is below $5 in December, all observations for that firm-year are removed from the dataset. The table in the Appendix, Table A.1, contains an overview of the average amount of monthly observations in several time-periods.

Besides, the returns in the dataset are winsorized at a 0.5% level, in order to reduce the influence of the outliers, such as a monthly return of +12500%. The effect of this winsorizing can be seen in Table A.2. The mean of the observations dropped because of the winsorizing, which is caused by the fact that the upward outliers had more extreme values than the downward outliers.

Section IV.II: Methodology

This subsection contains an overview of the methods that are applied to the data, which is covered in the previous subsection. As mentioned in Section IV.I consists the dataset of monthly observations. The first sub-subsection explains how the measures for the strategies are computed, the second sub-sections elaborates on the subsequent steps in testing the strategies.

Section IV.II.I: The strategy measures

Momentum

An investor using the momentum-strategies goes long in the stocks that were the biggest winners, and goes short into the biggest losers. In order to create this zero-investment portfolio, the dataset will be divided into deciles based on the historical return of the firms. This ranking is done in three different ways. First, the historical return is calculated over the past year excluding the last month. This is noted as [-12, -2] and represents a widely used application of momentum strategy. The approach of Novy-Marx (2012) gave an interesting insight in the momentum strategy. This approach is also used in this thesis, and is executed by ranking the stocks on the return in the interval [-12, -7]. The third application of the momentum strategy that is used in this thesis, is called the short term reversal [-1]. In the rest of this paper, the short term reversal is the same as the notation MOM[-1], there the construction of the short term reversal is comparable with the construction of the conventional momentum strategies. The short term reversal is tested looking at the returns in the last month, and applying a contrarian approach, which implies shorting the past winners and buying the past losers. The three different momentum strategies are all tested with a monthly rebalancing and a holding period of a month, which is in line with the Novy-Marx (2012) paper.

The firms are ranked on date and on the momentum-measure. This momentum measure differs per interval, but is always computed by summing the returns in the interval, which is possible because the returns are calculated using logarithms. For all three intervals, observations are only included if there are 12 preceding observations for the firm, and there are no missing values in the data.

Technical moving average

An investor using the TMA strategy buys stocks that have high current returns relative to historical returns. In order to compare the TMA strategy with the momentum strategy, the TMA-measurements are based on the same time-intervals as used for testing the momentum strategy, thus [-12, -2] and [-12, -7]. The interval [-12, -2] compares the average return over this period with the return on t-1. Many academics used the closing prices of the stocks to determine the correct TMA-measure. The conventional TMA strategy buys a stock if the last closing price of a portfolio is above the average closing price in a certain interval.

However, the approach using returns is proved to be also effective (Han, Huang, & Zhou, 2015). This approach is less complicated, because it does not need the price of a portfolio of stocks to decide which stocks are bought or sold. This thesis uses the approach of Han, Huang and Zhou (2015). The TMA-measure is then computed by subtracting the average return over the relevant time-interval from the past monthly return. Just as with the momentum-strategies, observations are only included if the 12 preceding observations are from the same firm, and there is no missing value in the data. If it turns out that the results for the TMA strategy are not according to the literature, a robustness check will be done using a TMA-measure based on standardized stock prices.

Section IV.II.II: creating portfolios

This thesis compares the momentum- and the Technical moving average-strategy for three different intervals, leading to five different strategies. The stocks are ranked on date and the measure of one of the five investment strategies. Every observation includes thus five strategy-related measures and the rank the stock has for these measures relative to other stocks. The measures are used to divide all stocks into deciles, which is done separately for all strategies. The top decile for momentum consists of the firms with the most positive historical return, while the bottom decile contains the losers. For the short-term reversal, thus momentum [-1], the opposite is the case. Because a reversal in sign is expected, the top decile consists of the biggest losers. The TMA-measure is positive if the last return of a firm is above the long term average of the same firm. The observations with the most positive measure form together the top decile. For all five strategies, the top decile is expected to outperform the bottom decile.

The third table in the appendix, Table A.3 gives an insight in distribution of the measures for the five different investment strategies. It is not surprising that the measures for all three momentum-factor are positive on average, because these measures are the sum of monthly returns. The TMA-measures are almost equal to zero, which also is not surprising. Assuming the random walk that is implied by the

efficient market hypothesis, the difference between the last return and the long term average return is on average expected to be equal to zero. The computed measures are used to rank all firms. After ranking, the firms are every month divided into deciles for the five different strategies. For all strategies, the bottom decile is expected to perform the worst, while the top decile is expected to perform best.

When all deciles are computed, the returns for all of the five different strategies are computed. The average monthly returns can be found in the table below. The return of the zero-investment portfolio, equals the difference between the top and the bottom decile. Because the top decile is expected to outperform the other deciles, this portfolio can be executed by buying the 10^{th} decile and shorting the 1^{st} decile.

Section IV.II.III: Asset pricing models

The average monthly returns per strategy are presented earlier in this section. These returns represent the average monthly return on a decile, which is the average of the returns of individual firms. The monthly returns per decile, thus not averaged through time, are used in a regression as the dependent variable.

Different sets of independent variables are used to test how the deciles perform in the three-, four- and five-factor model. This is done using the following three formulas:

$$R(t) - R_f(t) = \alpha + \beta_{mkt}(MKT) + \beta_{SMB}(SMB) + \beta_{HML}(HML)$$

$$R(t) - R_f(t) = \alpha + \beta_{mkt}(MKT) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{WML}(WML)$$

$$R(t) - R_f(t) = \alpha + \beta_{mkt}(MKT) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{RMW}(RMW) + \beta_{CMA}(CMA).$$

The left side of the formula equals the monthly excess return on a decile, while the right side of the formula represents one of the three asset pricing models. The different factors are briefly explained in the theoretical framework in Section II. The alpha is the intercept of the model, and indicates whether a strategy over- or underperforms relative to its level of risk.

Multicollinearity

Table A.4 gives an overview of the correlation between the factors of the different asset pricing models. The three factors for the three-factor model are not heavily correlated, multicollinearity does not seem to be a problem for this model. The momentum factor, WML, is also not heavily correlated with one of the other factors. However, the correlation between the value factor (HML) and the investment factor (CMA) is very high, 0,778 to be exact. This correlation does influence the estimates for the five factor, but has no influence on the other models.

Robustness check and double-sorting

As a robustness check, the dataset will be double-sorted. This means practically that, for example, the deciles for the momentum [-12, -2] strategy will be divided into deciles based on the TMA [-12, -2] strategy. If the returns within the first decile still are different, then can be concluded that this thesis looks at two different investment strategies rather than comparing two very similar strategies.

This section gave an insight in the data and the methodology of this thesis. The performance of the deciles for all strategies will be tested, using the different asset pricing models. The output of these regression can be found in the next section, Section V Results. This section also provides the result of double-sorting.

Section V: Results

This section presents the results of this research. The first subsection covers the profitability of the investment strategies. The correlations between the returns are discussed in the second subsection. The third subsection contains the output of the regressions for each strategy and the subsequent subsection elaborates the effect of the double sorting. The last subsection presents the additional robustness checks. The result in this section will be used to answer the research question and analyze the hypotheses.

Section V. I: Returns

The strategies will first be compared in terms of profitability. The figure below contains the returns on the deciles for all five investment strategies. Both applications of the technical moving average-strategy result in negative returns on the zero-investment portfolio, while the return on the zero-investment momentum portfolios is negligibly positive. Both findings are unexpected. Both the results of momentum and TMA will be discussed.

Table 1: Return on deciles

Return on deciles

This table present the return on the deciles of the different investment strategy. At the bottom of the table, the difference between the return on the top and bottom deciles are showed, with the corresponding t-statistic below.

Decile	MOM [-12, -2]	MOM [-12, -7]	MOM [-1]	TMA [-12, -2]	TMA [-12, -7]
1	0,0144	0,0123	0,0140	0,0197	0,0204
2	0,0114	0,0109	0,0108	0,0145	0,0154
3	0,0116	0,0102	0,0107	0,0134	0,0134
4	0,0116	0,0109	0,0115	0,0128	0,0130
5	0,0107	0,0119	0,0113	0,0127	0,0128
6	0,0114	0,0125	0,0119	0,0125	0,0117
7	0,0125	0,0131	0,0124	0,0108	0,0102
8	0,0120	0,0136	0,0139	0,0105	0,0103
9	0,0141	0,0152	0,0148	0,0091	0,0089
10	0,0170	0,0161	0,0156	0,0101	0,0101
Difference	0,0026	0,0038	0,0016	-0,0096	-0,0103
T-statistic	0,898	1,688*	0,742	-4,332***	-4,480***

** = significant at 0.10, ** is significant at 0.05, *** is significant at 0.01*

Figure A.5 shows descriptive statistics on the five zero-investment portfolios. The mean for every zero-investment portfolio equals the return noted in Figure 1. The standard error of the mean is very large for the short-term reversal, while its range is comparable with those from the other investment strategies.

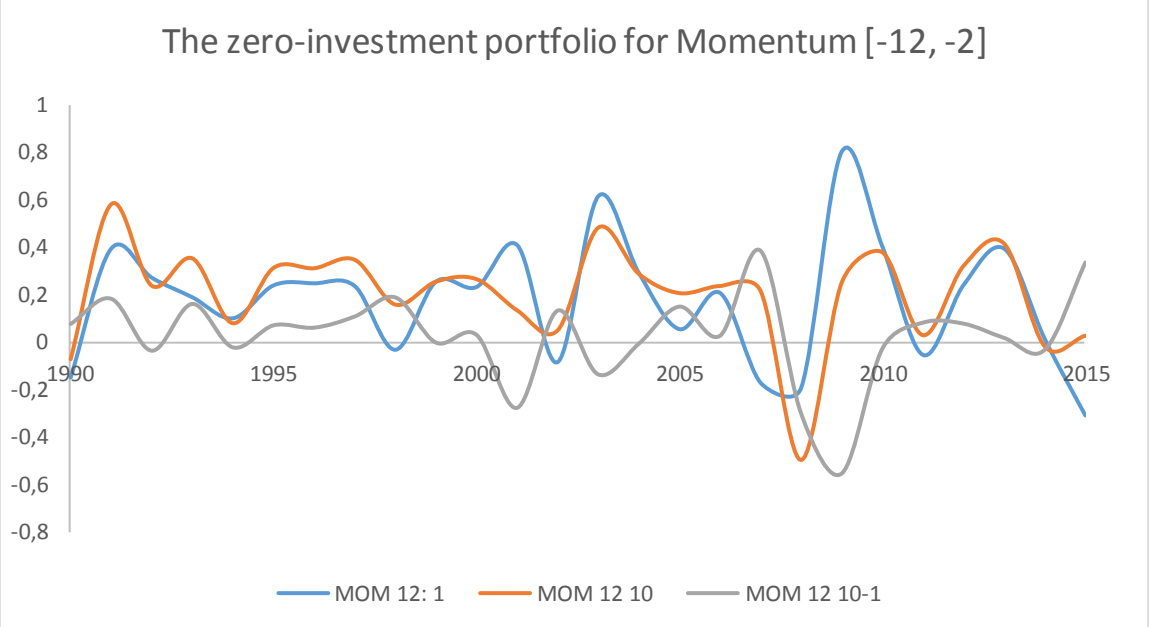
Momentum

The momentum-related findings are unexpected, there the momentum strategy is widely identified in different stock markets, among which the US. The return is small, although significant at the 10% level for the [-12, -7] interval. Interestingly, the first decile performs unexpectedly well for all three momentum-strategies. Looking at the top deciles, a monthly return of 1,7%, 1,6 and 1,9% are all very acceptable. Because the bottom decile also performs relatively well, the returns on the zero-investment portfolio for momentum are all negligible. Looking at this table, it would be better to short the second decile instead of the first. This would result in an average monthly return of 0,55%, 0,51% and 0,71% respectively, which is still below the returns found in earlier research. The performance of the zero-investment portfolio through the time could give a better insight of the cause of this unexpected result.

Figure 2 shows the returns for the top and the bottom decile for the Momentum [-12, -2] strategy. The green line represents the annual return on the zero-investment portfolio. Generally, this line is slightly above the x-axis, but in 2008/2009 the line is far below this axis. In line with the Daniel and Markowitz (2014) findings, the momentum strategy failed during the last financial crisis. This could be one of the explanations for the returns in Figure 1.

Figure 1: a zero-investment momentum portfolio through time

This graph depicts the annual returns on the momentum strategy based on the formation period [-12, -2]. The gray line represents the return on the zero-investment portfolio which is created by buying the top decile and shorting the bottom decile.



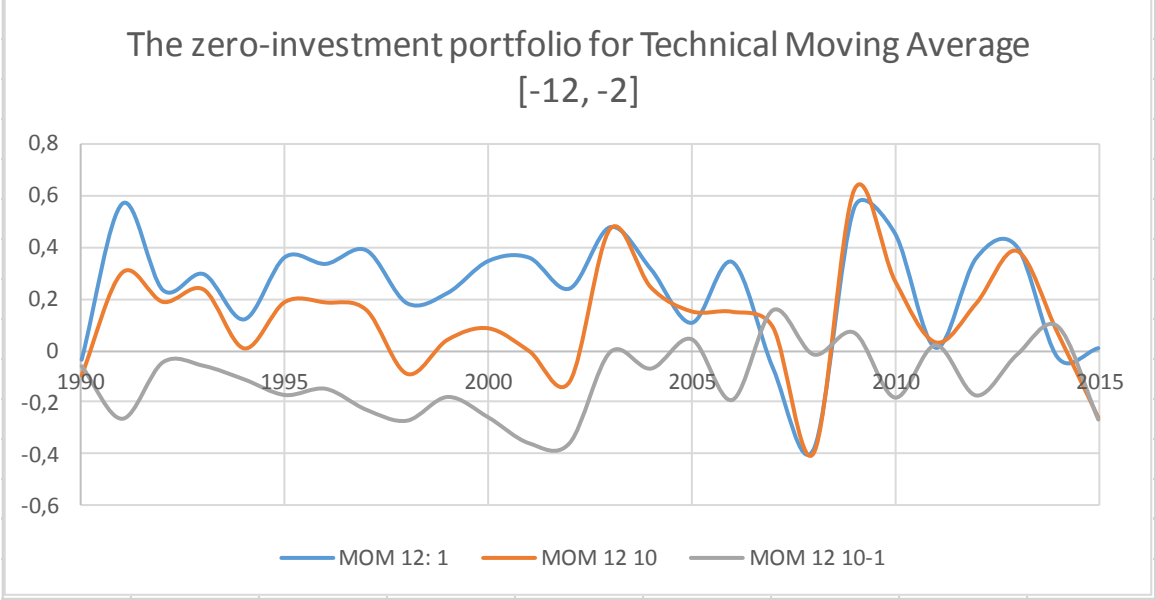
Based on the Figure 1, one would think that the momentum strategy is profitable during bullish markets. However, the crash of this strategy during a crisis is very large, with a negative annual return of almost 60% in 2009. Returns this negative can make disappear returns that are accumulated over the decades before, resulting in a relatively unprofitable strategy in an economy with crises. The negative return in 2008 seems to be caused by strong negative returns for the top decile, thus the past winners. The shock in 2009 is primarily due to an enormous growth for the bottom decile, thus the past losers, directly after the financial crisis. The Daniel and Moskowitz (2014) paper came up with the same source of the momentum-crash. They find that the momentum strategy experiences severe underperformance in the years 2001-2002 and 2008-2009, which is clear in the graph above. However, there they use a bigger time-window, these years influence their total results not as much as in this thesis.

Technical moving average

The returns on the technical moving average-portfolios can be, in contrast to the momentum strategy, very profitable. This high yield however cannot be accomplished by buying the top decile and shorting the bottom decile. Figure 1 shows that the returns on the deciles for TMA are decreasing per decile. The returns per decile are contrary to the expectations, but apparently the TMA-measure has some predictive power. The return on a zero portfolio, buying the bottom decile and shorting the top decile, equals around 1% per month on average. This return is significant even at the 1% level. The figure below shows that the bottom portfolio almost consistently outperforms the top portfolio.

Figure 2: a zero-investment momentum [-12, -2] portfolio through time

This graph depicts the annual returns on the technical moving average strategy based on the formation period [-12, -2]. The gray line represents the return on the zero-investment portfolio which is created by buying the top decile and shorting the bottom decile.



The bottom decile only resulted in negative annual return during the crisis, thus in 2008, and a slightly negative return in 2014. The negative return during the crisis is not strange, because most firms suffered heavily due to the crisis. The zero-investment portfolio, in this case decile 1 minus decile 10, is generally profitable. In the following steps of this thesis is the zero-investment portfolio related to a TMA strategy, unless mentioned otherwise, not the conventional top-minus-bottom portfolio, but the aforementioned bottom-minus-top portfolio.

The underperformance of the top decile relative to the bottom decile suggests an overreaction in the market to news, which is one of the most accepted explanations for the short term reversal. Those firms that performed better during the last month than they did on average during the formation period would have appreciated too much in the last month, which could result in a relative underperformance in the subsequent period. The reversal in the sign of the returns could be caused by the construction of the strategy measure in this thesis, which is different from the measure in most of earlier research. The TMA strategy is often tested by determining periodically whether to buy or sell a combination of stocks. This leaves the possibility that at a certain point in time all portfolios are bought, or that all portfolios are sold. This thesis uses deciles in order to execute this strategy, resulting in long- and short-transactions every period.

Comparison

The first hypothesis of this thesis states that the excess and abnormal returns on the technical moving average strategy will exceed the returns on the momentum strategies, including the short term reversal. Table 1 showed that is it possible to generate more returns with the TMA strategy than with the momentum strategy, although this does not mean that the findings are in line with literature. The low returns on the momentum strategy are probably caused by two periods of prolonged negative returns, while the returns on the TMA strategy are possibly caused by an overreaction in the market.

Section V.II: Correlation between strategies

Table 2 on the next page contains the correlations between the five zero-investment portfolios, which are computed based on the monthly returns on the zero-investment portfolio. Note that the TMA-portfolios in this table represent the portfolio which is expected to produce abnormal returns according to the literature. Figures 1 and 3 already showed that a profitable zero-investment is created by taking the opposite positions.

Table 2: correlation between zero-investment portfolios

Correlation table						
The table below contains the bivariate correlation coefficients between the returns of the zero-investment portfolios of the momentum strategies, including the short term reversal, and the technical moving average strategies.						
	MKT	SMB	HML	RMW	CMA	WML
MKT	-	0,234	-0,224	-0,378	-0,446	-0,141
SMB	0,234	-	-0,330	-0,545	-0,328	0,217
HML	-0,224	-0,330	-	0,429	0,778	-0,247
RMW	-0,378	-0,545	0,429	-	0,381	-0,042
CMA	-0,446	-0,328	0,778	0,381	-	-0,084
WML	-0,141	0,217	-0,247	-0,042	-0,084	-

The two conventional momentum-portfolios are highly correlated and are both negatively correlated with the short term reversal-portfolio. These results are in line with expectations. The TMA-portfolios have a high correlation coefficient with regard to the other TMA-portfolio, while the correlation with the momentum strategies are low. These low correlation coefficients suggest that the momentum- and TMA strategy are two different investment strategies. The sign and size of these coefficients are corresponding with the findings of Han, Yang and Zhou (2013). Because the zero-investment portfolios for the TMA strategy are only profitable if the first decile is bought and the top decile is shorted, the correlations between the applied TMA strategy and momentum strategy are positive.

The second hypothesis states that the TMA strategy is not significantly correlated with the momentum strategy. This is the case for the [-12, -2] strategies, but the TMA [-12, -7] and the momentum [-12, -7] are significantly correlated, however, the coefficient is relatively small. The hypothesis cannot be fully rejected, although the table above shows that the TMA and momentum strategies are relatively unrelated investment strategies.

Section V.III: Output regressions

Sections II and IV elaborate on the three asset pricing models used in this thesis. All three models are used to test the five different investing strategies. The alpha is interesting to indicate whether the strategy has a significant outperformance relative to other stocks with equal levels of risk. However, comparing the coefficients for the different factors between deciles within strategies, and between strategies both also can provide more insight in the strategies. The momentum strategy [-12, -2] will be compared with the technical moving average strategy [-12, -2], and the [-12, -7] strategies for momentum and technical moving average will also be compared. Different tables with output of regressions will be presented in this sub-section, these tables contain the output of 33 regressions. These 33 regressions are used to test one strategy on three asset pricing models, which means 11 regressions per asset pricing model. The first 10 regressions are done using the monthly excess return of one decile as dependent variable, the last regression is done using the excess return on a zero-investment portfolio that is constructed by either top-minus-bottom (momentum-strategies) or bottom-minus-top (TMA-strategies).

Section V.III.I: The momentum strategy

The momentum strategies will be covered first, the three applications of this strategy will be compared in terms of abnormal returns and factor sensitivity.

Momentum [-12, -2]

Looking at Table 3 on the next page, it can be stated that the Momentum [-12, -2] strategy generates no significant positive abnormal returns. Not all asset pricing models give the same conclusion, but this strategy either produces negative abnormal returns or negligible abnormal returns if a zero-investment portfolio is created.

It remains ambiguous what the sensitivity of the zero-investment portfolio to the market factor is. The three-factor model finds a significant negative market factor coefficient, which is significant at the 5% level, while the four-factor model finds a significant positive market factor coefficient, significant at the 1% level. The five-factor finds no significant coefficient at all. Looking back at the performance of this strategy during a crisis, a positive market coefficient would be expected. The four-factor model is by far best in explaining the zero-investment portfolio, making the coefficient estimates more reliable. The coefficient in this model is in line with the expectation based on the momentum crashes, thus a significant positive market factor. However, one should be careful with drawing conclusions on this matter.

Table 3: output for the Momentum [-12, -2] strategy

Regressions on the Momentum [-12,-2] portfolio

This table contains the output of the three-, four- and five-factor models on the momentum strategy based on the timeinterval [-12, -2]. The right hand collumn shows the output on the zero-investment portfolio, which in this case equals decile 10 minus decile 1. All regressions are done using OLS, the standard deviation is noted in parentheses beneath the coefficients. MKT represents the market factor, SMB the size factor and HML the value factor. WML is a momentum factor, RMW a factor based on profitability and CMA a factor based on investment. The same abbreviations are used in the other figures.

Decile / Model	1	2	3	4	5	6	7	8	9	10	Difference (10-1)
Observations	306	306	306	306	306	306	306	306	306	306	306
Three-factor model											
Intercept	0,002	0,001	0,002	0,002	0,001	0,002	0,003	0,002	0,005	0,006	0,002
	(0,002)	(0,001)	(0,001)	(0,001)**	(0,001)*	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,002)***	(0,003)
MKT	1,275	1,101	0,998	0,945	0,908	0,874	0,877	0,920	0,950	1,110	-0,167
	(0,047)***	(0,033)***	(0,027)***	(0,023)***	(0,020)***	(0,020)***	(0,020)***	(0,022)***	(0,026)***	(0,039)***	(0,071)**
SMB	0,700	0,461	0,402	0,336	0,336	0,282	0,323	0,405	0,478	0,710	0,013
	(0,068)***	(0,048)***	(0,039)***	(0,032)***	(0,028)***	(0,029)***	(0,029)***	(0,032)***	(0,037)***	(0,056)***	(0,103)
HML	0,715	0,621	0,593	0,552	0,509	0,514	0,450	0,488	0,407	0,353	-0,365
	(0,064)***	(0,045)***	(0,037)***	(0,031)***	(0,027)***	(0,027)***	(0,027)***	(0,030)***	(0,035)***	(0,053)***	(0,097)***
Adjusted R-Square	0,761	0,817	0,843	0,874	0,894	0,882	0,881	0,878	0,853	0,791	0,048
Four-factor model											
Intercept	0,007	0,004	0,004	0,004	0,002	0,003	0,003	0,002	0,003	0,004	-0,006
	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)	(0,001)***	(0,001)*	(0,001)***	(0,001)**	(0,002)***
MKT	1,120	0,993	0,908	0,893	0,880	0,855	0,879	0,944	1,002	1,200	0,078
	(0,031)***	(0,022)***	(0,020)***	(0,020)***	(0,019)***	(0,020)***	(0,021)***	(0,022)***	(0,023)***	(0,034)***	(0,044)*
SMB	0,872	0,580	0,491	0,393	0,368	0,303	0,321	0,377	0,420	0,610	-0,259
	(0,044)***	(0,032)***	(0,029)***	(0,028)***	(0,027)***	(0,028)***	(0,030)***	(0,031)***	(0,033)	(0,048)***	(0,062)***
HML	0,513	0,481	0,490	0,485	0,473	0,489	0,452	0,520	0,475	0,471	-0,046
	(0,041)***	(0,030)***	(0,028)***	(0,026)***	(0,026)***	(0,027)***	(0,028)***	(0,029)***	(0,031)***	(0,045)***	(0,059)
WML	-0,567	-0,393	-0,291	-0,190	-0,103	-0,071	0,007	0,090	0,192	0,331	0,895
	(0,027)***	(0,019)***	(0,018)***	(0,017)***	(0,017)***	(0,018)***	(0,018)***	(0,019)***	(0,020)***	(0,029)***	(0,038)***
Adjusted R-Square	0,904	0,923	0,917	0,911	0,905	0,888	0,880	0,886	0,886	0,853	0,664
Five-factor model											
Intercept	0,002	0,000	0,001	0,000	0,000	0,000	0,001	0,000	0,002	0,003	-0,001
	(0,002)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)*	(0,001)	(0,001)**	(0,002)**	(0,003)
MKT	1,243	1,127	1,025	1,011	0,968	0,945	0,961	1,020	1,032	1,201	-0,043
	(0,054)***	(0,037)***	(0,0030)***	(0,024)***	(0,021)***	(0,021)***	(0,020)***	(0,021)***	(0,026)***	(0,040)***	(0,081)
SMB	0,724	0,546	0,492	0,441	0,434	0,394	0,457	0,545	0,634	0,927	0,204
	(0,075)***	(0,052)	(0,043)***	(0,034)***	(0,029)***	(0,029)***	(0,028)***	(0,030)***	(0,036)***	(0,056)***	(0,113)*
HML	0,855	0,607	0,546	0,412	0,385	0,368	0,275	0,262	0,260	0,232	-0,627
	(0,102)***	(0,071)***	(0,058)***	(0,046)***	(0,040)***	(0,039)***	(0,037)***	(0,041)***	(0,049)***	(0,076)	(0,152)***
RMW	0,086	0,259	0,272	0,310	0,288	0,333	0,395	0,411	0,467	0,656	0,566
	(0,103)	(0,071)***	(0,058)***	(0,046)***	(0,040)***	(0,3039)***	(0,038)***	(0,041)***	(0,049)***	(0,077)***	(0,154)***
CMA	-0,261	-0,055	-0,003	0,139	0,120	0,143	0,173	0,253	0,103	0,001	0,265
	(0,127)**	(0,088)	(0,072)	(0,057)**	(0,017)***	(0,048)***	(0,047)***	(0,051)***	(0,061)*	(0,095)	(0,190)
Adjusted R-Square	0,764	0,824	0,851	0,891	0,910	0,906	0,914	0,912	0,886	0,831	0,087

* = significant at 0.10, ** = significant at 0.05 and *** = significant at 0.01

The output with regard to the size factor, SMB, is also inconclusive. All factor models show that the most extreme deciles have the highest sensitivity to the SMB-factor which is not surprising, there small firms tend to experience more extreme returns, either positive or negative. This characteristic of small firms causes small firms to be relatively often included in the top or bottom decile. The four-factor model generates a significantly negative SMB-sensitivity for the zero-investment portfolio. This suggests that the zero-investment portfolio performs better when small firms are outperformed by big-firms. This is in line with the finding of Wu (2002). The five-factor model finds a positive coefficient, but this one is only significant at the 10% level. Besides, the adjusted R-squared makes the four-factor model the more reliable estimator.

The three- and five-factor models both find significant negative coefficients for the value-factor HML. This finding suggests that the zero-investment portfolio is primarily sensitive to the low-value stocks. This finding again is in line with the findings of Wu (2002). The four-factor model does generate a

significant coefficient, but the coefficient is negative. All three asset pricing models show declining sensitivities to the HML factor per decile.

What is in line with the expectations are the estimates for the WML-factor, these estimates increase every decile, and lead to a, at the 1% level, coefficient of 0.895 for the zero-investment portfolio. It is not surprising that a portfolio which is based upon momentum, is this sensitive to the momentum-factor. The five-factor model again shows a significantly negative loading on the HML-factor, and a significantly positive relation between the profitability factor, RMW, and the return on the zero-investment portfolio. However, because of the danger of multicollinearity this results should be used carefully.

Momentum [-12, -7]

This application of the momentum strategy is not based on an often-used selection period, but because of the findings of Novy-Marx (2013) it is worth looking at. Table 4 contains the factor sensitivity for the three different asset pricing models. The intercept in the three-factor model is increasingly positive for every decile, implying an average abnormal return of 0,5% per month on the top 2 deciles. The bottom deciles have no significant intercept, which suggests that the top decile performs better relative to its risk level than the bottom decile. The intercept of the zero-investment portfolio however is not significant. The four- and five-factor models have similar result with regard to the intercept.

The four-factor model is the only asset pricing model which finds a significant dependence for the zero-investment portfolio on the size-factor, SMB. This factor has a significantly negative coefficient of -0.160. The top- and bottom decile have the highest coefficient for the SMB-factor, but the coefficient of the bottom-decile is higher, resulting in a negative coefficient for the zero-investment portfolio. The sensitivity to the HML-factor for the zero-investment portfolio is significantly negative for every pricing model, implying that this portfolio primarily focusses on low-value firms. Theory and empirical evidence state that these firms underperform high-value firms. The relation between the market factor and the zero-investment portfolios remains uncertain. The four-factor model finds a positive coefficient for the market factor, which is significant at the 1% level. The market factor coefficient is also positive in the other two asset pricing models, but are both insignificant. Findings on all three factors are according to the findings of Wu (2002).

This Novy-Marx momentum strategy has a strong dependence on the momentum-factor, which is showed by the WML-coefficient in the four-factor model. This coefficient of 0,528 is significant at a 1% level, and is caused by an almost consistently increasing coefficient through the deciles. The sensitivity of the zero-investment portfolio to the profitability factor is also significantly positive, this factor also has consistently increasing coefficients per decile. This results, however, should be treated carefully because of the severe multicollinearity.

Table 4: output for the Momentum [-12, -7] strategy

Regressions on the Momentum [-12,-7] portfolio

This table contains the output of the three-, four- and five-factor models on the momentum strategy based on the timeinterval [-12, -7]. The right hand collumn shows the output on the zero-investment portfolio, which in this case equals decile 10 minus decile 1. All regressions are done using OLS, the standard deviation is noted in parentheses beneath the coefficients.

Decile / Model	1	2	3	4	5	6	7	8	9	10	Difference (10-1)
Observations	306	306	306	306	306	306	306	306	306	306	306
Three-factor model											
Intercept	0,001	0,001	0,000	0,001	0,003	0,003	0,004	0,004	0,005	0,005	0,002
	(0,002)	(0,001)	(0,001)	(0,001)*	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,002)
MKT	1,168	1,011	0,983	0,950	0,907	0,901	0,891	0,942	1,013	1,180	0,011
	(0,036)***	(0,032)***	(0,023)***	(0,020)***	(0,019)**	(0,020)***	(0,021)***	(0,024)***	(0,026)***	(0,033)***	(0,054)
SMB	0,689	0,478	0,391	0,352	0,318	0,315	0,343	0,398	0,463	0,687	0,000
	(0,052)***	(0,040)***	(0,033)***	(0,028)***	(0,028)***	(0,029)***	(0,030)***	(0,035)***	(0,037)***	(0,048)**	(0,078)
HML	0,684	0,597	0,626	0,547	0,533	0,508	0,458	0,460	0,445	0,346	-0,341
	(0,049)***	(0,038)***	(0,031)***	(0,027)***	(0,026)***	(0,027)***	(0,028)***	(0,033)***	(0,035)***	(0,045)***	(0,073)***
Adjusted R-Square	0,821	0,848	0,884	0,910	0,898	0,887	0,882	0,861	0,864	0,848	0,070
Four-factor model											
Intercept	0,004	0,003	0,002	0,003	0,003	0,004	0,004	0,004	0,005	0,004	-0,003
	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,002)
MKT	1,064	0,933	0,926	0,911	0,879	0,884	0,885	0,944	1,026	1,221	0,155
	(0,028)***	(0,022)***	(0,019)***	(0,018)***	(0,019)***	(0,020)***	(0,028)***	(0,025)***	(0,026)***	(0,033)***	(0,044)***
SMB	0,804	0,564	0,454	0,396	0,349	0,333	0,350	0,395	0,449	0,641	-0,160
	(0,039)***	(0,031)***	(0,027)***	(0,026)***	(0,027)***	(0,029)***	(0,030)***	(0,035)***	(0,037)***	(0,047)***	(0,062)**
HML	0,548	0,496	0,552	0,496	0,497	0,486	0,450	0,463	0,461	0,399	-0,153
	(0,037)***	(0,029)***	(0,026)***	(0,,024)***	(0,025)***	(0,028)***	(0,029)***	(0,033)***	(0,036)***	(0,045)***	(0,059)**
WML	-0,382	-0,283	-0,208	-0,143	-0,100	-0,061	-0,022	0,009	0,046	0,149	0,528
	(0,024)***	(0,019)***	(0,017)	(0,016)***	(0,016)***	(0,018)***	(0,019)	(,022)	(0,023)**	(0,029)***	(0,038)***
Adjusted R-Square	0,902	0,912	0,924	0,922	0,909	0,890	0,882	0,861	0,865	0,860	0,432
Five-factor model											
Intercept	0,000	0,000	-0,001	0,000	0,001	0,001	0,002	0,001	0,003	0,003	0,000
	(0,002)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)**	(0,001)	(0,001)***	(0,001)**	(0,002)
MKT	1,168	1,017	1,020	0,998	0,973	0,983	0,983	1,041	1,102	1,249	0,079
	(0,041)***	(0,032)***	(0,025)***	(0,021)***	(0,020)***	(0,019)***	(0,020)***	(0,024)***	(0,026)***	(0,036)***	(0,062)
SMB	0,750	0,528	0,473	0,448	0,432	0,462	0,476	0,555	0,618	0,851	0,102
	(0,058)***	(0,04)***	(0,035)***	(0,030)***	(0,027)***	(0,027)***	(0,028)***	(0,033)***	(0,037)***	(0,050)***	(0,087)
HML	0,742	0,623	0,569	0,465	0,403	0,354	0,258	0,256	0,274	0,257	-0,490
	(0,078)***	(0,060)***	(0,047)***	(0,040)***	(0,037)***	(0,036)***	(0,038)***	(0,045)***	(0,049)***	(0,067)***	(0,117)***
RMW	0,194	0,156	0,248	0,287	0,337	0,438	0,393	0,464	0,462	0,499	0,301
	(0,079)**	(0,060)**	(0,048)***	(0,050)***	(0,037)***	(0,036)***	(0,038)***	(0,045)***	(0,050)***	(0,068)***	(0,118)**
CMA	-0,157	-0,092	0,019	0,049	0,114	0,125	0,216	0,200	0,146	-0,004	0,156
	(0,98)	(0,075)	(0,059)	(0,050)	(0,046)**	(0,045)***	(0,047)***	(0,056)***	(0,062)**	(0,084)	(0,146)
Adjusted R-Square	0,825	0,852	0,893	0,915	0,920	0,923	0,915	0,899	0,895	0,871	0,086

* = significant at 0.10, ** = significant at 0.05 and *** = significant at 0.01

Short term reversal, Momentum [-1]

The previous application of the momentum strategy slightly differed from the conventional strategy, the short term reversal is actually betting against momentum in the short run. The output for this strategy can be found in Table 5. One result that can be noted directly, is the negative sensitivity to the momentum factor WML. Because this application of the momentum strategy bets against momentum, this negative relationship is in line with earlier literature which points to an overreaction in the market.

Table 5: output for the Momentum [-1] strategy

Regressions on the Momentum [-1] portfolio

This table contains the output of the three-, four- and five-factor models on the momentum strategy based on the timeinterval [-1]. The right hand collumn shows the output on the zero-investment portfolio, which in this case equals decile 10 minus decile 1. All regressions are done using OLS, the standard deviation is noted in parentheses beneath the coefficients.

Decile / Model	1	2	3	4	5	6	7	8	9	10	Difference (10-1)
Observations	306	306	306	306	306	306	306	306	306	306	306
Three-factor model											
Intercept	0,004	0,001	0,002	0,002	0,002	0,003	0,003	0,004	0,004	0,003	0,002
	(0,001)***	(0,001)	(0,001)*	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,002)*	(0,002)
MKT	1,013	0,913	0,887	0,887	0,901	0,899	0,977	1,031	1,103	1,335	0,323
	(0,029)***	(0,024)***	(0,020)***	(0,019)***	(0,018)***	(0,018)***	(0,022)***	(0,025)***	(0,028)***	(0,040)***	(0,052)***
SMB	0,621	0,437	0,335	0,355	0,343	0,352	0,379	0,427	0,543	0,681	0,058
	(0,042)***	(0,034)***	(0,029)***	(0,027)***	(0,027)***	(0,026)***	(0,031)**	(0,036)***	(0,041)***	(0,058)***	(0,075)
HML	0,538	0,425	0,477	0,489	0,530	0,513	0,476	0,568	0,589	0,596	0,061
	(0,039)**	(0,032)***	(0,027)***	(0,026)	(0,025)***	(0,024)***	(0,030)***	(0,034)***	(0,038)***	(0,054)***	(0,071)
Adjusted R-Square	0,846	0,858	0,887	0,897	0,905	0,910	0,886	0,876	0,864	0,824	0,115
Four-factor model											
Intercept	0,003	0,001	0,002	0,002	0,002	0,003	0,004	0,005	0,006	0,007	0,005
	(0,001)***	(0,001)	(0,001)**	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,002)***
MKT	1,024	0,920	0,884	0,883	0,888	0,885	0,940	0,985	1,038	1,227	0,205
	(0,029)***	(0,025)***	(0,020)***	(0,020)***	(0,019)***	(0,018)***	(,021)***	'(0,023)***	(0,025)***	(0,032)***	(0,046)***
SMB	0,621	0,429	0,339	0,361	0,358	0,368	0,380	0,477	0,615	0,801	0,190
	(0,042)***	(0,035)***	(0,029)***	(0,028)***	(0,027)***	(0,026)***	(0,029)***	(0,033)***	(0,035)***	(0,046)***	(0,065)***
HML	0,553	0,434	0,473	0,483	0,513	0,495	0,429	0,509	0,504	0,455	-0,093
	(0,040)***	(0,033)***	(0,028)***	(0,026)***	(0,025)***	(0,025)***	(0,028)***	(0,031)***	(0,033)***	(0,043)***	(0,062)
WML	0,042	0,027	-0,012	-0,018	-0,048	-0,051	-0,133	-0,167	-0,238	-0,395	-0,433
	(0,026)	(0,022)	(0,018)	(0,017)	(0,016)***	(0,016)***	(0,018)***	(0,020)***	(0,021)***	(0,028)***	(0,040)***
Adjusted R-Square	0,847	0,858	0,887	0,897	0,908	0,912	0,903	0,898	0,905	0,894	0,363
Five-factor model											
Intercept	0,002	0,000	0,000	0,000	0,000	0,001	0,001	0,002	0,003	0,002	0,003
	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)	(0,001)*	(0,001)**	(0,002)	(0,002)
MKT	1,068	0,976	0,953	0,959	0,977	0,962	1,046	1,092	1,149	1,353	0,287
	(0,031)***	(0,024)***	(0,020)***	(0,019)***	(0,019)***	(0,018)***	(0,023)***	(0,027)***	(0,032)***	(0,046)***	(0,060)***
SMB	0,766	0,580	0,461	0,479	0,455	0,458	0,453	0,539	0,638	0,766	-0,001
	(0,043)***	(0,034)***	(0,028)***	(0,026)***	(0,026)***	(0,026)***	(0,032)***	(0,037)***	(0,044)**	(0,064)***	(0,084)
HML	0,481	0,334	0,361	0,350	0,364	0,389	0,337	0,456	0,512	0,612	0,136
	(0,058)	(0,046)***	(0,038)***	(0,035)***	(0,035)***	(0,035)***	(0,043)***	(0,051)***	(0,060)***	(0,086)***	(0,114)
RMW	0,443	0,431	0,376	0,369	0,328	0,313	0,336	0,335	0,285	0,264	-0,176
	(0,058)***	(0,046)***	(0,08)***	(0,036)***	(0,035)***	(0,035)***	(0,044)***	(0,051)***	(0,060)***	(0,087)***	(0,115)
CMA	-0,039	0,020	0,080	0,121	0,178	0,113	0,131	0,086	0,042	-0,107	-0,071
	(0,072)	(0,057)	(0,047)*	(0,044)***	(0,044)***	(0,043)***	(0,054)**	(0,063)	(0,074)	(0,107)	(0,142)
Adjusted R-Square	0,871	0,889	0,915	0,925	0,928	0,929	0,905	0,890	0,875	0,829	0,116

* = significant at 0.10, ** = significant at 0.05 and *** = significant at 0.01

The intercept is increasing for the four-factor model, leading to a significant monthly abnormal return of 0,5% on average for the zero-investment portfolio. The three- and five-factor models also show positive intercepts, but both are insignificant. The market factor coefficient for the zero-investment portfolio is consistently positive and significant at the 1% level. Which indicates that the short term reversal generally performs better when the market on average is performing well.

The effect of the SMB and HML factors are generally insignificant, the sensitivity to these factors remains ambiguous. However, using the four-factor model, this strategy has a significantly positive dependence on the SMB-factor.

Comparison

The three applications of the momentum strategy are all strongly related to the momentum factor, the four-factor model is the best model to explain every one of the applications. The zero-investment portfolios of the [-12, -2] and [-12, -7] strategy are positively related to the momentum factor, which is not surprising because this is the philosophy behind the strategies. The short term reversal strategy is negatively related to the momentum factor, which is also in line with expectations.

The intercepts of the zero-investment portfolios are also relevant. There is uncertainty with regard to the intercept of the [-12, -2] portfolio, but the results point carefully at a negative intercept. The intercept of the [-12, -7] is insignificant in every asset pricing model, and the coefficient is very small. The short term reversal strategy performs best with regard to the intercept, there the four-factor model finds a significantly positive intercept for this strategy. The absence of a significant intercept could be caused by the financial crisis, there most of the profits were erased in two years of bearish markets. This is line with the paper of Daniel and Markowitz (2014).

The influence of the market factor on the conventional momentum strategies remains unclear, contrary to the influence on the short term reversal. The short term reversal has a positive market factor coefficient in all three models. The market sensitivity for the conventional momentum strategies stays ambiguous, while the short term reversal generates more returns when the market performs well. The three momentum-strategies show some similarities in the findings on the SMB-factor, there the extreme portfolios have the highest SMB-coefficients. This is, as aforementioned, not surprising, because small stocks experience more extreme results. The conventional momentum strategies have a significant negative sensitivity to this factor, while the short term reversal has no clear sensitivity to the size factor.

The zero-investment portfolio based on a momentum [-1] strategy, the short term reversal, has no statistically significant sensitivity to the value factor. However, the zero-investment portfolios of the two other momentum-strategies have significantly negative dependence on the value-factor. For both strategies, unregarded the used asset pricing model, the coefficient for the HML-factor declines between almost every decile. Apparently, the top deciles buy relatively many low-value, or growth, stocks, while the bottom decile contains more high-value stocks.

Generally, the findings on the momentum factor are in line with the paper of Wu (2002). Some things are worth mentioning. The abnormal returns are practically absent in this thesis, which is probably caused by market crashes. Furthermore, it is striking that the short term reversal has almost opposite factor sensitivities relative to the conventional momentum strategies.

Section V.III.II: The technical moving average strategy

After comparing the different applications of the momentum strategy, the same will be done with the technical moving average strategy. Afterwards, the momentum strategy and technical moving average strategy will be compared.

Technical moving average [-12, -2]

Table 6 contains the output for the TMA [-12, -2] strategy. The intercept is significantly positive for the first deciles, regardless of the asset pricing model. For all models, the intercept decreases per decile, leading to a significantly positive alpha of 1% per month on average on the zero-investment portfolio. This portfolio is created by buying the bottom decile and shorting the top decile. The market factor also has a significantly positive coefficient with regard to this portfolio in every asset pricing model, the size of the coefficients is comparable. The zero-investment portfolio performs better when the market in general experiences higher returns, which is caused by the high market-betas of the bottom decile. The coefficients of the market-factor are all significant at the 1% level.

The momentum-factor WML also has consistently, thus for all deciles, significantly negative returns. The coefficients are relatively small compared to the other factors. The coefficient for the zero-investment portfolio is negligible with 0.012 and is not significant. The SMB- and HML-factors all have significant coefficients for every decile and every model, however, the difference between the coefficients of the top and bottom decile is very small leading to negligible coefficients. Interestingly, the extreme deciles have generally higher coefficients than the deciles in the middle. The zero-investment portfolio of this TMA strategy generally buys and shorts relatively small and high-value firms. The three models perform almost equally well in explaining the zero-investment portfolio. The three models lead to similar adjusted R-square with regard to this portfolio.

Table 6: output for the Technical Moving Average [-12, -2] strategy

Regressions on the Technical Moving Average [-12, -2] portfolio

This table contains the output of the three-, four- and five-factor models on the technical moving average strategy based on the timeinterval [-12, -2]. The right hand collumn shows the output on the zero-investment portfolio, which in this case equals decile 1 minus decile 10. All regressions are done using OLS, the standard deviation is noted in parentheses beneath the coefficients.

Decile / Model	1	2	3	4	5	6	7	8	9	10	Difference (1-10)
Observations	306	306	306	306	306	306	306	306	306	306	306
Three-factor model											
Intercept	0,007	0,004	0,003	0,003	0,004	0,003	0,002	0,001	-0,001	0,000	0,010
	(0,002)***	(0,001)***	(0,001)	(0,001)***	(0,001)***	(0,001)***	(0,001)**	(0,001)	(0,001)	(0,001)	(0,002)***
MKT	1,307	1,106	1,013	0,985	0,905	0,905	0,901	0,899	0,937	0,994	0,314
	(0,036)***	(0,029)***	(0,024)***	(0,021)***	(0,021)***	(0,019)***	(0,018)***	(0021)***	(0,023)***	(0,032)***	(0,052)***
SMB	0,701	0,484	0,370	0,352	0,327	0,365	0,369	0,394	0,404	0,649	0,050
	(0,052)***	(0,041)***	(0,034)***	(0,030)***	(0,030)***	(0,028)***	(0,027)***	(0,031)***	(0,034)***	(0,046)	(0,074)
HML	0,563	0,550	0,495	0,532	0,485	0,521	0,455	0,504	0,528	0,573	-0,007
	(0,049)***	(0,039)***	(0,032)***	(0,028)***	(0,028)***	(0,026)***	(0,025)***	(0,029)***	(0,032)***	(0,044)	(0,070)
Adjusted R-Square	0,849	0,858	0,878	0,897	0,882	0,899	0,905	0,879	0,869	0,814	0,117
Four-factor model											
Intercept	0,008	0,005	0,004	0,004	0,004	0,004	0,003	0,002	0,000	0,001	0,010
	(0,002)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)***	(0,001)**	(0,001)	(0,001)	(0,002)***
MKT	1,278	1,085	0,987	0,967	0,885	0,878	0,901	0,869	0,304	0,952	0,328
	(0,037)***	(0,029)***	(0,024)***	(0,021)***	(0,021)***	(0,019)***	(0,018)	(0,021)***	(0,023)***	(0,032)***	(0,053)***
SMB	0,733	0,507	0,398	0,372	0,349	0,395	0,399	0,427	0,440	0,696	0,034
	(0,052)***	(0,042)***	(0,034)***	(0,030)***	(0,030)***	(0,027)***	(0,025)***	(0,030)***	(0,032)***	(0,045)***	(0,076)
HML	0,525	0,523	0,462	0,508	0,458	0,486	0,421	0,465	0,485	0,518	0,012
	(0,049)***	(0,039)***	(0,032)***	(0,029)***	(0,028)***	(0,025)***	(0,024)***	(0,028)***	(0,031)	(0,043)***	(0,072)
WML	-0,106	-0,075	-0,093	-0,067	-0,074	-0,099	-0,097	-0,109	-0,120	-0,156	0,053
	(0,032)***	(0,026)***	(0,021)***	(0,018)***	(0,018)***	(0,016)***	(0,016)***	(0,018)***	(0,020)***	(0,028)***	(0,047)
Adjusted R-Square	0,854	0,861	0,886	0,901	0,887	0,909	0,916	0,891	0,883	0,832	0,118
Five-factor model											
Intercept	0,006	0,002	0,002	0,001	0,002	0,001	0,000	0,000	-0,002	-0,002	0,010
	(0,002)***	(0,001)*	(0,001)	(0,001)	(0,001)**	(0,001)*	(0,001)	(0,001)	(0,001)**	(0,001)	(0,002)***
MKT	1,338	1,165	1,085	1,055	0,986	0,978	0,951	0,954	0,993	1,035	0,305
	(0,040)***	(0,031)***	(0,025)***	(0,025)***	(0,021)***	(0,019)***	(0,020)***	(0,022)***	(0,025)***	(0,036)***	(0,060)***
SMB	0,822	0,623	0,502	0,478	0,443	0,482	0,457	0,512	0,518	0,742	0,079
	(0,056)***	(0,043)***	(0,034)***	(0,030)***	(0,030)*	(0,027)***	(0,028)***	(0,031)***	(0,035)***	(0,051)***	(0,083)
HML	0,565	0,470	0,364	0,401	0,304	0,371	0,358	0,419	0,436	0,516	0,053
	(0,076)***	(0,058)***	(0,047)***	(0,040)***	(0,040)***	(0,037)***	(0,037)***	(0,042)***	(0,047)***	(0,069)***	(0,113)
RMW	374,000	0,420	0,397	0,378	0,341	0,347	0,263	0,355	0,345	0,283	0,094
	(0,076_***	(0,058)***	(0,047)***	(0,040)***	(0,041)***	(037)***	(0,038)***	(0,042)***	(0,047)***	(0,069)***	(0,114)
CMA	-0,118	0,005	0,098	0,104	0,199	0,146	0,083	0,033	0,048	0,009	-0,130
	(0,094)	(0,072)	(0,058)*	(0,050)**	(0,050)***	(0,046)***	(0,047)*	(0,052)	(0,059)	(0,085)	(0,141)
Adjusted R-Square	0,861	0,878	0,902	0,920	0,906	0,922	0,918	0,901	0,889	0,823	0,116

* = significant at 0.10, ** = significant at 0.05 and *** = significant at 0.01

Technical moving average [-12, -7]

This strategy is not conventional, but is useful for comparing the TMA strategy with the momentum strategy. The bottom decile has a relatively high intercept for all asset pricing models, while the top decile has a relatively low intercept. The result is a significant and positive intercept for all three asset pricing models, implying an average monthly abnormal return of 1%-1.1% on the zero-investment portfolio.

The models also show comparable coefficients for the market factor. The zero-investment portfolio is positively related to the market factor; the coefficients are all significant at the 1% level. The other factors contribute significantly to explaining the individual deciles, but have no explanatory power with regard to the zero-investment portfolio. Just as with the TMA strategy based on [-12, -2] are the most extreme deciles more sensitive to the factors than the middle deciles. All models are performing equally well in explaining the returns on the individual deciles and the zero-investment portfolio.

Table 7: output for the Technical Moving Average [-12, -7] strategy

Regressions on the Technical Moving Average [-12, -7] portfolio

This table contains the output of the three-, four- and five-factor models on the technical moving average strategy based on the timeinterval [-12, -7]. The right hand collumn shows the output on the zero-investment portfolio, which in this case equals decile 1 minus decile 10. All regressions are done using OLS, the standard deviation is noted in parentheses beneath the coefficients.

Decile / Model	1	2	3	4	5	6	7	8	9	10	Difference (1-10)
Observations	306	306	306	306	306	306	306	306	306	306	306
Three-factor model											
Intercept	0,008	0,005	0,003	0,003	0,004	0,003	0,001	0,001	-0,001	0,000	0,010
	(0,002)***	(0,001)***	(0,001)***	(0,001)***	(0,001)**	(0,001)***	(0,001)	(0,001)	(0,001)	(0,001)	(0,002)***
MKT	1,334	1,119	1,019	0,965	0,927	0,876	0,882	0,900	0,947	0,982	0,353
	(0,038)***	(0,029)***	(0,24)***	(0,021)***	(0,020)***	(0,018)***	(0,019)***	(0,021)***	(0,023)***	(0,032)***	(0,053)***
SMB	0,698	0,456	0,378	0,365	0,345	0,357	0,357	0,347	0,430	0,677	0,019
	(0,055)***	(0,042)***	(0,034)***	(0,031)***	(0,028)***	(0,026)***	(0,028)***	(0,030)***	(0,033)***	(0,047)***	(0,077)
HML	0,548	0,528	0,525	0,532	0,489	0,490	0,492	0,482	0,556	0,564	-0,013
	(0,051)***	(0,040)***	(0,032)***	(0,029)***	(0,027)***	(0,025)***	(0,026)***	(0,028)***	(0,031)***	(0,044)***	(0,072)
Adjusted R-Square	0,840	0,854	0,878	0,890	0,897	0,902	0,892	0,883	0,877	0,814	0,134
Four-factor model											
Intercept	0,009	0,006	0,004	0,004	0,004	0,003	0,002	0,002	0,000	0,001	0,011
	(0,002)***	(0,001)***	(0,001)***	(0,001)****	(0,001)***	(0,001)***	(0,001)**	(0,001)**	(0,001)	(0,001)	(0,002)***
MKT	1,294	1,095	0,993	0,946	0,906	0,859	0,855	0,873	0,914	0,944	0,352
	(0,038)***	(0,030)***	(0,024)***	(0,021)***	(0,020)***	(0,018)***	(0,019)***	(0,020)***	(0,022)***	(0,032)***	(0,055)***
SMB	0,743	0,483	0,408	0,387	0,369	0,375	0,387	0,377	0,467	0,719	0,020
	(0,054)***	(0,042)***	(0,034)***	(0,031)***	(0,028)	(0,026)***	(0,027)***	(0,029)***	(0,031)***	(0,046)***	(0,078)
HML	0,496	0,497	0,490	0,506	0,461	0,468	0,457	0,447	0,513	0,515	-0,015
	(0,051)***	(0,040)***	(0,032)***	(0,029)***	(0,027)***	(0,025)***	(0,026)***	(0,027)***	(0,030)***	(0,044)***	(0,074)
WML	-0,146	-0,086	-0,098	-0,071	-0,079	-0,061	-0,098	-0,099	-0,121	-0,139	-0,004
	(0,033)***	(0,026)***	(0,021)***	(0,019)***	(0,017)***	(0,016)***	(0,017)***	(0,018)***	(0,019)***	(0,028)***	(0,048)
Adjusted R-Square	0,849	0,859	0,886	0,894	0,904	0,906	0,903	0,894	0,898	0,828	0,131
Five-factor model											
Intercept	0,007	0,003	0,002	0,001	0,002	0,001	0,000	-0,001	-0,003	-0,002	0,010
	(0,002)***	(0,001)**	(0,001)*	(0,001)*	(0,001)**	(0,001)	(0,001)	(0,001)	(0,001)***	(0,001)	(0,002)***
MKT	1,362	1,119	1,078	1,041	1,009	0,946	0,940	0,954	0,997	1,023	0,341
	(0,042)***	(0,031)***	(0,025)***	(0,022)***	(0,020)***	(0,019)***	(0,021)***	(0,022)***	(0,024)***	(0,036)***	(0,061)***
SMB	0,830	0,608	0,501	0,482	0,460	0,465	0,456	0,457	0,545	0,777	0,052
	(0,058)***	(0,043)	(0,035)***	(0,031)***	(0,028)***	(0,026)***	(0,029)***	(0,030)***	(0,034)***	(0,051)***	(0,086)
HML	0,574	0,412	0,433	0,373	0,304	0,340	0,379	0,391	0,486	0,513	0,064
	(0,079)***	(0,058)***	(0,048)***	(0,042)***	(0,038)***	(0,035)***	(0,039)***	(0,041)***	(0,046)***	(0,069)***	(0,116)
RMW	0,409	0,455	0,370	0,346	0,335	0,319	0,292	0,329	0,345	0,302	0,110
	(0,080)***	(0,059)***	(0,048)***	(0,042)***	(0,038)***	(0,036)***	(0,039)	(0,041)***	(0,046)***	(0,069)***	(0,117)
CMA	-0,168	0,055	0,041	0,160	0,207	0,154	0,100	0,053	0,012	-0,007	-0,164
	(0,099)*	(0,073)	(0,059)	(0,052)***	(0,047)***	(0,044)***	(0,049)***	(0,051)	(0,057)	(0,086)	0,000
Adjusted R-Square	0,854	0,878	0,898	0,911	0,921	0,924	0,902	0,903	0,896	0,825	0,135

* = significant at 0.10, ** = significant at 0.05 and *** = significant at 0.01

Comparison

The output for the two applications of the TMA strategy are very comparable. Both strategies produce significant and positive abnormal return in every asset pricing model, with coefficient of 0,010 of 0,011. Both applications of the TMA-strategies are very sensitive to the market factor and not really sensitive to the other factors. The zero-investment portfolios have significantly positive coefficients for the market factor, and are not depending statistically on the other factors. The sensitivity to the market factor is very constant, there both strategies have market factors between 0,3 and 0,4, where can be noticed that the coefficients are slightly higher for the [-12, -7] strategy. All other factors do not add substantial explanatory power.

Section V.III.III: A comparison between strategies

Comparisons within the main strategies are already made, this subsection compares the momentum strategies with the technical moving average strategies.

When looking at the abnormal returns, the alpha or intercept from the model, it is clear that the technical moving average strategy is able to generate abnormal return, while the conventional momentum strategies are unable to do so. The intercept of the short term reversal remains inconclusive, although the result point carefully at a positive abnormal return. The first hypothesis of this thesis looks at the excess and abnormal returns on the TMA strategy relative to those on the momentum strategy. Section V.I showed already that the TMA strategy outperformed the momentum strategy in terms of excess return. The output of the regressions provide support for the hypothesis that the technical moving average strategy outperforms the momentum strategy in terms of abnormal returns.

The conventional momentum strategies are not significantly sensitive to the market factor, while both the short term reversal and the technical moving average strategies are significantly positively depending on the market factor. These portfolios perform better when the market performs well. The conventional momentum strategies also show similar coefficients with regard to the size factor. Both zero-investment portfolios have a significantly negative coefficient to the SMB factor, while the three other strategies have no significant sensitivity to this factor. All zero-investment portfolio consist primarily of small stocks, there both the top and the bottom decile contain primarily small stocks. As earlier mentioned, this is caused by their extreme returns with regard to big stocks.

Generally, the momentum strategies are relatively depending on low-value stocks, regarding the significantly negative coefficient of the HML factor. The short term reversal and technical moving average are not significantly depending on the value factor.

The coefficients of the momentum factor, WML, are complete in line with expectations. Both the [-12, -2] and the [-12, -7] strategy have high and positive WML coefficients, while the reverse momentum

strategy has a strongly negative WML coefficient. Both TMA strategies are not significantly influenced by the market factor.

The technical moving average strategy is compared with the momentum strategy with regard to the factor coefficients. Looking at these coefficients, the two strategies seem to have different sources of their return. However, there are surprisingly much similarities between the short term reversal and the technical moving average strategies. Both have a positive intercept, significantly positive sensitivity to the market factor, while the sensitivities to the other factors are generally small and insignificant. There the zero-investment portfolios of the technical moving average are constructed in the same way as the portfolio of the short term reversal and the results are comparable, it looks like this thesis tested a short term reversal within the technical moving average. The TMA measure is, just like the short time reversal measure, heavily depending on the performance of a stock in the last month. A reversal in the short run could explain the finding of the bottom decile outperforming the top decile.

The third hypothesis states that the technical moving average strategy and the momentum strategy are sensitive to different factors. The output on the regressions provided support for this statement, there the technical moving average is significantly depending on the market factor, while the momentum strategy has a significant sensitivity to the size, value and momentum factors.

The next subsection will double sort the dataset, in order to check if the TMA strategy is also profitable within the momentum deciles and vice versa.

Section V.IV: Double sorting

The results in the previous subsection already give an insight in the differences between the momentum strategies and the technical moving average strategies. Applying a double-sorting process on the dataset can give extra information. Is the TMA strategy still profitable within momentum deciles? If this is the case, this would be extra support for the conclusion that the two strategies are truly different strategies. The notation MOM [-12, -7] TMA [-12, -7] means that the dataset is firstly ranked based on MOM [-12, -7] and subsequently on the TMA [-12, -7] strategy. The tables with the output can be found in the appendix in Tables A.7 – A.10.

Tables A.7 and A.8 show the results of dividing the momentum decile into deciles based on the corresponding TMA-measure. The TMA-measure is consistently able to generate additional returns within the momentum deciles. Again, the bottom decile of the TMA strategy performs consistently better than the top decile. Interesting to note is that the TMA strategy generates most profits in the low deciles of the momentum strategy. Apparently is the TMA strategy able to divide the ‘good losers’, those losers that turn into winners, from the ‘bad losers’, those that remain losers. However, it is harder to separate the ‘good’ from the ‘bad’ winners.

Tables A.9 and A.10 show that the momentum strategy is unable to consistently generate additional profits within the TMA-measures. For both formation periods is the average additional returns neglibible with 0.0% or 0.1% monthly. However, the momentum strategy can generate a profit of +1.1% within the top TMA-decile, but a 0.9% loss within the bottom decile erases this result. On average, the momentum strategy adds no value to the TMA strategy. The short-term reversal is left out of this analysis, because the TMA [-1] strategy is not tested in this paper. The double-sorting shows again that the TMA strategy and momentum strategy are quite unrelated. This because the TMA strategy is able to produce substantial returns within every momentum decile.

Section V.V: Additional robustness checks

The previous subsections shed some light on the differences between the momentum and technical moving average strategies. However, the results are still surprising: the momentum strategy seems not profitable and the bottom decile of the TMA strategy outperforms the top decile. In order to test if this results are not accidental, two additional robustness checks are executed. The applied holding period in this thesis is one month, but several momentum strategies are tested using a three month holding period. Therefore, the profitability of the three momentum strategies is tested using a three month holding period. The surprising returns on the TMA strategy could be caused by the way of computing the TMA-measure. Often, this is done using prices, but in this thesis the measure is computed using returns. In order to check if this causes the returns, the TMA strategy is also tested with a measure based on prices.

Three month holding period

The momentum strategy is now tested with a holding period of three months, but a new portfolio is formed every month. For month t, the return is then the average of the returns on the three relevant portfolios, which are the portfolios of the last three months. The table with the returns on the corresponding strategy can be found in Table A.11.

The short term reversal is as expected less effective with a three month holding period relative to the one month holding period. The two other applications of momentum strategy are also not improved. Apparently, the returns do not change substantially using another holding period. The figure on the next page shows that the output using the asset pricing models is also comparable, although not identical. The output of this strategy using the asset pricing models is presented in Table A.12.

Measure based on price

Earlier, the TMA-measure was based on returns, which is used several times. However, an approach where the measure is based on stock prices is more conventional. Because the decile performed opposite to expectations, it is good to check whether this is cause by this return-related approach or not. Therefore, TMA-measures based on standardized prices are computed. The prices are standardized using the following formula:

$$P_o = \frac{P_0 - \frac{p_0 + p_{-1} + \cdots + P_{-11}}{12}}{\frac{p_0 + p_{-1} + \cdots + P_{-11}}{12}}.$$

Deciles are created based on these measures, and Table A.13 shows the performance of these deciles.

The returns per decile are comparable with the returns earlier presented, and the size of the difference is almost identical. And again, the bottom decile outperforms the top decile clearly. This is a support for the initial methodology of using returns to compute the TMA-measures. Looking at this thesis is the TMA strategy able to create abnormal returns and is it even able to generate these returns within momentum deciles.

This section contains many figures with output for the five different investment strategies. Most of the results are mentioned in this section. Now the analysis is done, and the output is also analyzed, it is time to answer the research question using the hypotheses. This will be done in the next section.

Section VI: Conclusion

The research question, **"**To what extent are the momentum strategy, the short-term reversal and the technical moving average strategy related?", will be answered in this section. In order to do this, the hypotheses will be used. The hypothesis all represent one part of the comparison between the investment strategies: profitability, correlation and factor sensitivity.

The first hypothesis, "There is no significant difference between the technical moving average, the short term reversal and the momentum strategy in term of excess and abnormal returns", implies that the strategies are comparable in terms of profitability. In the results section it became clear that the technical moving average strategy generates significant abnormal returns of 1% per month, while none of the momentum strategies produced significant abnormal returns. The excess returns on the momentum strategies were not significant at the conventional 5% significance level, although one of the applications yielded positive excess returns which are significant at the 10% level. The applications of the technical moving average both generated similar excess returns, both significant at the 1% level. Even more support for the superior performance of the technical moving average strategy was produced by the double sorting. The technical moving average is able to consistently create returns within the momentum deciles, while the momentum strategy is unable to do the same in the technical moving average deciles. Based on these different sources of evidence, the null hypothesis should be rejected. It seems that the technical moving average outperforms the momentum strategy in terms of excess and abnormal returns.

However, it should be noted that the zero-investment portfolio for this strategy is not constructed as expected. The bottom decile clearly outperforms the top decile, while the opposite was expected. The same is the case for a TMA-measure based on prices instead of returns. The used construction of the strategy is different from earlier research, which could cause the difference in findings. This thesis every month buys the top (bottom) decile and sells the bottom (top) decile, while earlier research tested this strategy by deciding every period whether a group of stocks should be bought or sold. These findings could be explained by an overreaction in the market. Those firms that performed recently better than they did on average during the formation period have increased too much in value, while the relative losers' price depreciated too much. If this overreaction would be corrected in the subsequent period, the bottom decile is expected to outperform the top decile, which is the empirical result of this thesis. There the holding period is only one month, it is possible that reversal is found in the technical moving average strategy.

The second hypothesis states that the momentum strategy and technical moving average strategy are not significantly correlated. This hypothesis is tested with regard to the excess returns on the zero-investment portfolios. Looking at the correlations between these excess returns, there is some support for this hypothesis, but the hypothesis cannot be fully rejected. The correlation between several applications is insignificant, but there are also applications with significant correlation. Although it

cannot be concluded that the momentum strategy and technical moving average strategy are not significantly correlated, it is possible to conclude that the correlation between the two is not strong. The correlation between the technical moving average portfolios and the short term reversal has the highest absolute coefficient, but is still only -0.335.

The anterior hypotheses already show that the technical moving average-portfolios and momentum-portfolios are not very similar. The last hypothesis can help in finding the differences in the portfolios, there it looks at the sensitivity to the factors in the three-, four- and five-factor model. The alphas of these models are already covered by the first hypotheses, because the alpha represents the abnormal return. When looking at the market factor, it is clear that the TMA-portfolios have a higher factor sensitivity then the conventional momentum-portfolios. The TMA-portfolios profit more from high market returns, but lose value when the market has negative returns. The short term reversal has a sensitivity to the market factor that is comparable to that of the technical moving average strategy. However, contrary to the momentum-portfolios does the TMA-portfolio not crash during the financial crisis in 2008/2009. The link between the conventional momentum strategies and the market factor is ambiguous.

The [-12, -2] and [-12, -7] momentum-portfolios are the only zero-investment portfolios in this thesis with a significant link with the SMB-factor, which is in line with expectations. Both portfolios perform better when small firms underperform relative to big firms, which is usually not the case. This sensitivity is due to the bottom decile, which consists primarily of small firms. It is worth mentioning that all five zero-investment portfolios include many small stocks, either in a long or a short position. The three momentum strategies have a significant sensitivity to the value factor, with the short time reversal being the only one with a negative coefficient. The TMA-portfolios have no significant sensitivity to this factor, with negligible coefficients. The [-12, -2] and [-12, -7] momentum-portfolios generate extra returns when high-value firms outperform low-value stocks, while the opposite is true for the short term reversal. The results on the momentum-factor are complete in line with expectations. The short-term reversal has a significantly negative coefficient for this factor, while the other momentum factors have significantly positive coefficients for this factor. The TMA-portfolios have no significant sensitivity to this factor. The two remaining factors, the investment- and profitability-factors do not seem to add explanatory power.

The different factor-sensitivities for the five strategies again poses support for the statement that the TMA-strategies and momentum-strategies are quite uncorrelated. The two conventional momentum strategies are indeed almost the opposite of the short term reversal, which is not surprising looking at the methodology. The TMA strategy shows almost no similarities with the momentum strategy in terms of profitability, correlation and factor sensitivities, which answers the research question of this thesis.

Future research

This thesis provides new knowledge on the differences between the momentum and the technical moving average strategy. It was yet quite unknown how the two are related to each other. Besides, the momentum strategy seemed unprofitable, which is caused by the financial crisis. Earlier research proved that is possible to predict such a crisis, it would be interesting to construct a momentum strategy which anticipates on the future market state and see how this influences the profitability relative to the technical moving average. Besides, it would be interesting to look whether the profitability of the strategies differ per time period, and what causes the differences.

One of the limitations of this thesis is the dependence on the factor data from E. Fama, because it limits the possible time frame to investigate and it brings the obligation to use monthly data. Because daily data can result in higher power for the statistical tests and it is interesting to use the asset pricing models for earlier decades, a research using daily data would certainly be an addition to the financial literature. However, this will be time consuming regarding the fact that all factor data must be computed.

The results for the technical moving average-strategy are very interesting, but are not in line with the literature. Some academics looked critical at the papers providing support for the success of the, conventional, technical moving average-portfolio, but the results were not expected to be the other way around. The robustness checks within this thesis already support the initial findings, but it would be good to look more into it, by looking at different markets, asset classes and time periods. The overreaction in the market, which is already explained several times, could explain the results of this thesis. In order to test this, the technical moving average should be test with different holding periods. Just as with the momentum strategy, the return of the most recent month could be ignored. The return on t-2 could be used as the short term average, and the [-12, -2] interval could be used as the long term average. Testing this technical moving average strategy with several holding periods could shed more light on the findings in this thesis and find source of the reversed return on the technical moving average.

Bibliography

Avramov, D., Chordia, T., & Goyal, A. (2006). Liquidity and autocorrelations in individual stock returns. *Journal of Finance, 61*, 2365-2394.

Ball, R., Kothari, S., & Shanken, J. (1995). Problems in measuring portolio performance: An application to contrarian investment strategies. *ournal of Financial Economics, 38*, 79-107.

Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 3-18.

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

Carhart, M. (1997, March). On Persistence in Mutual Fund Performance. *Journal of Finance, 52*(1), 57-82.

Chincarini, L., & Kim, D. (2006). Quantative Equity Portfolio Management: An Active Approach to Portfolio Construction and Management.

Da, Z., Liu, Q., & Schaumburg, E. (2014). A closer look at the short-term return reversal. *Management Science, 60*(3), 658-674.

Daniel, K., & Moskowitz, T. (2014). Momentum crashes. *Working paper*, 1-50.

De Bondt, W., & Thaler, R. (1985, July). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805.

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

Fama, E., & French, K. (1993). Common risk factors in the returns of stock and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E., & French, K. (1995). Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance, 50*, 131-155.

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

Goh, J., Jiang, F., Tu, J., & Zhou, G. (2013). Forecasting Government Bond Risk Premia Using Technical Indicators. *Revies of Financial Studies*.

Han, Y., Huang, D., & Zhou, G. (2015). Anomalies Enhanced: The value of higher frequency information. *Working paper*, 1-54.

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

Hou, K., & Moskowitz, T. (2005). Market frictions, price delay, and the cross-section of expected returns. *Reiew of Financial Studies*, 981-1020.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance, 45*(1), 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners ans selling losers; Implications for stock market efficiency. *Journal of Finance*, 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: an evaluation of aternative explanations. *The Journal of Finance*, 699-720.

Lakonishok, J., Shleifer, A., & Vishny, R. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance, 49*(5), 1541-1578.

LeBaron, B. (1999). Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics*, 125-143.

Lee, C., & Swaminathan, B. (2000). Price Momentum and Trading Volume. *Journal of Finance, 55*, 2017-2069.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock porfolios and capital budgets. *Review of Economics and Statistics, 47*, 13-37.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 34*, 768-783.

Neeley, C. (2002). The temporal pattern of trading rule returns and exchange rate intervention: intervention does no generate technical trading profits. *Journal of International Economics, 58*, 211-232.

Neely, C., Rapach, D., Tu, J., & Zhou, G. (2013). Forecasting the Equity Risk Premium: the Role of Technical Indicators. *Management Science*.

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, 429-453.

Okunev, J., & White, D. (2003). Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis, 38*, 425-448.

Rouwenhorst, K. (1998). International momentum stragegies. *The Journal of Finance*, 267-284.

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance, 19*, 429-442.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: a Journal of Selected papers*, 25-45.

Sullivan, R., Timmermann, A., & White, H. (1999). Data-snooping, technical trading rule performance, and the bootstrap. *Journal of Financial Economics*(53), 1647-1691.

Titman, S. (2001). The Modigliani and Miller Theorem and Market Efficiency. *National Bureau of Economic Research*.

Van der Sar, N. L. (2011). *Stock Pricing and Cororate Events.* Rotterdam: Erasmus Universiteit.

Wu, X. (2002). A conditional multifactor analysis of return momentum. *Journal of Banking & Finance*, 1675-1696.

Zakamulin, V. (2014). The real-life performance of market timing with moving average and time-series momentum rules. *Journal of Asset Management, 15*, 261-278.

Zakamulin, V. (22014). The real-life performance of market timing with moving average and time-series momentum rules. *Journal of Asset Management*(14), 261-278.

Zhu, Y., & Zhou, G. (2009). Technical analysis: an asset allocation perspective on the use of moving averages. *Journal of Financial Economics, 92*, 219-544.

Appendix

Table A.1: number of observations through time

Average monthly observations	
Period	Frequency
1990-1995	1581
1995-2000	1904
2000-2005	1576
2005-2010	1432
2010-2015	1299

Table A.2: The effect of winsorizing

Effect of winsorizing		
This figure shows some descriptive statistics of the raw dataset before and after winsorizing. RET is the original return data, while RET_W is the return data after winsorizing.		
	RET	**RET_W**
N	484373	484373
Mean	0,0149	0,0137
Std. Error of Mean	0,0002	0,0002
Median	0,010526	0,010526
Variance	0,0105	0,0130
Skewness	4,214	0,3190
Kurtosis	261,5	2,9
Range	13,44	1,14
Minimum	-0,9375	-0,6788
Maximum	12,5	0,4615

Table A.3: Descriptive statistics for strategy measures

Descriptive statistics of strategy measures					
This figure contains some descriptive statistics on the strategy measures. The measures are constructed using the winsorized dataset, without the penny stocks and firm-years with insufficient data available					
Description	Measure MOM12	Measure MOM6	Measure MOM1	Measure TMA12	Measure TMA6
N	31200	31200	31200	31200	31200
Mean	0,1587	0,0817	0,0128	-0,0009	-0,0013
Std. Error of mean	0,0020	0,0014	0,0006	0,0006	0,0006
Median	0,1513	0,0789	0,0097	-0,0044	-0,0033
Variance	0,1240	0,0650	0,0110	0,0120	0,0130
Range	3,7316	3,0750	1,0123	1,1263	1,1214
Minimum	-1,8726	-1,4758	-0,5508	-0,5087	-0,5536
Maximum	1,8590	1,5992	0,4615	0,6176	0,5678

Table A.4: Check for multicollinearity

Correlation table						
This table presents the bivariate correlation coefficients between the six risk-factors that are part of the used asset pricing models.						
	MKT	SMB	HML	RMW	CMA	WML
MKT	-	0,234	-0,224	-0,378	-0,446	-0,141
SMB	0,234	-	-0,330	-0,545	-0,328	0,217
HML	-0,224	-0,330	-	0,429	0,778	-0,247
RMW	-0,378	-0,545	0,429	-	0,381	-0,042
CMA	-0,446	-0,328	0,778	0,381	-	-0,084
WML	-0,141	0,217	-0,247	-0,247	-0,084	-

Table A.5: Descriptive statistics on zero-investment portfolios

Descriptive statistics return on strategy					
This table shows some descriptive statistics of the zero-investment portfolios. The statistics describe the distribution of the monthly returns on the portfolios					
Descriptive	MOM [-12, -2]	MOM [-12, -7]	MOM [-1]	TMA [-12, -2]	TMA [-12, -7]
N	306	306	306	306	306
Mean	0,003	0,004	0,002	-0,010	-0,010
Std. Error of mean	0,003	0,002	0,023	0,002	0,002
Variance	0,003	0,002	0,002	0,002	0,002
Range	0,458	0,277	0,348	0,329	0,361
Miminum	-0,281	-0,133	-0,159	-0,189	-0,204
Maximum	0,177	0,144	0,189	0,139	0,158
Skewness	-1,052	-0,210	0,653	-0,425	-0,340
Kurtosis	4,528	1,440	3,838	2,774	3,181

Output of double sorting: A.6 – A.9

Table A.6: Double sorting on the MOM and TMA [-12, -2] strategies

Double sorting: MOM [-12, -2] and TMA [-12, -2]

The table below presents the outcome of the double sorting. First, the dataset is ranked on the measure for momentum, based on the formation period [-12, 2]. Deciles are created, and within these deciles are the stocks ranked on the measure for the technical moving average, based on the same formation period. The rows represent the momentum deciles, and the collumns the technical moving average deciles within the momentum deciles.

Decile	1	2	3	4	5	6	7	8	9	10	Difference
1	0,033	0,016	0,020	0,017	0,013	0,011	0,012	0,008	0,008	0,003	-0,030
2	0,018	0,016	0,015	0,013	0,012	0,009	0,007	0,008	0,008	0,006	-0,012
3	0,015	0,016	0,015	0,012	0,011	0,012	0,010	0,011	0,007	0,006	-0,009
4	0,017	0,014	0,012	0,012	0,012	0,011	0,011	0,009	0,005	0,009	-0,008
5	0,015	0,013	0,013	0,011	0,012	0,011	0,009	0,009	0,008	0,007	-0,008
6	0,016	0,014	0,012	0,011	0,011	0,011	0,011	0,009	0,006	0,009	-0,007
7	0,015	0,012	0,012	0,012	0,011	0,012	0,013	0,011	0,011	0,013	-0,002
8	0,013	0,014	0,012	0,011	0,014	0,011	0,012	0,011	0,009	0,011	-0,002
9	0,019	0,017	0,015	0,015	0,014	0,013	0,011	0,012	0,011	0,014	-0,005
10	0,021	0,019	0,020	0,017	0,014	0,013	0,014	0,016	0,016	0,020	-0,001

Table A.7: Double sorting on the MOM and TMA [-12, -7] strategies

Double sorting: MOM [-12, -7] and TMA [-12, -7]

The table below presents the outcome of the double sorting. First, the dataset is ranked on the measure for momentum, based on the formation period [-12, 7]. Deciles are created, and within these deciles are the stocks ranked on the measure for the technical moving average, based on the same formation period. The rows represent the momentum deciles, and the collumns the technical moving average deciles within the momentum deciles.

Decile	1	2	3	4	5	6	7	8	9	10	Difference
1	0,022	0,012	0,015	0,013	0,013	0,009	0,010	0,008	0,009	0,011	-0,011
2	0,020	0,012	0,013	0,011	0,010	0,009	0,008	0,008	0,007	0,009	-0,011
3	0,020	0,013	0,015	0,012	0,011	0,011	0,011	0,009	0,007	0,009	-0,011
4	0,016	0,013	0,013	0,012	0,009	0,011	0,008	0,010	0,008	0,007	-0,009
5	0,020	0,013	0,015	0,012	0,011	0,011	0,011	0,009	0,007	0,009	-0,011
6	0,023	0,010	0,012	0,013	0,012	0,011	0,011	0,009	0,010	0,011	-0,012
7	0,015	0,015	0,013	0,014	0,013	0,012	0,011	0,011	0,012	0,012	-0,004
8	0,017	0,017	0,016	0,012	0,014	0,014	0,013	0,010	0,010	0,012	-0,005
9	0,021	0,019	0,018	0,017	0,014	0,014	0,015	0,012	0,012	0,011	-0,011
10	0,024	0,021	0,017	0,015	0,017	0,015	0,015	0,010	0,013	0,016	-0,008

Table A.8: Double sorting on the TMA and MOM [-12, -7] strategies

Double sorting: TMA [-12, -2] and MOM [-12, -2]

The table below presents the outcome of the double sorting. First, the dataset is ranked on the measure for the technical moving average, based on the formation period [-12, 2]. Deciles are created, and within these deciles are the stocks ranked on the measure for momentum, based on the same formation period. The rows represent the technical moving average deciles, and the collumns the momentum deciles within the technical moving average deciles.

Decile	1	2	3	4	5	6	7	8	9	10	Difference
1	0,029	0,020	0,016	0,018	0,016	0,017	0,020	0,020	0,023	0,020	-0,009
2	0,017	0,015	0,015	0,014	0,012	0,012	0,014	0,014	0,013	0,018	0,001
3	0,019	0,013	0,012	0,011	0,011	0,014	0,011	0,013	0,015	0,013	-0,006
4	0,017	0,011	0,013	0,013	0,010	0,013	0,011	0,012	0,012	0,015	-0,002
5	0,017	0,014	0,013	0,011	0,009	0,011	0,011	0,012	0,011	0,017	0,000
6	0,013	0,013	0,012	0,013	0,011	0,013	0,013	0,012	0,012	0,014	0,001
7	0,013	0,011	0,011	0,010	0,009	0,011	0,009	0,010	0,011	0,012	-0,001
8	0,013	0,011	0,008	0,010	0,009	0,009	0,009	0,013	0,008	0,013	0,000
9	0,013	0,009	0,007	0,007	0,007	0,010	0,005	0,008	0,010	0,015	0,002
10	0,010	0,005	0,005	0,007	0,007	0,009	0,011	0,013	0,011	0,022	0,011

Table A9: Double sorting on the TMA and MOM [-12, -7] strategies

Double sorting: TMA [-12, -7] and MOM [-12, -7]											
The table below presents the outcome of the double sorting. First, the dataset is ranked on the measure for the technical moving average, based on the formation period [-12, 7]. Deciles are created, and within these deciles are the stocks ranked on the measure for momentum, based on the same formation period. The rows represent the technical moving average deciles, and the collumns the momentum deciles within the technical moving average deciles.											
Decile	1	2	3	4	5	6	7	8	9	10	Difference
1	0,026	0,020	0,018	0,020	0,016	0,023	0,019	0,020	0,021	0,022	-0,004
2	0,014	0,014	0,014	0,013	0,013	0,015	0,018	0,019	0,017	0,016	0,002
3	0,014	0,013	0,013	0,013	0,011	0,014	0,014	0,011	0,015	0,015	0,001
4	0,015	0,012	0,011	0,013	0,013	0,011	0,013	0,013	0,014	0,014	-0,001
5	0,014	0,012	0,011	0,012	0,012	0,011	0,014	0,014	0,014	0,015	0,001
6	0,014	0,012	0,010	0,009	0,011	0,013	0,013	0,012	0,012	0,012	-0,001
7	0,012	0,009	0,009	0,010	0,011	0,012	0,011	0,009	0,011	0,009	-0,003
8	0,010	0,010	0,011	0,008	0,009	0,010	0,010	0,012	0,010	0,012	0,002
9	0,013	0,007	0,007	0,007	0,005	0,006	0,010	0,009	0,008	0,014	0,001
10	0,014	0,008	0,009	0,006	0,008	0,009	0,009	0,008	0,013	0,016	0,002

Additional robustness checks: A.11 – A.13

Table A11: Momentum returns with holding period of three months

Momentum hold three months			
This figure shows the return on the three momentum-related zero-investment portfolios, with a holding period of three months.			
	MOM12	MOM6	MOM1
1	0,0155	0,0147	0,0156
2	0,0133	0,0127	0,0127
3	0,0130	0,0118	0,0125
4	0,0131	0,0125	0,0126
5	0,0125	0,0129	0,0128
6	0,0127	0,0134	0,0132
7	0,0131	0,0142	0,0135
8	0,0132	0,0141	0,0139
9	0,0143	0,0152	0,0150
10	0,0172	0,0163	0,0162
Difference	0,0016	0,0016	0,0006

Table A.12: Output of momentum with three month holding period

Output of momentum strategies with three months holding period									
The table below shows the return on the bottom decile, the top decile and the difference between these deciles for three momentum related investment stratetgies. The holding period of these strategies equals three months.									
Strategy	MOM[-12, -2]			MOM [-12, -7]			MOM [-1]		
Model	Decile 1	Decile 10	Difference	Decile 1	Decile 10	Difference	Decile 1	Decile 10	Difference
Three-factor model									
Alpha	0,002	0,005	0,003	0,002	0,004	0,002	0,004	0,003	-0,001
	(0,002)	(0,002)***	(0,003)	(0,001)	(0,001)***	(0,002)	(0,001)***	(0,001)**	(0,001)
MKT	1,227	1,134	-0,093	1,150	1,185	0,040	1,056	1,251	0,194
	(0,043)***	(0,037)***	(0,065)	(0,034)***	(0,031)***	(0,048)	(0,022)***	(0,032)***	(0,034)***
SMB	0,676	0,714	0,038	0,700	0,659	-0,041	0,667	0,648	-0,019
	(0,061)***	(0,053)***	(0,093)	(0,049)***	(0,045)***	(0,069)	(0,032)***	(0,046)***	(0,049)
HML	0,717	0,330	-0,387	0,689	0,340	-0,349	0,556	0,563	0,007
	(0,058)***	(0,050)***	(0,088)***	(0,046)***	(0,042)***	(0,065)***	(0,030)***	(0,044)***	(0,046)
Adjusted R-square	0,783	0,815	0,062	0,835	0,864	0,093	0,913	0,865	0,092
Four-factor model									
Alpha	0,007	0,003	-0,004	0,005	0,003	-0,002	0,004	0,006	0,002
	(0,001)***	(0,001)**	(0,002)**	(0,001)***	(0,001)***	(0,002)	(0,001)***	(0,001)***	(0,001)**
MKT	1,087	1,120	0,123	1,053	1,206	0,153	1,058	1,156	0,098
	(0,028)***	(0,033)***	'(0,041)***	(0,026)***	(0,032)***	(0,040)***	(0,023)***	(0,024)***	(0,027)***
SMB	0,832	0,630	-0,202	0,809	0,635	-0,173	0,665	0,752	0,087
	(0,039)***	(0,047)***	(0,059)***	(0,037)***	(0,045)***	(0,057)***	(0,032)***	(0,034)***	(0,038)**
HML	0,533	0,429	-0,105	0,561	0,368	-0,194	0,559	0,440	-0,118
	(0,037)***	(0,045)***	(0,056)*	(0,035)***	(0,043)***	(0,054)***	(0,031)***	(0,032)***	(0,036)***
WML	-0,515	0,276	0,791	-0,357	0,079	0,437	0,006	-0,345	-0,352
	(0,024)***	(0,029)***	(0,036)***	(0,023)***	(0,028)***	(0,035)***	(0,020)	(0,021)***	(0,023)***
Adjusted R-square	0,913	0,857	0,638	0,909	0,868	0,402	0,913	0,929	0,484
Five-factor model									
Alpha	0,002	0,003	0,000	0,001	0,002	0,001	0,002	0,002	0,000
	(0,002)	(0,001)*	(0,003)	(0,001)	(0,001)*	(0,002)***	(0,001)**	(0,001)*	(0,00)
MKT	1,208	1,222	0,014	1,151	1,247	0,096	1,115	1,268	0,153
	(0,049)***	(0,038)***	(0,073)	(0,039)***	(0,033)***	(0,055)*	(0,021)***	(0036)***	(0,039)***
SMB	0,708	0,925	0,217	0,765	0,819	0,053	0,815	0,722	-0,093
	(0,068)***	(0,053)***	(0,102)**	(0,054)***	(0,046)***	(0,077)	(0,030)***	(0,051)***	(0,055)*
HML	0,818	0,218	-0,600	0,749	0,268	-0,481	0,488	0,574	0,086
	(0,092)***	(0,071)***	(0,138)***	(0,073)***	(0,062)***	(0,103)***	(0,040)***	(0,069)***	(0,074)
RMW	0,108	0,638	0,530	0,206	0,484	0,278	0,450	0,231	-0,219
	(0,093)	(0,072)***	(0,139)***	(0,074)***	(0,063)***	(0,104)***	(0,041)***	(0,069)***	(0,074)***
CMA	-0,202	-0,007	0,195	-0,164	-0,029	0,135	-0,023	-0,089	-0,066
	;(0,115)*	(0,089)	(0,172)	(0,092)*	(0,077)	(0,129)	(0,050)	(0,086)	(0,092)
Adjusted R-square	0,785	0,853	0,101	0,841	0,887	0,110	0,939	0,870	0,112
* equals significant at 0.10, ** significant at 0.05 and significant *** at 0.01									

Table A.13: Return on price-related TMA deciles

TMA based on prices		
This table presents the excess return on two applications of the technical moving average. The measures are computed using stock prices instead of returns.		
Decile	TMA12	TMA6
1	0,026	0,025
2	0,016	0,015
3	0,014	0,014
4	0,012	0,012
5	0,011	0,011
6	0,011	0,011
7	0,011	0,011
8	0,010	0,010
9	0,011	0,012
10	0,014	0,014
Difference	-0,012	-0,011