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The Cross-Sectional Profitability of a Moving Average Timing Strategy on Factor Investing

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Abstract

This paper investigates the cross-sectional performance of a moving average timing strategy on portfolios formed on the volatility and momentum anomaly. Building on past research, the results show that a moving average timing strategy with relative shorter lags is able to significantly increase the performance of particularly the higher volatility portfolios. Furthermore, similar results are obtained when using the moving average timing strategy on portfolios sorted on momentum. The highest significant increase in performance is found in the losers' portfolio with a 20-day lag moving average.

Keywords: moving average, timing strategy, factor investing, momentum, low volatility

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I. Introduction

Investments strategies can be divided into two broad categories: strategies based on fundamental analysis and those based on technical analysis. Where fundamental analysis focusses on firm specific characteristics, also known as factor investing, technical analysis focusses solely on past prices. The most common form of technical analysis is a moving average (MA), which uses the data on past prices to forecast future prices, or trends. Much research has been done in search of the relevance of technical analysis as a proper investment strategy, however, the results have been ambiguous. Early research (see, e.g., Alexander, 1961, 1964; Fama and Blume, 1966; Jensen, 1970) concluded that technical analysis is not a good predictor for stock behavior and that there is no discernible relation between the predictability of stock returns from past returns. More recent empirical research, however, shows evidence to the contrary and that these conclusions might have been premature (Brock, Lakonishok and LeBaron, 1992).

The main question this paper tries to answer is if the performance of portfolios sorted on the momentum and low volatility anomalies can be improved upon by using a moving average timing strategy. The research about the cross-sectional profitability of a moving average timing strategy has been relatively new, starting with Han, Yang and Zhou (2013). They find that a moving average timing strategy can significantly improve the performance of all volatility and size deciles. In order to add to the understanding of this new anomaly, it is important to investigate its foundations as a possible anomaly by exploring its potential to increase the performance of other anomalies as well.

The main findings on the volatility portfolios are similar to those of Han, Yang and Zhou (2013). There is a significant improvement in risk adjusted returns in the lowest and highest volatility decile. The former showing an increase in average returns of 3.74% and the latter showing an increase of 9.46%. This result, however, is not significant for all alternative lags. The shorter lags, e.g. 10-, and 20-day lag, provide significant better results for the high volatility deciles, whereas for longer lags there is an increase in the amount of deciles that have a significant improvement in performance. Additionally, the results show that this increase in performance has decreased in the most recent period, but has not disappeared.

Furthermore, the results show that the moving average timing strategy can also significantly enhance the performance of portfolios sorted on momentum. The losers portfolio's average return increases by 21.05%, while the winners portfolio's returns on average increases by 0.78%. Similar to the volatility portfolios, it is the shorter lags that show the largest increase in performance. Both the winners and losers portfolios show significant improvement, with the latter showing the largest improvement. The increase in performance is lower in the most recent subperiod. However, that could be a result from the overall decrease in performance of the momentum portfolios. The results for the winners and losers portfolios are persistent throughout the most recent subperiod as well.

This paper builds on the research done by Han, Yang and Zhou (2013) in two ways. First, it shows that the moving average timing strategy still significantly increases the performance of the volatility portfolios after extending the sample period to include the most recent years. And secondly, it extends the research on the cross-sectional profitability of a moving average strategy by showing that there is a significant improvement in performance on portfolios sorted on momentum as well.

The remainder of this paper is organized as follows: section 2 will review the literature on the moving average strategy and factor investing strategies used in this paper. Section 3 explains the methodology, data and formed hypothesis. Section 4 shows the regression results and tests the robustness of the moving average strategy on the volatility portfolios. Section 5 shows the results on the extension of the moving average strategy to portfolios sorted on momentum. Finally, section 6 will conclude with key findings and suggestions for future research on this topic.

II. Literature review

Although there are different strategies in technical analysis, this paper focusses only on the moving average strategy. The moving average strategy has generally been the focus of study when investigating the profitability of technical analysis. There are several reasons why technical analysis is not generally accepted in the academic world. First, most research about stock markets assume the random-walk hypothesis. This hypothesis states that stock prices follow a random walk and are just unpredictable. It follows that any technical analysis that uses past prices to forecast future prices is in sharp contrast with this theory. Secondly, there is no real theoretical evidence that can fully explain why technical analysis might be profitable. Finally, earlier research about technical analysis, and in particular a moving average strategy, has come up with mixed and ambiguous results (see, e.g. Fama and Blume, 1966; Cowles, 1933).

More recent studies have tried to add to the relative unknown theoretical part of technical analysis. In their paper, Zhu and Zhou (2009) provide theoretical justification for the use of technical analysis by using a moving average. In their theoretical framework, combining fixed asset allocation rules in an unpredictable market with a moving average, the use of a moving average provides information for the optimal strategy. Although much of the research have used an asset allocation approach, Reitz (2005) suggests a different rationale for the application of a moving average strategy. He suggests that the oscillator model based on moving averages is able to infer in some part information about the hidden fundamentals and that this can be interpreted as a form of Bayesian learning. The hypothesis is tested in the exchange rate market and the findings are statistically significant, showing that "technical trading appears to be a sensible learning device when the exchange rate is driven by hidden fundamentals*"*.

Furthermore, recent studies find evidence for the persistence of abnormal returns using technical analysis. Starting with Brock et al. (1992), who find that technical analysis helps to predict stock price changes in the US stock market, and that the patterns cannot be explained fully by changes in volatility and first order autocorrelation. Therefore, their results are not consistent with the random walk hypothesis. They conclude that it is quite possible that technical rules pick up some of the hidden patterns in stock prices. Hudson et al. (1996) replicate the method by Brock et al. in the UK market, and find results quite similar to those found by Brock et al. However, their research also shows limitations to the use of technical analysis: its need for a lengthy time period and the presence of trading costs. Additionally, Gunasekarage and Power (2000) find that technical trading rules, in the form of average returns, have predictive ability in South Asian markets.

Technical analysis, in the form of a moving average strategy, has been more accepted in the foreign exchange market. Taylor (1992) reports the questionnaire on behalf of the Bank of England and reports that at least 90 per cent of the respondents use in some way or another technical analysis at one or more time horizons. In particular, there is a skew towards technical analysis at shorter time horizons. This skew smoothens, however, as the horizon lengthens. Lui and Mole (1998) find similar results and report that, at shorter horizons, there is a skew towards the use of technical analysis instead of fundamental analysis in the Hong Kong foreign exchange market. Although this skew reverses as the time horizon lengthens, it suggests the power of technical analysis for short term trend predictions. They find that a moving average strategy is used significantly more to predict turning points.

A different aspect of the moving average lies in its ability to enhance the profitability of other strategies. Han, Huang and Zhou (2015) find that the use of a moving average on portfolios sorted on the eight most common anomalies increases the average returns while having the same or even lower risk. They attribute this enhancement effect to the use of higher frequency information by a moving average strategy. This is in line with the earlier research done by Han, Yang and Zhou (2013). When they apply a moving average on portfolios that are sorted on volatility, they observe highly significant abnormal returns, even when adjusted for exposure to the market factor and the Fama-French size and value factor. In addition to volatility portfolios they test several alternative firm characteristics and find significant abnormal returns for all them. They attribute the results to information uncertainty, the less informative the fundamentals are the more profitable a moving average strategy becomes.

Besides some empirical evidence pointing to the benefit of technical analysis and some doubting its relevance, it is also noteworthy that many financial firms in practice still provide technical commentary as either a service or analysis of the market. Also, many top traders and investors still use a moving average strategy either partially or exclusively (see, e.g., Schwager, 1993; Covel, 2005; Lo and Hasanhodzic, 2010).

Fundamental analysis, in the form of factor investing, is based on firm-specific characteristics. Traditionally stock returns were believed to be fully explained by the market return and that its systematic risk would be reflected in the beta coefficient. Fama & French (1993) added two more factors to this traditional Capital Asset Pricing Model (CAPM); value and size. They find that value stocks outperform growth stocks and small-cap stocks outperform large-cap stocks. The addition of these two factors significantly increased the explanatory power of their asset pricing model. Carhart (1997) expands on this model by adding a momentum factor, which increased the explanatory power of the Fama-French three-factor model. Technically, momentum has similarities with technical analysis in the sense that it is also a strategy based on trends. It is however widely regarded as part of fundamental analysis. Further research on momentum has been done by Jegadeesh & Titman (1993) and Novy-Marx (2012). Both find significant outperformance by portfolios based on a momentum strategy, even though they use different horizons in their approach. Although the momentum factor is a trend looking strategy, it has been around for decades now and has been widely accepted by academia. Furthermore, Hang, Yang and Zhou (2013) provide evidence for a low correlation between a moving average strategy and the momentum strategy, indicating that although they are similar in their trend following behavior, they capture different effects. This paper also uses portfolios formed on the low volatility effect as put forward by Blitz and van Vliet (2007) and Ang et al. (2006). They find that, on average, low volatile stocks tend to outperform high volatile stocks in the sense of risk-adjusted returns. This contrasts with the traditional high risk high reward relation between stock returns and market risk.

III. Methodology, hypothesis and data

Based on the method of Hang, Yang and Zhou (2013), all stocks are sorted into volatility deciles. The returns of each stock for the time period of 2000 to 2016 are calculated using prices from the Center for Research in Security Prices (CRSP) database. Using the daily returns of the prior year I estimate the annualized standard deviation and based on this estimate the stocks are sorted into deciles. Once the stocks are assigned to the portfolios I calculate the equal weighted mean return and indexed price of each portfolio. The MA of the portfolio prices is defined as follows:

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

Where P_{jt} (j = 1,…10) is the portfolio price, L is the lag (10, 20, 50 or 100) and $A_{jt,L}$ is the average index price of portfolio *j* at time *t*. In the cross-sectional analysis of the moving average strategy, the MA timing signal follows from the difference between the last portfolio index price (P_{jt-1}) and last moving average index price ($A_{jt-1,\,L}$). If the portfolio index price on t-1 is higher than the moving average price on t-1, $P_{jt-1} > A_{jt-1,L,}$ this is defined as a buy signal because this signals an upward trend in the portfolio price. If the portfolio index price on t-1 is equal or lower than the moving average price on t-1, $P_{jt-1} \leq A_{jt-1,L}$, I invest in the risk free asset instead. The risk free return on each day is taken from the Kenneth French database and represents the daily return on the 1 month T-bill. In line with Hang, Yang and Zhou (2013) I define the return on the MA strategy and the return on MA portfolios as follows:

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

Here $\check{R}_{jt,L}$is the return on the *j*th volatility portfolio on day *t* given the time lag *L*, and r_{ft} is the risk free rate on day *t*. I am interested in the cross-sectional profitability of the MA timing strategy, and thus I am interested in the relative outperformance of the MA enhanced volatility portfolios compared to the buy-and-hold volatility portfolios. This outperformance is reflected in the difference between these returns $\check{R}_{jt,L}$ - R_{jt}. This difference is called the return on the MA portfolio (MAP). A MAP can be seen as a zero-cost portfolio that takes a long position in the MA enhanced portfolio and a short position in the underlying volatility portfolio. This method of sorting deciles based on a firm's return volatility and then applying a moving average timing strategy can be applied to other firm characteristics as well. To be more exact, I can use this method to investigate the cross-sectional profitability of a moving average strategy on any of the fundamental factors described earlier.

I would expect that the MA timing strategy results in higher risk adjusted returns than the underlying volatility deciles. Furthermore, I would expect that this outperformance cannot be fully explained by the traditional risk-based models, resulting in positive alphas in CAPM-regressions and FF-regressions. Additionally, would I expect that the extension of this strategy to portfolios formed on momentum will provide similar results, that is, I expect to see significant improvement in the MA timing portfolios' performance relative to the underlying momentum portfolios.

The data obtained is from the CRSP database, containing daily holding returns for all stocks traded on the NYSE, AMEX and NASDAQ in the period of 2000 to 2016. In total, the panel data contains 16,421 unique stocks, over a span of 16 years making up a total of more than 28 million observations. This database is merged with the daily Fama-French factors which contain the excess market return, size factor and value factor and the daily risk free rate, taken from the Kenneth French database. The daily holding returns are log transformed in order to make them additive over time.

IV. Moving average and volatility portfolios

Table 1 shows the summary statistics of the volatility decile portfolios, the moving average timing portfolios and the return on the MAP's for a 10-day MA timing strategy. Panel A shows the results for the volatility decile portfolios. The results show that, on average, there is a positive relation between risk and return. However, when looking at risk adjusted returns, as measured by the Sharpe ratio, the results are in line with more recent research about the low volatility anomaly (e.g. Blitz and van Vliet (2007) and Ang et al. (2006)), and Frazzini and Pedersen (2013), which report decreasing risk adjusted returns for higher volatile deciles. This result holds for all deciles except for the highest decile which is higher than the previous deciles, but still lower than the lowest decile. The risk adjusted returns decrease from 0.68 for the lowest volatile decile to 0.39 for second highest decile, and then it jumps to 0.62 for the highest decile. Panel B shows the improvement of a MA timing strategy over the simple buy-and-hold strategy for the lowest two and highest three deciles. In the middle, a decrease in average return can be observed. However, across all deciles the standard deviation has significantly decreased. As a result, the Sharpe ratios of the MA timing strategy shows improvement for nearly all decile portfolios. Furthermore, it seems that besides the lowest volatile decile, it is in particular the high volatile deciles that show the most improvement from the MA timing strategy when looking at the improvement of the Sharpe ratio. Finally, panel C shows the cross-sectional profitability of a MA timing strategy as the difference in return between the MA timing portfolio and the underlying volatility portfolio. The results show that the largest increase in returns is concentrated in the highest decile. The negative differences in returns reported in deciles 3 to 7 does not necessarily mean that the MA timing strategy does not work. Since MAP reports the improvement of the MA timing strategy relative to the underlying volatility portfolio, this could follow from either an increase in return, a decrease in the volatility, or both. This can be seen from the increases in Sharpe ratios, as reported in panel B. Additionally, panel C looks at the success rate, which is defined as the fraction of trading days that the MA timing strategy improved upon, or was equal to, the underlying volatility portfolio. An unsuccessful day is a day on which the return on the MA timing strategy was below the risk free rate. Reversely, a successful day is a trading day on which the return on the MA timing strategy is equal or above the risk free rate. The results shown in panel C indicate that on average and across all portfolios on 72% to 67% of the trading days the MA timing strategy had equal or improved returns relative to the underlying volatility decile. Again, the lowest and highest deciles show the highest success rates, indicating that the MA timing strategy is in particular effective for these deciles.

The results of table 1 suggest that a MA timing strategy can increase the performance of a volatility strategy, either because of increased returns, decreased volatility or both. Furthermore, the increase in performance is higher for the more volatile deciles. In order to determine if the improvement over the volatility deciles can be explained by other risk factors, the MAP returns are used in a regression using two distinct models. Consider first the CAPM regression of the MAP's on the market factor, the regression looks as follows:

$$MAP_{jt,L} = \alpha_j + \beta_{j,MKT} r_{MKT,t} + \varepsilon_{jt} \qquad j = 1,2\ldots,10 \qquad (3)$$

In this regression $r_{MKT,t}$ is the excess market return over the risk free rate at time t, j is the volatility decile ranging from 1 to 10 and L is the lag used in the timing strategy. Table 2 shows the results of this regression for the 10-day MA strategy. The annualized alphas, or abnormal risk adjusted returns, are consistently higher than the average returns reported in panel C of table 1. The alphas are positive across all deciles, but insignificant for decile 2 to 7. The remaining deciles show significant alphas, suggesting that increase in performance cannot be explained by the market factor, i.e. a simple risk-return relation. The estimated alphas are higher for the higher volatile deciles, 5.28% to 14.23%, when compared to the lowest decile, 4.78%. This is consistent with the results from table 2, which suggests that the biggest increase in performance, as measured by the MAP return, occurs for the highest three deciles. The fact that the alphas, or risk adjusted abnormal returns, are higher than the average returns on the MAP's stems from the negative beta estimate of the market factor. The beta estimate is negative across all deciles, decreasing from -0.150 for decile 1 to -0.695 for decile 10. Hang, Yang and Zhou (2013) argue that the negative betas are a logical consequence of the method used in forming the MA timing portfolios. They state that the mechanics behind the MA timing strategy is to avoid negative portfolio returns. When the portfolio returns do turn negative this is likely to be the result of a market downturn. Because of the MA timing strategy, however, the resulting portfolio returns are better than the underlying volatility returns. As a result, the MAP return will turn out to be positive even when the market is experiencing a downturn. For positive portfolio returns, the market is likely to go up as well; since the MA timing strategy is designed to be cautious for positive returns, i.e. it reacts with a lag, the MA timing portfolios may have lower returns than the underling volatility portfolio. It then follows that the MAP return will be negative on those days since the underlying volatility portfolio return is higher than the return on the MA timing. As a result, there should exist a negative correlation between the MAP returns and the market factor, which is exactly what Hang, Yang and Zhou observe in their research and is also reflected in my results.

In order to see if the abnormal risk adjusted returns can be explained by other risk factors I perform an additional regression using the Fama-French three-factor model. This model uses the size and value factor in addition to the market factor to explain returns. The regression model looks as follows:

$$MAP_{jt,L} = \alpha_j + \beta_{j,MKT} r_{MKT,t} + \beta_{j,SMB} r_{SMB,t} + \beta_{j,HML} r_{HML,t} + \varepsilon_{jt} \qquad j = 1,2\ldots..10 \qquad (4)$$

In addition to the daily market excess return, this model now includes the daily excess return of the small-minus-big factor, $r_{SMB,t}$, and the daily excess return of the high-minus-low factor, $r_{HML,t}$. Table 3 shows the results of this regression. The results are quite similar to the CAPM regression. The risk adjusted abnormal returns for decile 8 to 10 are again significantly positive and slightly higher for decile 8 to 10. The alpha for the lowest decile is also significant but at a slightly lower value compared to the CAPM model. Across all deciles, the adjusted R^2's are higher, indicating that the Fama-French 3-factor model does a better job at explaining the returns than the regular CAPM model, but this increase is negligible. The market betas are, again, significantly negative, and decreasing as volatility deciles increase. The estimates are similar to those obtained by the CAPM regression. The size betas seem to be positive for the first 4 deciles, but only significant for the first decile, after which it turns significantly negative and more negative over volatility deciles 5 to 10. The negative exposure to the size factor indicates that, similar to the market exposure, there is simply less exposure to this risk factor in the MA timing strategy. In contrast, the exposure is significantly positive for the first decile, meaning that the exposure to the size factor has slightly increased for this decile. The value betas are significantly negative for the first 7 decile, except for decile 1 which has an insignificant negative beta. Only the highest volatility decile returns a significant positive beta. This indicates that the MAP's have less exposure to the value factor for the first 7 deciles, and only for decile 10 there seems to be a slight increase in exposure. Although most of the estimates for the size and value factors appear to be negative, indicating that the MAP's have less exposure to these factors than the underlying volatility portfolio, I cannot conclude that this is the case for all portfolios. However, when looking at the value of the betas, in particular the high value of the market beta compared to the size and value beta, I can conclude that, overall, portfolio 1 and 8 to 10 have less exposure to the risk factors combined. This is reflected in the significant positive alphas that are higher than the corresponding MAP returns.

Therefore, the results of the CAPM and Fama-French 3-factor regressions seem to support the earlier notion that a MA timing strategy is able to improve on the performance of the underlying volatility portfolio. In particular, the results show that the biggest and significant abnormal returns are in the lowest and highest decile, with the highest increase is shown in the most volatile decile. Furthermore, the increase in performance cannot be fully explained by taking more or less exposure to the market, size or value factors. The improved returns are, therefore, not a result from simply increasing or decreasing the risk exposure.

In order to check if the results that are obtained are robust, I first look at alternative time lags for the MA timing strategy, which are the 20-, 50-, and 100-day lags. The results are shown in table 4. The results show that for the alternative lags the MA timing strategy still outperforms the underlying volatility portfolio. All risk adjusted returns, as defined by the Sharpe ratio, are higher across all portfolios and all lags compared to the underlying volatility portfolio. The degree of outperformance differs across the different lags in terms of average returns and Sharpe ratio. However, for the lowest decile and the highest volatility decile there seems to be a gradually declining outperformance, as measured by the MAP return, with increasing time lags. The success rate of the timing strategy is similar to the ones reported in table 1. The deciles that showed negative MAP returns in table 1 seem to be showing less negative returns with increasing time lags. In panel C of table 4, only decile 4 still shows negative returns, while all others show positive MAP returns and higher Sharpe ratios. Therefore, the results suggest that the MA timing strategy is able to significantly outperform the underlying volatility portfolio for alternative lags as well.

Additionally, table 5 reports the alphas of the CAPM and Fama-French regressions of the alternative time lags. Panel A shows that the 20-day lag strategy is similar to the 10-day strategy. The significant alphas are concentrated at the extreme deciles, with 4.88% on an annualized basis for the lowest volatile decile and 11.43% for the highest decile. Additionally, deciles 2, 8 and 9 are also significantly positive and similar in value as those reported in table 3. Panel B reports the results for the 50-day lag strategy. These results actually show lower and insignificant alphas for the highest volatile decile, while the alphas for decile 6 to 9 are significant. For the lowest two deciles, the alphas are significantly positive and slightly below the value of the 10- and 20-day lag. Panel C shows some interesting results, except for the lowest decile, all other deciles are significant and positive. The alphas are increasing with higher volatile deciles, except for the highest decile which has an alpha of 6.38%. The results of panel B and C show that with longer lags the value of the alphas in the extreme deciles decrease, even becoming insignificant, while the deciles in between show significant alphas of around 4% to 6%. Again, these results suggest that the MA timing strategy significantly improves in performance over the underlying volatility portfolios, and that at least a part of this outperformance cannot be attributed to the market, size and value risk factors. Furthermore, the results suggest that the outperformance, as measured by the Fama-French alpha, is more consistently significant with higher time lags, in particular the 50-, and 100-day lag seem to consistently be more significant across the deciles than the 10-, and 20-day lag. However, longer time lags do not seem to work as effectively for the extreme deciles, low and high. For those deciles, the best strategy seems to work with a shorter time lag of 10 or 20 days.

Similar to the volatility portfolios, I investigate if the MA timing strategies' outperformance has changed, or behaved differently for different periods in my sample. A reason for a significant change in the performance of the strategy could be the financial crisis that started in 2007. I divided my subsample into 2 periods, effectively splitting the sample into 2 subsamples. The first subsample runs from 3rd of January 2000 to the 30th of June 2008. The second subsample runs from the first of July 2008 to the 30th of December 2016. Table 6 reports the average returns on the MAP's and the Fama-French 3-factor alpha for the 10-day timing strategy for the 2 subsamples. Panel A shows the results for the first subsample which are similar to the ones observed in table 1. The MA timing strategy seems to significantly enhance the risk adjusted returns of the higher volatility deciles, but also for the very lowest decile. Both the MAP returns and the corresponding alphas of these deciles are significantly positive and higher than those reported of the full sample. Therefore, the MA timing strategy is more profitable in this subsample when compared to the full sample. As expected, panel B tells a different story. The average returns on the volatility portfolios are quite similar to those of panel A, but slightly lower. The big difference is shown in the returns and Sharpe ratios of the MA timing portfolios. Compared to panel A they are significantly lower, more than twice as low for the highest volatile decile. The only improvement in risk adjusted returns is shown in the highest and lowest decile. This is confirmed by the MAP returns, which are mostly negative except for the lowest decile, and the Fama-French alphas. The alphas are only significant for the lowest and highest decile, the former being similar to the first subsample and the latter having decreased by approximately half. It is clear from this table that the effectiveness of the MA timing strategy is lower in the second half of the full sample compared to the first half. This is especially true for the higher volatility deciles, which report significantly lower alphas. However, the 10-day timing strategy seems to be equally effective throughout both subsamples for the low volatility decile.

To sum up, the MA timing strategy can significantly improve the performance of a volatility based strategy. This improvement is clearly present in the highest volatility decile and less in the lowest volatility decile. The Fama-French alphas seem to decline with longer time lags for the timing strategy and it starts to lose the high effectiveness in the highest and lowest volatility decile. A longer time lag does seem to smooth out the effectiveness of the strategy across all deciles, as only the lowest volatility decile turned back an insignificant result. The highest alphas can be obtained in the highest volatility decile in combination with a short lag on the timing strategy, either a 10-day lag or 20-day lag. Lastly, the effectiveness of the MA timing strategy seems to be persistent throughout my entire sample, but only for the highest and lowest decile. Furthermore, the alpha for the highest decile has more than halved in the latter period of the sample, while the alpha for the lowest decile has remained constant. The traditional low volatility strategy is to invest in the lowest decile because this generates the highest risk adjusted returns. When using the MA timing strategy, however, the strategy might change. Depending on the performance target of the investor, one can use the timing strategy on the lowest portfolio to gain the highest risk adjusted returns as measured by the Sharpe ratio. However, if the target is to obtain the highest possible abnormal returns, as measured by the Fama-French alpha, the best strategy would be to use the timing strategy on the highest volatility portfolio. Noteworthy is that for all portfolios the standard deviation has decreased significantly when applying the moving average timing strategy. This effect seems to decrease with higher lags, but is still persistent. This is in line with the results by Hang, Huang and Zhou (2015) who find that use of higher frequency information enhances profitability of the anomalies. The intuitive mechanics behind this is the ability of the strategy to decrease downside risk while also decreasing upside potential. It is not clear if both are reduced by the same amounts, resulting in positive skewness of the timing portfolios. I will not go further into these risk characteristics in this paper, but they might be an interesting topic for future research.

V. Moving average and momentum portfolios

In this section, I explore the potential profitability of the MA timing strategy on portfolios based on momentum. The momentum portfolios are formed using the cumulative returns over the past 12 months, with a 1 month lag, and sorted into deciles. Decile 1 holds the losers' stocks, while decile 10 holds the winners' stocks. The portfolios are formed and updated on a monthly frequency, while the MA timing decision is based on a daily frequency. Similar to the low volatility approach, the decision to invest in the momentum portfolio today depends on the index price of the portfolio and the moving average of that index price. If the index price on t-1 of the portfolio is higher than the moving average index price on t-1, a buy signal is generated. If the index price on t-1 is lower than the moving average on t-1, the decision is to invest at the risk free rate.

Table 7 reports the results based on the 12 month cumulative return momentum strategy and the corresponding performance of the 10-day timing strategy. Panel A shows the average returns and Sharpe ratios of the momentum strategy. In line with the findings of Jegadeesh and Titman (1993) and Novy-Marx (2012), the results show that winners outperform losers, and the average returns and Sharpe ratio are increasing from lowest to highest decile. The traditional momentum strategy is to go long in the winners portfolio and short in the losers portfolio. The results of panel A supports the notion that the largest part of the momentum profit in a zero-cost portfolio comes from the short leg. The winners portfolio has an average return of 1.28%, whereas the losers portfolio on average makes a loss of 12.29%. The zero-cost portfolio would then result in a positive average return of 13.57%. Panel B shows the results of the 10-day MA timing strategy on the momentum portfolios. Interestingly, there seems to be little improvement of the higher deciles relative to the underlying momentum portfolio both in average returns and Sharpe ratios. Only the winners decile actually improves to an average return of 2.06% and a Sharpe ratio of 0.16, which was 0.06 before. In contrast, the lower deciles, including the losers portfolio, have both higher average returns and higher Sharpe ratios. The biggest increase is for the losers portfolio which has an average return of 8.75%. These results are less prominent in deciles 2 and 3, however, they also obtain much higher risk adjusted returns. The previous mentioned long-short strategy does not seem to be profitable when applying the MA timing strategy. Instead, in order to create a profitable zero-cost portfolio, one has to go long in the losers portfolio and short in the winners portfolio for an average return of 6.69%. Lastly, panel C reports the average return on the MAP's and the corresponding success rate. The biggest improvement, by far, is reported in the losers portfolio.

Again, I employ a Fama-French three-factor regression of the 10-day lag MAP's in order to explain the returns. The results are shown in table 8. Similar to the results of the volatility portfolios, market betas are significantly negative across all deciles. Furthermore, the betas on the size factor are also negative and significant across all deciles. There does not seem to be a clear increasing or decreasing relationship between the market and size betas and the portfolios. The market beta fluctuates between -0.434 and -0.720 across all portfolios, indicating that momentum timing strategy reduces exposure to the market almost equally across all deciles, except for the extreme deciles whose reduction in exposure is larger. The relation between the value factor and the MAP returns is unclear. The only significant betas for the value factor are for decile 4 to 7 and show up negative. The Fama-French alphas are significantly positive only for the first four deciles, ranging from 4.38% for decile 4 to 26.5% on an annualized basis for the losers portfolio. This indicates that the timing strategy is unable to significantly increase performance of the winner stocks. However, the timing strategy is able to significantly increase the performance of the losers portfolio. This result corresponds to the ones obtained in table 7, where no or little improvement of performance is observed for the higher deciles, but high improvement in the average returns for the losers portfolio. The alpha for the winners portfolio is borderline insignificant though, indicating that the improvement in performance may not be attributable to the timing strategy. The results on the volatility timing strategy proves that the effectiveness of the timing strategy may change when using alternative lags, therefore I use the same alternative lags for momentum to explore the potential of the momentum timing strategy.

Table 9 shows the summary statistics and Fama-French alphas of several alternative time lags. Panel A shows the results for the 20-day lag, which are similar to the 10-day lag strategy. The losers portfolio, 8.63%, outperforms the winners portfolio, 3.57% and the Sharpe ratio, MAP return and the Fama-French alpha of the losers portfolio are higher compared to the winners portfolio. In contrast to the previous results, the winners portfolio now has a significant alpha of 6.53%. Furthermore, it seems all alphas are higher than those reported for the 10-day lag, which indicates that a 20-day lag might perform better than the 10-day lag. Panel B and C report the results for the 50-day lag and 100-day lag respectively. In contrast to the short lag strategies, the average returns on the timing portfolios and the corresponding Sharpe ratios are higher for the winners portfolio compared to the losers portfolio. Therefore, the improvement of the performance as a result of the timing strategy with longer time lags goes down for the losers portfolio, while going up for the winners portfolio. As a result, the optimal strategy for the momentum timing strategy for a zero-cost portfolio would be to go long on the winners and short in the losers. However, the resulting average returns would be lower than the same strategy for the underlying momentum portfolios resulting in an underperformance of the timing strategy. The results of the individual timing portfolios, however, are higher for both the losers and winners portfolios, for all time lags. Therefore, for longer time lags, it is more profitable to use a long-only strategy and invest in the winners portfolio as the average returns are almost three times as big as the underlying momentum portfolio. For the shorter lags, a zero-cost portfolio also underperforms compared to the underlying momentum portfolios. However, using a long-only strategy by investing in the losers portfolio will still outperform any of the underlying momentum portfolios. The particular strategy to use in a momentum timing strategy is again dependent on the investors preference.

In addition to alternative lags I also look at the performance of the momentum strategy and timing strategy in different subperiods. The chosen subperiods are the same as for the volatility strategy and the results are shown in table 10. As is clearly shown in panel A and B, the momentum strategy itself is far less effective in the latter subperiod. The zero-cost portfolio for the normal momentum strategy provides an average return of 22.36% per annum in the first subperiod, compared to the 6.07% in the second subperiod. Interestingly though, the zero-cost portfolio for the momentum timing portfolio is not profitable in the first subperiod, neither for winners minus losers or vice versa. It seems that in this period the most profitable strategy would be a long-only strategy. For the second time period, it seems that the zero-cost portfolio of losers-winners would return a positive average return of 11.22%, much higher than the same strategy for the underlying momentum portfolios. However, since the Fama-French alpha for the winners portfolio is insignificant, the increase in performance by the timing strategy of this portfolio may not be significant, resulting in an inconclusive result. The strategies' performance has clearly changed over the duration of the entire sample and so has the underlying momentum strategy itself, making it impossible to state one clear strategy that clearly outperforms the others in the 10-day timing strategy.

To further investigate the timing strategy in the most recent subsample, I also look at the performance of the alternative time lags in this period. Table 11 reports the results of the MA timing portfolio and the Fama-French alphas for the alternative lags for the second subsample. Results of the 20-day lag show that the zero-cost portfolio for the timing strategy, which consists of going long in the losers and short in the winners, has an average return of

5.92% and now both alphas are significant. For the 50- and 100-day lag there is no clear profit to be gained from making a zero cost portfolio in the timing strategy since both the winners and losers portfolio have almost equal returns. These results therefore suggest that in the most recent period the best zero-cost portfolio timing strategy would be to go long in the losers portfolio while short in the winners portfolio using a 20-day moving average timing strategy.

Therefore, using a moving average timing strategy on momentum portfolios can yield higher risk adjusted returns than the underlying momentum strategy. Depending on the preferences of the investor, one can use a reversed zero-cost portfolio by going long in the losers portfolio and short in the winners portfolio. This strategy only outperforms when using the shorter time lags, i.e. 10-day and 20-day lag. The alternative strategy is to go long-only in either the winners or losers portfolio. With longer lags, however, the increase in performance for the losers portfolio decreases, while that of the winners increases. For all lags, the risk adjusted returns of the winners portfolio are significantly higher than the underlying momentum portfolio. Fama-French regressions on the MAP returns, the difference in returns between the timing strategy returns and the underlying momentum strategy returns, show that the increase in performance are partially a result from the decrease in exposure to the size and market factor while at the same time a significant portion, the alpha, cannot be explained by the risk factors. Both the effectiveness of the momentum strategy and the timing strategy has changed over time, making it difficult to determine if the reduced effectiveness of the timing strategy for the momentum portfolios is a result of the change in the effectiveness of momentum itself or the timing strategy. In the most recent period, shorter time lags are particularly effective at increasing the performance of the losers portfolio, while longer lags smooth out the performance over all portfolios while also enjoying higher increases in performance for the winners portfolio.

VI. Conclusion

The research done in this paper builds on the research done by Han, Yang and Zhou (2013) in two ways. First, I extend the time period of their timing strategy on volatility portfolios while also using a different method for building the volatility portfolios. Secondly, I use the method for the timing strategy on volatility sorted portfolios and extend it to portfolios sorted on momentum, thereby increasing the understanding of the profitability of the MA timing strategy.

The results on the extended time period of the volatility portfolios show that the performance of the timing strategy has decreased but is not gone. The highest and lowest volatility deciles still show significant improvement by using the MA timing strategy on the underlying volatility portfolios. The highest average returns are obtained using a 10- or 20-day lag moving average on the lowest or highest volatility deciles, where the latter holds the highest average returns while the former holds the highest risk adjusted returns. The improvement in performance over the underlying volatility deciles does not results from taking additional exposure to traditional risk factors, as the betas were significantly negative indicating there was actually less exposure to these risk factors.

For the momentum portfolios, I find similar results as for the volatility portfolios. The timing strategy is capable of significantly increasing returns for the winners and losers portfolios, while also substantially decreasing the volatility of the portfolios. An analysis of the subsamples showed that the significance of the 10-lag strategy has decreased over time, but that a 20-day lag strategy is still significantly increasing average returns. Furthermore, the results show that the short lags are especially effective at increasing the performance of the losers portfolio, while the longer lags are more effective for the winners portfolio. This makes it difficult to make a zero-cost portfolio that would actually outperform the zero-cost portfolio of the underlying momentum portfolios. The results show that the construction of such a portfolio would be in contradiction of what the momentum anomaly suggest. That is, instead of going long on the winners and short in the losers, with the timing strategy its optimal to go long in the losers portfolio while short in the winners portfolio. However, since the ability to go short may not be used much in practice, a long-only strategy seems to be the most viable alternative. In that case it's the losers portfolio that have the highest returns when using short lags for the timing strategy, while it's the winners portfolio that outperforms when using higher lags.

The high decrease in the standard deviation of all portfolios using a timing strategy may indicate a significant reduction of downside risk and upside potential. As a result, the strategy could avoid negative returns resulting in higher average returns. The effect on the upside potential is ambiguous as the results show that for some portfolios the average returns actually decreases. A possible explanation would be that, when using the timing strategy, there is a trade-off of the ability to avoid downside risk at the cost of upside potential. Further exploration on this topic might be interesting for future research. At the same time, my research has not considered transaction costs. Because the timing strategy is based on a daily frequency, the transaction cost may have a significant impact on some portfolios. However, the Fama-French alphas of most extreme portfolios are of such a high value that is unlikely that this would make the strategy not worth pursuing.

VII. Appendix: Tables

Table 1
Summary Statistics

The 10-day moving average timing portfolios are created according to formula (1) and (2). If the t-1 portfolio price is higher than the 10-day moving average, the portfolio is considered as in-the-money and as a result a buy signal is given. If the t-1 portfolio price is lower than the 10-day moving average, the reverse is true and I invest at the risk free rate. The volatility decile portfolios are created using the previous year annualized standard deviation and they are updated on a yearly basis. I report the annualized average return of the decile portfolios along its standard deviation and Sharpe ratio. Panel A reports the summary statistics of the volatility decile portfolios, panel B reports the summary statistics using the 10-day MA timing strategy and Panel C reports the difference in returns between the MA timing strategy and the underlying volatility decile and the success rate. The sample period is from Jan. 3, 2000, to Dec. 30, 2016 and based on daily data. The returns, standard deviations and Sharpe ratios are annualized.

	Panel A: Volatility portfolios			Panel B: MA(10) Timing strategy			Panel C: MAP's	
	Avg.Ret	Std.Dev	Sharpe ratio	Avg.Ret	Std.Dev	Sharpe ratio	Avg.Ret	Success
Low	6.30%	7.24%	0.68	10.04%	3.79%	2.30	3.74%	75%
2	7.87%	12.79%	0.51	8.04%	7.82%	0.86	0.18%	73%
3	7.98%	14.97%	0.44	6.68%	9.51%	0.56	-1.30%	72%
4	8.45%	16.48%	0.43	5.67%	10.85%	0.40	-2.78%	73%
5	8.13%	17.76%	0.38	5.90%	11.66%	0.39	-2.23%	73%
6	9.17%	18.95%	0.41	6.18%	12.65%	0.38	-2.99%	73%
7	9.57%	20.31%	0.40	8.75%	13.90%	0.53	-0.82%	73%
8	9.79%	21.83%	0.39	10.23%	15.03%	0.59	0.44%	74%
9	10.77%	24.17%	0.39	13.66%	16.72%	0.74	2.89%	74%
high	17.52%	25.88%	0.62	26.98%	17.91%	1.43	9.46%	76%

Table 2
CAPM regressions

This table reports the alphas, betas and adjusted R^2's of the regression of the MAP's on the market factor. The MAP's in this table are formed from the 10-day MA timing strategy. Alphas and betas are shown per volatility decile, and the sample period is from Jan. 3, 2000, to Dec. 30, 2016. The reported alphas are annualized. The market factor is the daily excess return of the market over the risk free rate and taken from the Kenneth French database

	Low	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	High
β_{MKT}	-0.158***	-0.374***	-0.443***	-0.480***	-0.539***	-0.575***	-0.608***	-0.642***	-0.699***	-0.695***
	(-7.940)	(-17.28)	(-20.18)	(-20.66)	(-23.69)	(-24.57)	(-25.10)	(-26.67)	(-27.02)	(-26.50)
α	4.78***	2.36	1.21	0.09	1.89	0.78	3.35	5.28*	8.25**	14.23***
	(3.508)	(1.277)	(0.590)	(0.0413)	(0.501)	(0.309)	(1.235)	(1.821)	(2.556)	(3.883)
Obs	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016
Adj. R^2	0.241	0.496	0.528	0.524	0.555	0.555	0.546	0.542	0.525	0.463

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3
Fama-French 3-factor regressions

Table 3 reports the alphas, betas and adjusted R^2's of the Fama-French 3-factor model regressions for the MAP's. The MAP's are formed using the 10-day MA timing strategy. The market factor is the excess return of the market return over the risk free rate. The size factor is the excess return of the small stocks over big stocks, as measured by market capitalization, and the value factor is the excess return of high value stocks over low value stocks. The sample period is from Jan. 3, 2000, to Dec. 30, 2016. Reported alphas are on an annualized basis and in percentages.

	Low	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	High
β_{MKT}	-0.158***	-0.370***	-0.437***	-0.467***	-0.523***	-0.558***	-0.590***	-0.629***	-0.689***	-0.700***
	(-7.031)	(-16.14)	(-19.24)	(-19.69)	(-22.70)	(-23.75)	(-24.20)	(-26.30)	(-26.64)	(-26.62)
β_{SMB}	0.0526*	0.0424	0.0188	0.0773***	-0.100***	-0.141***	-0.202***	-0.252***	-0.283***	-0.286***
	(1.714)	(1.530)	(0.690)	(-2.695)	(-3.548)	(-4.845)	(-6.323)	(-8.032)	(-8.291)	(-8.208)
β_{HML}	-0.0279	-0.0569*	-0.0666**	-0.0879**	0.0993***	-0.0938**	-0.0747*	-0.00278	0.0484	0.181***
	(-0.907)	(-1.826)	(-2.091)	(-2.570)	(-2.892)	(-2.571)	(-1.930)	(-0.0713)	(1.067)	(3.676)
α	4.70***	2.40	1.35	0.59	1.79	1.49	4.20	6.05**	9.05***	14.58***
	(3.383)	(1.284)	(0.653)	(0.262)	(0.757)	(0.592)	(1.561)	(2.125)	(2.832)	(4.073)
Obs	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016
Adj. R^2	0.249	0.500	0.531	0.531	0.563	0.565	0.559	0.560	0.545	0.490

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4
Summary statistics for alternative lags

Table 4 shows summary statistics for alternative lags to the MA timing strategy. The statistics shown are the average return on the MA timing portfolio, the Sharpe ratio, the average return on the MAP and the success rate. All results are annualized daily results. Panel A shows these results for the 20-day lag, panel B for the 50-day lag, and panel C for the 100-day lag timing strategy. The sample period is from Jan. 3, 2000, to Dec. 30, 2016.

	Panel A: MA(20) Timing strategy				Panel B: MA(50) Timing strategy				Panel C: MA(100) Timing strategy			
Deciles	Average return	Sharpe ratio	Average MAP return	Success	Average return	Sharpe ratio	Average MAP return	Success	Average return	Sharpe ratio	Average MAP return	Success
Low	10.02%	2.39	3.71%	74%	8.15%	1.86	1.85%	73%	6.87%	1.46	0.57%	72%
2	9.71%	1.11	1.84%	72%	9.11%	1.07	1.25%	70%	8.49%	1.00	0.62%	69%
3	7.48%	0.67	-0.50%	71%	7.94%	0.75	-0.03%	70%	8.62%	0.86	0.65%	69%
4	6.28%	0.48	-2.17%	72%	8.80%	0.76	0.35%	71%	8.36%	0.74	-0.09%	70%
5	5.59%	0.37	-2.54%	72%	7.32%	0.55	-0.81%	70%	8.59%	0.70	0.46%	70%
6	9.10%	0.64	-0.07%	72%	10.01%	0.73	0.84%	71%	9.81%	0.75	0.64%	70%
7	8.85%	0.56	-0.72%	72%	9.69%	0.64	0.12%	71%	9.66%	0.67	0.09%	71%
8	10.82%	0.65	1.04%	73%	10.09%	0.62	0.31%	72%	11.55%	0.76	1.76%	71%
9	13.81%	0.78	3.04%	74%	12.46%	0.71	1.69%	73%	11.95%	0.69	1.18%	72%
high	23.38%	1.26	5.85%	75%	19.54%	1.04	2.02%	73%	18.85%	1.02	1.33%	72%

Table 5
Alphas of alternative time lags strategies

This table shows the CAPM and Fama-French 3-factor alphas for alternative time lags to the MA timing strategy. Panel A shows the results for the 20-day lag, panel B for the 50-day lag and finally panel C shows the results for the 100-day lag timing strategy. The sample period for the regressions is from Jan. 3, 2000, to Dec. 30, 2016. The reported alphas are on an annualized basis and in percentages.

	Panel A: MA(20) Timing strategy		Panel B: MA(50) Timing strategy		Panel C: MA(100) Timing strategy	
	CAPM α	FF α	CAPM α	FF α	CAPM α	FF α
Low	4.88*** (3.566)	4.70*** (3.387)	3.15** (2.315)	2.95** (2.151)	1.85 (1.349)	1.64 (1.182)
2	4.18*** (2.261)	4.15** (2.225)	4.13** (2.244)	4.00** (2.185)	3.73** (2.042)	3.63** (2.004)
3	2.21 (1.078)	2.36 (1.143)	3.33 (1.639)	3.28 (1.626)	4.35** (2.184)	4.45** (2.242)
4	1.00 (0.442)	1.44 (0.639)	4.15* (1.842)	4.40** (1.964)	3.93* (1.754)	4.28* (1.924)
5	0.98 (0.413)	1.55 (0.652)	3.38 (1.422)	3.80 (1.605)	5.05** (2.129)	5.53** (2.363)
6	4.0 (1.581)	4.75* (1.903)	5.35** (2.127)	5.90** (2.357)	5.70** (2.260)	6.35* (2.553)
7	3.83 (1.410)	4.63* (1.726)	5.00* (1.908)	5.63** (2.103)	5.58** (2.042)	6.40** (2.379)
8	6.43** (2.236)	7.13* (2.518)	5.45* (1.908)	6.10** (2.161)	7.70*** (2.667)	8.60*** (3.041)
9	9.18*** (2.817)	9.83*** (3.082)	6.83** (2.154)	7.40** (2.366)	7.30** (2.333)	8.13*** (2.640)
high	11.43*** (3.120)	11.73*** (3.284)	5.23 (1.463)	5.60 (1.599)	5.83* (1.712)	6.38* (1.890)

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6
Subsamples of volatility portfolios

This table shows the average return on the volatility portfolios, the MA timing portfolios and their corresponding Sharpe ratios. Additionally it reports the average return on the MAP's and the Fama-French alphas. The results are based on the 10-day timing strategy, and the returns and alphas are annualized and in percentages. Panel A shows the results for the first subsample running from the 3rd of January 2000 to the 30th of June 2008. Panel B shows the second subsample, running from Jan. 3, 2000, to Dec. 30, 2016.

	Panel A: Jan 2000 - Jun 2008					
	Volatility portfolio		MA(10) timing strategy		MAP	
	Return	Sharpe ratio	Return	Sharpe ratio	Return	FF-α
Low	7.87%	0.95	11.92%	2.92	4.06%	5.58***
2	9.91%	0.78	10.29%	1.25	0.38%	2.26
3	9.12%	0.58	9.68%	0.94	0.56%	2.67
4	9.29%	0.54	8.05%	0.65	-1.24%	1.54
5	8.09%	0.39	6.85%	0.45	-1.23%	1.91
6	9.90%	0.49	7.61%	0.49	-2.29%	0.93
7	10.02%	0.45	13.19%	0.94	3.17%	6.58**
8	11.34%	0.45	16.23%	1.04	4.89%	8.55**
9	9.75%	0.31	19.99%	1.12	10.25%	12.35***
High	18.38%	0.59	38.24%	1.99	19.86%	18.5***

	Panel B: Jul 2008 - Dec 2016					
	Volatility portfolio		MA(10) timing strategy		MAP	
	Return	Sharpe ratio	Return	Sharpe ratio	Return	FF-α
Low	4.92%	0.56	8.60%	1.99	3.68%	5.25**
2	6.08%	0.39	5.85%	0.63	-0.23%	3.98
3	6.91%	0.38	4.07%	0.36	-2.84%	2.03
4	7.65%	0.39	3.52%	0.27	-4.13%	1.20
5	8.13%	0.39	4.95%	0.36	-3.18%	3.15
6	8.47%	0.38	4.89%	0.33	-3.58%	3.45
7	9.01%	0.38	5.03%	0.31	-3.98%	3.63
8	8.44%	0.35	5.19%	0.31	-3.25%	4.90
9	11.41%	0.44	8.12%	0.44	-3.29%	5.85
High	16.21%	0.63	15.67%	0.87	-0.53%	9.10*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7
Summary statistics of the momentum anomaly

This table reports the summary statistics of using the MA timing strategy on portfolios sorted by a 12 month lag momentum. Panel A shows the average return of the momentum portfolios, their standard deviation and corresponding Sharpe ratio. Panel B shows the same statistics for the 10-day MA timing strategy. Finally, panel C shows the average returns on the MAP's based on the 10-day MA timing strategy and the success rate. The success rate is defined as the percentage of trading days that the MA timing strategy performs equal or better than the risk free rate on that day. The sample period is from Jan. 3, 2000, to Dec. 30, 2016. Reported average returns, standard deviations and Sharpe ratios are on an annualized basis.

	Panel A: Momentum portfolios			Panel B: MA(10) Timing strategy			Panel C: MAP's	
	Avg. Ret.	Std.dev	Sharpe ratio	Avg. Ret.	Std.dev	Sharpe ratio	Avg. Ret.	Succes
Losers	-12.29%	26.49%	-0.46	8.75%	17.34%	0.50	21.05%	77%
2	-1.10%	20.78%	-0.05	8.06%	13.65%	0.59	9.16%	75%
3	1.99%	18.02%	0.11	5.79%	11.70%	0.49	3.79%	74%
4	3.09%	16.73%	0.18	4.01%	10.67%	0.38	0.92%	73%
5	5.27%	15.92%	0.33	4.57%	10.17%	0.45	-0.70%	73%
6	6.45%	15.21%	0.42	4.53%	9.59%	0.47	-1.92%	73%
7	6.92%	15.15%	0.46	4.11%	9.49%	0.43	-2.81%	72%
8	6.72%	15.52%	0.43	4.50%	9.67%	0.47	-2.22%	72%
9	6.77%	17.01%	0.40	3.27%	10.47%	0.31	-3.51%	73%
Winners	1.28%	21.09%	0.06	2.06%	12.58%	0.16	0.78%	73%

Table 8
Fama-French 3-factor regressions

Table 8 reports the alphas, betas and adjusted R^2's of the Fama-French 3-factor model regressions for the MAP's based on the momentum anomaly. The MAP's are formed using the 10-day MA timing strategy. The market factor is the excess return of the market return over the risk free rate. The size factor is the excess return of the small stocks over big stocks, as measured by market capitalization, and the value factor is the excess return of high value stocks over low value stocks. The sample period is from Jan. 3, 2000, to Dec. 30, 2016. Reported alphas are on an annualized basis and in percentages.

	Losers	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Winners
β_{MKT}	-0.720***	-0.600***	-0.534***	-0.497***	-0.461***	-0.440***	-0.434***	-0.445***	-0.484***	-0.595***
	(-25.74)	(-24.61)	(-23.19)	(-20.40)	(-19.01)	(-19.03)	(-18.28)	(-22.45)	(-23.20)	(-24.13)
β_{SMB}	-0.209***	-0.0923***	-0.0512*	-0.0486*	-0.0632**	-0.0645**	-0.0721**	-0.128***	-0.172***	-0.286***
	(-5.713)	(-3.082)	(-1.902)	(-1.716)	(-2.218)	(-2.357)	(-2.453)	(-5.287)	(-6.375)	(-8.615)
β_{HML}	0.0138	-0.0304	-0.0604	-0.0833**	-0.0953***	-0.0932***	-0.0548*	-0.0438	-0.0280	0.0360
	(0.247)	(-0.725)	(-1.630)	(-2.305)	(-2.725)	(-2.843)	(-1.677)	(-1.572)	(-0.972)	(1.051)
α	26.50***	13.33***	7.38***	4.38*	2.55	1.18	0.19	0.89	-0.26	4.73
	(7.307)	(4.852)	(3.112)	(1.949)	(1.171)	(0.561)	(0.0886)	(0.413)	(-0.111)	(1.565)
Obs	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016	4,016
Adj. R^2	0.500	0.546	0.563	0.561	0.544	0.538	0.518	0.529	0.522	0.508

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9
Momentum alternative timing strategies

This table reports several statistics and the alpha obtained from a Fama-French 3-factor regression for the momentum portfolios formed by alternative time lags. The statistics reported are the average return (Avg Ret.) and Sharpe ratio for the MA timing strategy and the average returns on the corresponding MAP's. Additionally, the alpha from the Fama-French regressions are shown. Panel A reports these for the 20-day lag, panel B for the 50-day lag and panel C for the 100-day lag. The sample period is from January 2000 to December 2016. All reported values are on an annualized basis and the significance of the alphas is reported in p-values. *** p<0.01, ** p<0.05, * p<0.1

		Portfolio deciles									
		Losers	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Winners
Panel A (MA20)	Avg. Ret.	8.63%	8.25%	6.68%	5.14%	6.61%	6.12%	4.33%	5.63%	5.10%	3.57%
	Sharpe Ratio	0.52	0.65	0.60	0.51	0.69	0.67	0.48	0.61	0.51	0.30
	MAP Ret	20.93%	9.35%	4.68%	2.05 %	1.34%	-0.33%	-2.59%	-1.09%	-1.68%	2.29%
	FF α	27.25***	14.1***	8.70**	5.78***	4.88**	2.95	0.57	2.21	1.90	6.53**
Panel B (MA50)	Avg. Ret.	4.51%	6.39%	5.72%	5.26%	5.67%	6.99%	6.91%	8.29%	8.76%	6.72%
	Sharpe Ratio	0.30	0.53	0.54	0.55	0.60	0.76	0.76	0.90	0.88	0.56
	MAP Ret	16.80%	7.49%	3.73%	2.17%	0.40%	0.54%	-0.01%	1.57%	1.98%	5.44%
	FF α	22.08***	11.93***	7.88***	6.23***	4.13*	4.00*	3.43	5.10**	5.68**	9.75***
Panel C (MA100)	Avg. Ret.	3.77%	5.11%	5.99%	6.28%	7.20%	6.88%	7.89%	7.64%	7.20%	5.96%
	Sharpe Ratio	0.29	0.45	0.60	0.70	0.81	0.76	0.88	0.82	0.71	0.49
	MAP Ret	16.06%	6.21%	4.00%	3.19%	1.93%	0.43%	0.97%	0.92%	0.42%	4.68%
	FF α	22.38***	11.13***	8.68***	7.78***	6.15***	4.08***	4.63**	4.73**	4.38*	9.35***

Table 10
Subsamples of timing strategy on momentum

This table shows the average return and corresponding Sharpe ratio of the momentum portfolios and MA timing portfolios using a 10-day lag. Additionally the average return on the MAPs and Fama-French alpha of the MAPs are reported. Panel A reports these results for the first subsample period and panel B for the second subsample. All statistics are annualized, and the Fama-French alphas are in annualized percentages.

	Panel A: Jan 2000 - Jun 2008					
	Momentum portfolio		MA(10) timing strategy		MAP	
	Return	Sharpe ratio	Return	Sharpe ratio	Return	FF-α
Losers	-16.05%	-0.76	14.45%	0.78	30.49%	33.25***
2	-4.14%	-0.39	9.34%	0.61	13.47%	15.78***
3	1.18%	-0.11	7.62%	0.56	6.44%	8.65***
4	3.74%	0.08	6.24%	0.45	2.50%	4.65**
5	6.38%	0.34	6.04%	0.46	-0.34%	1.76
6	7.60%	0.45	7.14%	0.62	-0.46%	2.16
7	8.15%	0.48	6.13%	0.45	-2.02%	0.81
8	7.43%	0.38	6.93%	0.51	-0.50%	2.01
9	9.40%	0.48	8.73%	0.65	-0.67%	1.75
Winners	6.31%	0.20	13.05%	0.90	6.74%	9.9**

	Panel B: Jul 2008 - Dec 2016					
	Momentum portfolio		MA(10) timing strategy		MAP	
	Return	Sharpe ratio	Return	Sharpe ratio	Return	FF-α
Losers	-9.09%	-0.33	3.78%	0.19	12.87%	18.25***
2	1.49%	0.06	6.96%	0.44	5.47%	10.78**
3	2.69%	0.12	4.20%	0.30	1.51%	6.75*
4	2.53%	0.12	2.06%	0.15	-0.48%	5.13
5	4.33%	0.22	3.30%	0.26	-1.03%	4.45
6	5.46%	0.29	2.25%	0.19	-3.21%	2.07
7	5.87%	0.32	2.35%	0.20	-3.52%	1.71
8	6.12%	0.34	2.37%	0.21	-3.74%	1.72
9	4.53%	0.23	-1.54%	-0.14	-6.06%	-0.13
Winners	-3.02%	-0.13	-7.44%	-0.56	-4.42%	2.88

*** p<0.01, ** p<0.05, * p<0.1

Table 11
Second subsample with alternative lags

This table shows the average return on the momentum timing portfolios and the corresponding Fama-French alpha for alternative time lags for the second subsample. The subsample consist of data from July 1, 2008, to Dec. 30, 2016. The alternative lags are the 20-, 50- and 100-day lags. Returns and Fama-French alphas are annualized and in percentages.

	MA(20) timing strategy		MA(50) timing strategy		MA(100) timing strategy	
	Return	FF-α	Return	FF-α	Return	FF-α
Losers	4.32%	20.45***	1.66%	19.10***	3.46%	15.48***
2	6.65%	11.83***	3.81%	9.75**	5.76%	5.75
3	4.23%	7.85**	3.72%	7.95**	6.54%	5.73
4	3.50%	7.48**	2.68%	7.30**	6.38%	6.28*
5	5.11%	7.28**	4.13%	6.48*	7.25%	5.08
6	4.22%	4.78	4.93%	5.50*	6.59%	3.58
7	1.38%	1.35	5.25%	5.25	7.55%	4.43
8	2.89%	2.88	5.94%	5.70*	6.90%	4.05
9	1.30%	3.30	5.51%	6.83*	5.32%	3.78
Winners	-1.60%	8.93**	1.57%	10.90***	3.62%	9.95**

*** p<0.01, ** p<0.05, * p<0.1

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