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Master Thesis

LOW-PRICED STOCKS; THE DRIVER BEHIND THE LOW VOLATILITY ANOMALY AND THE MOVING AVERAGE STRATEGY

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Abstract

This thesis examines the relationship between the low volatility anomaly and the Moving Average strategy in the US stock market between 2007-2016. The specification of this paper is that it omits low-priced stocks for the low volatility strategy and the Moving Average strategy. The results are tested through an OLS regression with the Fama-French 3-factor model. The findings show that when omitting the low-priced stocks the low volatility anomaly disappears. Omitting low-priced stocks does not prevent a Moving Average strategy from working. It does however decrease the magnitude of the alphas gained by using the Moving Average strategy.

Keywords: Low volatility, Moving Average, low-priced stocks

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CHAPTER 1: Introduction

We know of the existence of the low volatility anomaly in the stock market. Its existence has been proven many times. Ang, Hodrick, Xing, and Zhang (2006) are the first to show the existence of the low volatility anomaly in the US stock market. Later Blitz and Van Vliet (2007) show that the low volatility anomaly holds for Europe and Japan as well. Baker, Bradley and Wurgler (2011) give several behavioral explanations for the existence of the low volatility anomaly. They argue that the persistent existence of the low volatility lays in the fact that it is not exploited by investment managers. Investment managers want excess return, whereas the low volatility produces stable returns, but with minimizing risk. According to academics technical analysis should have no predictability or added value in the stock market. However, practitioners apply these technical analyses in practice in firm reports (Linnainmaa, 2009). Technical analysis violates the Efficient Market Hypothesis since they create value by making use of past stock prices.

This thesis researches if low-priced stocks are the driving force behind the low volatility anomaly and the Moving Average strategy. Research on the low volatility anomaly or the Moving Average strategy isn't relatively new. However, a non-behavioral explanation that has been found recently for the low volatility anomaly is relatively new. Li, Sullivan & Garcia-Feijoo (2014) show that by omitting the low-priced stocks the alpha for a low volatility strategy is largely eliminated. Han, Yang and Zhou (2013) find that the low volatility decile portfolios can be enhanced by making use of a Moving Average strategy. In order to understand these anomalies, it is important to understand what drives these anomalies.

The results for the low volatility anomaly are similar to those of Li et al. (2014). I find that alpha is largely eliminated and disappears when low-priced stocks are omitted. I even find a significant positive alpha for the 10^{th} decile portfolio when low-priced stocks are omitted. Additionally, the results for the normal low volatility show that the magnitude of its alphas has decreased when compared to the results of Biltz and van Vliet (2007).

Furthermore, the results for the Moving Average show that a Moving Average strategy on low volatility decile portfolios enhances its alphas which is similar to the results found by Han, Yang and Zhou (2013). I find that the enhancement of the alphas caused by the Moving Average strategy becomes significantly smaller when low-priced stocks are omitted.

This thesis builds further on the research done by Han, Yang and Zhou (2013) and Li et al. (2014). First, it shows that low-priced stocks are a driver for the low volatility anomaly and that the anomaly disappears when low-priced stocks are omitted. Second, it shows that low-priced stocks influence the Moving Average strategy. This thesis therefore contributes to the understanding of the anomalies and what drives to anomalies.

This thesis follows the following structure: Chapter 2 elaborates on the literature regarding the low volatility anomaly and the Moving Average strategy. Chapter 3 provides information and mathematical details about the methodology used in this paper. It shows the mathematical relationship for the Moving Average strategy and elaborates on why a certain strategy was chosen. Chapter 4 gives a small summary about the data that was used for this paper. In chapter 5 shows the results of this paper. Chapter 6 contains the conclusion on this paper and gives a clear elaboration on the findings in the results.

CHAPTER 2: Literature

The low volatility anomaly states that stocks with a low stock return volatility earn higher risk-adjusted returns than stocks with a high stock return volatility (Blitz & Van Vliet, 2007). Blitz and Van Vliet (2007) show that this anomaly holds in the US, Europe and Japan. Dutt and Humphery-Jenner (2013) discovered that the low volatility anomaly even seems to hold in the emerging markets. Dutt and Humphrey also find supporting evidence that low volatility stocks have higher operating returns than high volatility stocks. They argue that this might explain why low volatility stocks earn higher risk-adjusted returns than high volatility stocks. They argue that higher operating returns lead to higher expected stock returns. According to Li, Sullivan, and Garcia-Feijoo (2014) the low volatility alphas significantly decrease when looking at equal weighted portfolios. The low volatility anomaly is present in value weighted portfolios, however when omitting low-priced (less than 5$) stocks the existence of alpha is largely eliminated. They therefore conclude that the abnormal returns are found concentrated among the low liquid and smaller stocks. Bradley and Wurgler (2011) give several behavioral explanations for the existence of the low volatility anomaly. They argue that the persistent existence of the low volatility lays in the fact that it is not exploited by investment managers. Investment managers want excess return, whereas the low volatility produces stable returns, but with minimizing risk.

According to Han et al. (2015) the use of more frequent return data increases the effect of market anomalies. Making use of more frequent data means portfolios are updated more frequent and thus a better optimization of returns. Therefore, it is important to use the right data to measure the magnitude of the anomalies. Especially when comparing different strategies this shows that it is important to use the same type of data. Anomalies are said to be either market inefficiencies or inadequacies in the underlying asset-pricing model (Schwert, 2003). However, this is not the case for technical trading analysis.

Technical trading analysis are based on past price information. This is conflicting with the Efficient Market Hypothesis that states that current stock prices reflect all of the available information about the value of a firm and therefore, no information about future stock prices can be gathered from past prices (Fama, 1970). The weak form of the Efficient Market Hypothesis states that current stock prices reflect all information of past stock prices. The semi strong form of the Efficient Market Hypothesis states that current stock prices reflect all information of past stock prices and all publicly available information. The strong form of the Efficient Market Hypothesis states that the current stock prices reflect all information of past stock prices, all publicly available information and all the private information about the stock (Fama, 1970). Therefore, according to all the forms of the Efficient Market Hypothesis, technical trading analysis should have no value creation effect.

A Moving Average strategy is among the most known technical trading analysis. A Moving Average strategy makes use of lagged averages. When the short-term average price is higher than the long-term average price, a buy signal is triggered. If the long-term average is higher than the short-term average a sell signal is triggered. The most popular moving average rule is 1-200, where the short-term average is 1 day and the long-term average is 200 days. Other popular rules are 1-50, 1-150, 5-150, 1-200 and 2-200. The moving average rules are often modified by introducing a one percent band. If the difference between the short-term and long-term average is within the one percent band no signal is triggered. This prevents "whiplash signals" (Brock, Lakonishok, & LeBaron, 1992). Han, Yang and Zhou (2013) use the rules 1-10, 1-20, 1-50, 1-100, 1-200. Han, Huang, and Zhou (2015) make use of the 50-200 rule. Brown and Jennings (1989) provide theoretical support for technical analysis. According to Brown and Jennings, investors can gain insight into private information by using past prices when there is incomplete information. Brock, Lakonishok, and LeBaron, (1992) show that a Moving Average strategy has predictable power and therefore creates value. Han, Yang and Zhou (2013) show that anomalies can be enhanced by making use of a Moving Average technical analysis applied to sorted portfolios. Using this strategy generates investment timing portfolios that can outperform a standard buy-and-hold strategy (Han, Yang, & Zhou, 2013). Neely, Rapach, Tu, and Zhou, (2014) show that using technical indicators for forecasting the stock market is just as good as using popular macroeconomic variables. Goh, Jiang, Tu, and Zhou (2013) show that technical indicators yield even a better forecast in the bond market than the popular macroeconomic variables.

However, according to Marshall et al. (2013) prior studies have shown, that since the mid-1980s using a Moving Average strategy on equities is not profitable. They themselves find that Moving Average is not profitable for large stocks, but Moving Average is profitable for mid- or small cap stocks. The prior studies that find that the Moving Average strategy is not profitable are for example (Fama & Blume, 1966)**.**

According to Zhang (2006) price continuation comes from underreaction of investors to new public information. Investors will underreact even more in case of greater information uncertainty. Zhu and Zhou (2009) show that if stock returns are predictable and technical analysis is used in combination with commonly used allocation rules that invest fixed proportions of wealth in stocks, technical analysis does create value. Pesaran and Timmermann (1994, 1995) were able to show that excess returns of common stocks for the S&P 500 and Dow Jones Industrial portfolios are predictable.

The existing literature contains conflicting evidence on whether a Moving Average strategy is profitable. If a Moving Average strategy is profitable is important to know because a profitable Moving Average strategy would be conflicting with the Efficient Market Hypothesis. This would indicate that our markets are not fully efficient and one could play the market. Combining the research of Pesaran and Timmermann (1994, 1995) and Zhu & Zhou (2009) could be a potential explanation for the conflicting evidence on whether a Moving Average strategy is profitable. Combining the researches shows that when stock returns are predictable a Moving Average strategy creates value. However, the indicators used to predict returns are often highly correlated with past returns. This correlation means that past prices still hold valuable information about future prices, which should not be possible according to the Efficient Market Hypothesis (Campbell & Yogo, 2006). The past prices containing valuable information about future prices is the same problem as to why a Moving Average strategy may be profitable.

As Han, Yang and Zhou (2013) show, combining a Moving Average strategy with an anomaly creates more value than the stand-alone value creation of a Moving Average strategy or an anomaly strategy. Therefore, the Moving Average strategy and the anomaly strategy should have a common factor that causes this increase in value creation. Li et al. (2014) show that when omitting low priced stocks, the low volatility strategy does not create value anymore. Zhang (2006) argues that price continuation and thus price predictability comes from the fact that investors underreact to new public information. For low-priced stocks this is more likely the case since low-priced stocks are on average more uncertain than high-priced stocks. This uncertainty comes from the fact that low-priced stocks are under less scrutiny of analysts than high-priced stocks. Due to this lesser scrutiny of analyst it could be that the current stock price does not fully reflect information from past prices. This explains why low-priced stocks could be the driving force behind the Moving Average strategy. Therefore, I investigate whether low-priced stocks could be the driving force behind the low volatility and Moving Average strategy.

I start by looking whether the low volatility anomaly is still present in our current time frame and if its alphas are largely eliminated when low-priced stocks are omitted. Lastly, I will test what happens with the value creation of the Moving Average strategy when low-priced stocks are omitted. The outperformance of the strategies will be tested against the Fama and French 3-factor model(Fama & French, 1993). Testing against this model is done to see which part of the outperformance of the low volatility strategy and Moving Average strategy is explained by other factors than the strategy itself.

CHAPTER 3: Methodology

Low volatility

Anomalies are market inefficiencies or inadequacies and therefore once known they can be exploited and disappear (Schwert, 2013). Therefore, I will first test whether the low volatility is still present in the US stock market in our current time frame from 2007-2017. Leading to the following hypothesis.

H1a: The low volatility anomaly is still present in the US stock market.

For constructing the low volatility decile portfolios, I make use of the methodology of Blitz and van Vliet (2007). In this methodology stocks are ranked on their average 3-year historical volatility and placed into ten equally weighted decile portfolios. Blitz and van Vliet (2007) make use of monthly data where as I make use of daily data to calculate the historical volatility. The portfolios are updated on a monthly basis. I make use of daily data as this leads to more accurate results as provided by Han et al. (2015). According to Li et al. (2014) the outperformance of the low volatility strategy is largely eliminated when low-priced stocks (stocks under $5) are omitted which leads to my next hypothesis

H1b: The low volatility anomaly will disappear when stocks priced lower than $5 are omitted.

The methodology used is the same as for hypothesis H1a except that stocks priced lower than $5 are now omitted from the dataset. Stocks are still ranked on their average 3-year historical daily volatility and placed into ten equally weighed decile portfolios. The portfolios are updated on a monthly basis.

To test the outperformance of the low volatility strategy I make use of the Fama-French 3-factor model (Fama & French, 1993). This is done by taking a multivariate OLS regression with the portfolio being the independent variable and the Fama and French factors being the dependent variables. The Fama-French 3-factor model consists of the factors, market premium, size factor and value factor. The Fama-French 3-factor model tries to explain market return through its three factors. If the intercept is significantly different from zero this means there is outperformance of the low volatility decile portfolio that cannot be explained by the three factors.. This is done for all the ten decile portfolios.

Moving Average

The Moving Average strategy makes use of lagged averages. A buy signal is triggered if the short-term average price is higher than the long-term average price. A sell signal is triggered when the long-term average price is higher than the short-term average price. If a sell signal is triggered the corresponding investment is sold and invested in the risk-free rate. The risk-free rate is taken from the Kenneth Fama database and represents the daily return on the 1-month T-bill. Mathematically this can be shown in the following way. The return of the volatility decile portfolios can be written as R_{jt} with j = 1,… 10 and their corresponding portfolio index prices can be written as P_{jt} with j = 1,… 10. The average lagged priced can be denoted in the following way.

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

I make use the following trading rules 1-10, 1-20, 1-50, 1-100, 1-200, and 50-200. Since I invest in the 30-day T-bill if the $A_{jt,L}$ is above the price and I invest in the portfolio if the $A_{jt,L}$ is below the price, the total return of the Moving Average portfolio can be mathematically written as

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

However this return $R^{*}_{jt,L}$ now captures the return generated by the Moving Average and the low volatility. To obtain the return of the Moving Average strategy I create a Moving Average Portfolio (MAP) by subtracting the return of the volatility decile portfolio from the enhanced volatility portfolio. Mathematically this can be written as

(3) $$MAP_{jt,L} = \tilde{R}_{jt,L} - R_{jt.L}, \quad j = 1,\dots, 10$$

This methodology used for creating the Moving Average analysis is in line with the methodology of Han et al. (2013). The strategy is no longer a buy and hold strategy anymore but now becomes a market timing strategy. This methodology is used the answer the following hypothesis.

H2a: A Moving Average strategy enhances the low volatility anomaly.

As Li et al. (2014) show, low-priced stocks are one of the drivers for the low volatility. Han et al. (2013) show that the anomaly can be enhanced by a MA strategy. Therefore, it is reasonable to assume that the profitably of a Moving Average strategy may lay in the low-priced stocks, this leads to the following hypothesis

H2b: A Moving Average strategy does not enhance the low volatility anomaly when low-priced stocks (stocks priced under $5) are omitted.

The MAP portfolios are tested against the Fama-French 3-factor model to test for significant outperformance. This is done by taking a multivariate OLS regression with the MAP portfolio returns being the independent variable and the Fama and French factors being the dependent variables. If the intercept is significantly different from zero this means there is outperformance of the Moving Average strategy.

CHAPTER 4: Data

Stock price and return data for the US is collected from the Center for Research in Security Prices (CRSP). Stock data of the NYSE, NASHDAQ and the AMEX is used. I make use of daily and monthly price and return data. Daily data is mainly used. First, it is used for constructing the low volatility deciles portfolios. Secondly it is used to implement a Moving Average strategy daily return data to calculate the buy and sell signals. Lastly, it is used to compare the daily results of the low volatility decile portfolios to the monthly results of the low volatility decile portfolios. Monthly data is used so that results for the low volatility anomaly can be compared with the results generated by Blitz and van Vliet (2007). Comparing to Blitz and van Vliet (2007) is done so that it is possible to see if the low volatility anomaly has either increased or decreased in size. The time frame of 2007-2016 was chosen to see if the low volatility anomaly is still present in our current market. Since anomalies are said to be either market inefficiencies or market inadequacies, one would expect them to disappear over time once known (Schwert, 2003). The dataset contains over 17 million observations of approximately eight thousand firms. The Fama and French factors and the risk-free rate are collected from the Kenneth French database.

CHAPTER 5: Results

Panel A in Table 1 shows the results for the low volatility strategy. I find a 0.53% monthly return for the first decile portfolio and a -2.28% monthly return for the 10th decile portfolio. The results show an increasing monthly return from the first to the 4th decile portfolio. After the 4th decile portfolio monthly returns are declining. The Sharpe ratio shows the risk-adjusted return. I find a Sharpe ratio of 0.26 for the first decile portfolio and a Sharpe ratio of -0.32 for the 10th decile portfolio. When looking at the Sharpe ratio I find gradually declining Sharpe ratios from the first decile portfolio until the 10th decile portfolio. The lower absolute returns for the high decile portfolios compared to the low decile portfolios and the gradually declining Sharpe ratios are in line with recent findings on the low volatility anomaly by Blitz and van Vliet (2007).

I have tested the low volatility decile portfolio returns against the Fama-French 3-factor model by regressing the Fama and French factors on the low volatility decile portfolio returns. The results of the Fama-French 3-factor model regression can be found in Table 2. I find a monthly alpha of 0.35% for the first decile portfolio, however this result is not significant. I find a monthly alpha of -2.94%, with a significance level of one-percent for the 10th decile portfolio. The alphas are gradually decreasing from the first decile portfolio to the 10th decile portfolio. The alphas become negative from the second decile portfolio, and are significant on a five-percent level from the 5th decile portfolio to the 10th decile portfolio. The market beta is increasing from the first decile portfolio to the 7th decile portfolio and is decreasing after the 8th decile portfolio. According the economic theory one would expect that the market beta would be increasing from the first decile portfolio to the 10th decile portfolio as the volatility is increasing from the first to the 10th decile portfolio. The size beta is increase from the first to the 9th decile portfolio. The value beta is increasing from the first decile portfolio to the 6th decile portfolio and decreasing afterwards. All the betas are significant at a one-percent level. The gradually decreasing alphas with the negative alphas for the high decile portfolios and the increase market, size and value betas are in line with the previous findings of Blitz and van Vliet (2007). However, Blitz and van Vliet find a positive significant alpha for the first decile portfolio. The increasing market beta is what one would expect from economic theory.

The results found in Table 2 can't be directly compared with the results that Blitz and Van Vliet (2007) find, as they use monthly data and I have used daily data. To be able to compare the results I performed the analysis again with monthly data. Table 3 shows the regression results for the Fama-French 3-factor model when monthly data is used. I find positive alphas for the low decile portfolios and negative alphas for the high decile portfolios except the 10th decile portfolio. All the alphas are significant on a one-percent level except for the alpha of the 10th decile portfolio. When comparing the alphas found by using monthly data to the alphas found by Blitz and van Vliet (2007) I find that the alphas have shrunk in magnitude. The market beta is now monotonically increasing from the first decile portfolio to the 10th decile portfolio. This is in line with what would be expected from economic theory. The size beta is also increasing from the first decile portfolio to the 10th decile portfolio. The value beta is increasing from the first to the 9th decile portfolio. When comparing the results from Table 2 where daily data is used, to the results of Table 3 where monthly data is used, I find that the magnitude of the alphas has increased. The findings of lower alphas when monthly data is used compared to when daily data is used is in line with the results of Han et al. (2015) that the use of more frequent data leads to higher results. I find that the low volatility anomaly is still present in the US stock market. However, the magnitude of its effect has shrunk when compared to the result Blitz and Van Vliet (2007) find. Therefore, hypothesis 1a is accepted.

Panel B in Table 1 shows the results for the low volatility decile portfolios enhanced by the Moving Average 1-10 timing strategy. For the first decile portfolio, I find a monthly return of 1.70% and for the 10th decile portfolio I find a monthly return of 4.62%. I find increasing monthly returns from the first decile portfolio to the 8th decile portfolio. After the 8th decile portfolio returns are declining. The returns of the enhanced low volatility portfolios are higher than the returns of the normal low volatility portfolios. I find that the standard deviation of enhanced low volatility portfolios are lower than the standard deviation of the normal low volatility portfolios. The higher absolute returns and the lower standard deviations lead to higher Sharpe ratios and thus higher risk-adjust return. I find increasing Sharpe ratios from the first decile portfolio until the 6th decile portfolio. After the 6th decile portfolios the Sharpe ratios are declining. Panel B in Tables 4 until Table 8 show the results for the 1-20, 1-50, 1-100, 1-200 and 50-200 Moving Average timing strategies. The results show that the longer the long-term average, the lower the monthly returns and the Sharpe ratios are. The results show that increasing the short-term average decreases the average returns, Sharpe ratios and increases the standard deviation for the low decile portfolios. Using the 50-200 signal obtains average returns and Sharpe ratios for the first to the 7th decile portfolio that are lower than the average returns and Sharpe ratio obtain by the normal low volatility portfolios and lower than the results obtained by the 1-200 signal. No matter which signal is used with a short-term average of 1, the returns and Sharpe ratios obtained by the enhanced portfolios are always higher than the returns and Sharpe ratios obtained by the normal low volatility portfolios.

Panel C in Table 1 shows the results for the MAP portfolios. The MAP portfolios are the difference between the low volatility portfolios enhanced by the Moving Average strategy and the low volatility portfolios. I find a 1.16% monthly return for the first decile MAP portfolio and a 6.90% monthly return for the 10th decile MAP portfolio. I find that the monthly return of the MAP portfolios is increasing from the first decile portfolio until the 10th decile portfolio. The high decile portfolios show the biggest average returns, this could be due to the fact that high volatility stocks are more uncertain (Zhang, 2006). The success rate is defined as the percentages of times that the Moving Average strategy triggered a buy signal and the return generated was higher than the risk-free rate. The success rate of the Moving Average 1-10 days timing strategy is around 70%. Panel C in Table 4 to 8 show the results for the 1-20, 1-50, 1-100, 1-200 and 50-200 Moving Average timing strategies. Again, I find that the longer the long-term average becomes, the lower the monthly returns and the success rates become. I even find negative returns for the first decile MAP portfolio as the long-term average is 100 days or more. Increasing the short-term average from 1 to 50 generates negative MAP average returns for the first to the 7th decile portfolio. Negative MAP returns don’t necessarily mean the Moving Average strategy is performing worse than the normal low volatility portfolios as the standard deviation has also decreased and therefore risk adjusted return can still be higher.

The alphas for the MAP generated by the Moving Average 1-10 timing strategy can be found in Table 9. I find a monthly alpha of 1.95% for the first decile portfolio and a monthly alpha of 10.95% for the 10th decile portfolio. The alphas are increasing from the first decile portfolio to the 10th decile portfolio. All the alphas are significant at a one-percent significance level. The highest alphas are concentrated among the highest decile portfolios. I find negative market betas, size betas and value betas all being significant on a one-percent level. The negative market, size and value betas mean that under the Moving Average timing strategy the exposure to these factors becomes less and they therefore have less influence on the returns generated by the Moving Average timing strategy. The findings of the negative market, size and value betas are also similar to the findings of Han et al. (2013). Table 10 to 14 show the results for the 1-10, 1-20, 1-50, 1-100, 1-200 and 50-200 strategies. I find that the longer the long-term average the lower the alphas become. I do find differences in the significance level for the first decile portfolio when the long-term average become longer than 100 days.

I find that a moving average strategy does enhance the low volatility anomaly, no matter what signal is used. Therefore, hypothesis 2a is accepted. However, the longer the long-term average, the lower the alpha becomes. The results I find for the low volatility portfolios enhanced by the Moving Average strategy are in line with the results found by Han et al. (2013).

To summarize, I find results indicating that the low volatility anomaly is still present in the US stock market. Its presence is most noticed in the high volatile decile portfolios where it generates significant negative alphas which means that high volatile stocks earn lower risk-adjusted returns. Even though it is still present in the US stock market, I find results indicating that its magnitude has shrunk when compared with the results that Blitz and Van Vliet (2007) find. The decline in magnitude could be due to the fact that once an anomaly is known, it will be exploited and the anomaly will be traded away over time and eventually disappear. I also find results indicating that a Moving Average strategy enhances the low volatility anomaly when used on the sorted decile portfolios. The biggest alphas generated by the Moving Average strategy are found among the highest decile portfolios. When the short-term average and/or the long-term average increases the alphas decrease in size.

Low-priced stocks are omitted

Panel A in Table 15 shows the results for the low volatility strategy performed when low-priced stocks are omitted. The results show a 0.49% monthly return for the first decile portfolio and a 1.44% monthly return for the 10th decile portfolio. The results are increasing from the first decile portfolio to the 5th decile portfolio. From the 5th to the 7th decile portfolio the returns are decreasing. After the 7th portfolio the returns increase again. Comparing the average monthly return in Panel A from Table 1 and 4 I find that for the first three decile portfolios the average returns only deviate up to 0.04% from each other. However, from the 4th decile portfolio on the portfolios where low-priced stocks are omitted, higher average returns are produced. I find lower standard deviations for the decile portfolios when low-priced stocks are omitted compared to when they are included. This means that the low-priced stocks are probably the more volatile stocks. This could come from the fact that they are under less scrutiny of analysts so that when information becomes available their stock return becomes more volatile. When looking at the Sharpe ratio I find this to range from 0.14 to 0.25. I find that the Sharpe ratio from the first to the 9th decile is overall decreasing with sometimes a small increase in the Sharpe ratio. The returns show that a low volatility strategy with going long in the first decile portfolio and short in the 10th decile portfolio (called a zero-cost portfolio from now on) would not be profitable. When looking solely at the average returns they indicate that the low volatility anomaly has disappeared. However, looking at the Sharpe ratio, they tend to be decreasing except for the 10th decile portfolio. Looking at the Sharpe ratio and thus the risk adjusted return, I still find an indication for the low volatility anomaly being present when low priced stocks are omitted. When comparing Sharpe ratios of Panel A from Table 1 and 15 the results show that omitting low priced stocks produces higher Sharpe ratios for the 3rd to the 10th decile portfolios. This finding indicates that the risk-adjusted returns become higher for the high decile portfolios when low-priced stocks are omitted. This also indicates again that the low-priced stocks are probably the more volatile stocks and are the cause for the underperformance of the high decile portfolios. The fact that the Sharpe ratios for the low decile portfolios are almost the same indicates that the low-priced stocks that are less volatile are not underperforming compared to normal-priced stocks with the same return volatility. Therefore, this is a strong indication that the low-priced stocks are the driver behind the low volatility anomaly.

Table 16 shows the regression of the Fama-French 3-factor model on the low volatility decile portfolios when low-priced stocks are omitted. I find a monthly alpha of 0.44% at a significance level of ten-percent for the first decile portfolio. For the 10th decile portfolio I find a monthly alpha of 0.95% at a significance level of one-percent. The alphas for the other decile portfolios are not significant except the alpha for the 7th decile portfolio. I find a higher significant alpha for the 10th decile than the first decile. Therefore, a zero-cost portfolio would generate a negative alpha. The results for the low volatility decile portfolios when low-priced stocks are omitted are in line with the results found by Li et al. (2014).

I find that the low volatility anomaly disappears in the US stock market when stocks priced lower than $5 are omitted. Hypothesis 1b is therefore accepted. Dutt and Humphery-Jenner (2013) find that low volatile stocks have higher operating returns. It could be that the underperformance of the low-priced in the high decile portfolios is related to this. It could also be that the underperformance of low-priced stocks is caused by the fact that they are under less scrutiny of analyst. This makes the stocks more uncertain and volatile. The relation between low-priced stocks and as to why they are the driver of the low volatility anomaly goes beyond the scope of this thesis. Follow up research could be conducted in this area.

Panel B in Table 15 shows the results for the low volatility portfolios enhanced by the Moving Average 1-10 timing strategy when low-priced stocks are omitted. I find a 1.43% monthly return for the first decile portfolio and a 5.93% monthly return for the 10^{th} decile portfolio. I find that the returns from the first decile portfolio to the 9^{th} decile portfolio are increasing. The standard deviation of enhanced low volatility portfolios are lower than the standard deviation of the normal low volatility portfolios. This is in line with what was expected. I find that the Sharpe ratio is increasing from the first decile portfolio to the 5^{th} decile portfolio. From the 6^{th} decile portfolio to the 9^{th} decile portfolio the Sharpe Ratio is increasing again. The Sharpe ratios for the enhanced low volatility portfolios are higher than for the normal low volatility portfolios. Table 17 to 21 show the results for the different Moving Average timing strategies. I find that the longer the long-term average, the lower the monthly returns, and the Sharpe ratios are. Increasing the short-term average from 1-200 to 50-200 leads to lower average returns and lower Sharpe ratios for all the decile portfolios.

Panel C in Table 15 shows the results for the MAP portfolios when low priced stocks are omitted. I find a 0.94% monthly return for the first decile MAP portfolio and a 4.49% monthly return for the 10^{th} decile MAP portfolio. I find that the monthly return is increasing from the first decile MAP portfolio to the 9^{th} decile MAP portfolio. The success rate of the Moving Average 1-10 days timing strategy is around 70%. This is not different from the success rate obtained when low-priced stocks are included. Panel C in Table 17 to 21 show the results I find for the different Moving Average timing strategies. I find that the longer the long-term average becomes, the lower the monthly returns become. I even find negative returns for the first decile MAP portfolio as the long-term average is 100 days or more. However, this does not necessarily means lower risk-adjusted returns.

The alphas for the MAP 1-10 strategy when low-priced stocks are omitted can be found in Table 22. The results show a monthly alpha of 1.58% for the first decile portfolio and a monthly alpha of 7.62% for the 10th decile portfolios. Alphas are increasing from the first decile to the 9th decile portfolio. This means that the increase in risk-adjusted return caused by the Moving Average strategy is higher for the high decile portfolios than for the low decile portfolios. Table 23 to 27 show the alphas for the different MAP strategies. I again find that the longer the long-term average becomes, the lower the alphas become. I find that the alphas for the MAP strategies when low-priced stocks are omitted are always lower than the alphas for the MAP strategies when all the stocks are included. In absolute and relative terms the alphas have decreased the most for the high volatile stocks compared to the low volatile stocks when low-priced stocks are omitted. Omitting the low-priced stocks leads to a decrease in alpha from 1.95% to 1.58% for the first decile portfolio and a decrease in alpha from 10.95% to 7.62% for the 10th decile portfolio.

The results show that using a Moving Average strategy on volatility decile portfolios when low-priced stocks are omitted still generates positive significant alphas. Therefore, hypothesis 2b is rejected. However, I find that these alphas are lower than when low-priced stocks are included in the investment universe. Omitting low-priced stocks also leads to lower standard deviations in the normal low volatility portfolios. This automatically leads to lower standard deviations in the enhanced portfolios. The increase in returns and the decrease in standard deviation leads higher Sharpe ratios. The results are still in line with the results of Han et al. (2013). Omitting the low-priced stocks has only decreased the magnitude of the results.

To summarize, I find results indicating that the low volatility anomaly disappears when low-priced stocks are omitted. Omitting low-priced stocks decreases the standard deviation, increases the Sharpe ratios and makes alphas become insignificant and close to zero. There is only one significant alpha found which is a positive alpha for the 10th decile portfolio, this is in contrast to the theory about the low volatility anomaly. The results for the Moving Average strategy show that a Moving Average strategy is still capable of enhancing the low volatility sorted portfolios when low-priced stocks are omitted. Omitting low-priced stocks leads to again to lower standard deviations and lower Sharpe ratios. However, this decrease in standard deviation is probably caused by the decrease in standard deviation in the sorted portfolios. The results show that the enhancement in returns and alphas is smaller when low-priced stocks are omitted. Omitting the low-priced stocks has the biggest impact on the high decile portfolios.

CHAPTER 6: Conclusion

This thesis builds on the research conducted by Han et al. (2013) and Li et al. (2014) in several ways. First it builds on Li et al. (2014) by using daily data for the portfolio sorting instead of monthly data. Secondly it builds on the research of Han et al. (2013) by omitting low-priced stocks. Lastly it adds value by using a different time frame, one that is closer to our current time frame. Thereby this thesis contributes to the understanding of the anomalies and tries to define a common driver.

The results show that the change in time frame does not leads to a disappearance of the low volatility anomaly when all stocks are included in the investment universe. However, it does indicate a decrease in the magnitude of the low volatility anomaly. When low-priced stocks are omitted the data shows new results regarding the low volatility anomaly. The results show that when low-priced stocks are omitted the alphas are highly eliminated which is in line with previous findings of Li et al. (2014). The alphas are eliminated to such an extent that they become insignificant and close to zero. From this I can conclude that once low-priced stocks are omitted the low volatility anomaly has disappeared.

The results that I found regarding the Moving Average strategy show that a Moving Average strategy still enhances the low volatility anomaly. This finding is similar with the finding of Han et al. (2013). Omitting low-priced stocks has a significant influence on the magnitude of the generated alphas. Omitting low-priced stocks generates lower standard deviations of the enhanced portfolios and higher Sharpe ratios. This shows that omitting low-priced stocks leads to higher risk-adjusted returns. The results also show lower alphas when low-priced stocks are omitted. Based on my findings I can conclude that low-priced stocks are part of the driver of the Moving Average strategy.

The disappearance of the low volatility anomaly and the decrease in the alphas generated by the Moving Average strategy due to omitting low-priced stocks could have two explanations. First, It may be that low-priced stocks are correlated with earlier findings by Dutt and Humphery-Jenner (2013) and that low-priced stocks are correlated with high operating returns. Second the scrutiny of analysts plays a role. Low-priced stocks get less scrutiny of analyst and therefore become more volatile. Due to this their risk-adjusted return would be to low and they would cause the low volatility anomaly. This lesser scrutiny makes the stocks more uncertain. Having uncertainty in stocks cause price continuation. This price continuation and uncertainty makes past price valuable and therefore a Moving Average strategy would be profitable. This could explain low-priced stocks being a partial driver of the Moving Average strategy. Further research should be conducted into low-priced stocks to find the exact reason of them being to cause for the low volatility anomaly and their influence on the Moving Average strategy.

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Appendix

Table 1

The table below shows the summary statistics for the 1-10 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(10) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.53%	1.66%	0.26	1.70%	1.20%	1.33	1.16%	1.29%	72.58%
2	0.77%	2.91%	0.23	3.56%	2.80%	1.24	2.79%	3.30%	69.39%
3	0.79%	3.34%	0.21	4.11%	2.38%	1.68	3.33%	2.83%	72.41%
4	0.85%	3.71%	0.20	4.63%	2.47%	1.83	3.77%	3.16%	72.32%
5	0.75%	4.09%	0.16	4.96%	2.61%	1.86	4.21%	3.55%	71.24%
6	0.56%	4.36%	0.11	5.29%	2.78%	1.87	4.72%	3.90%	70.84%
7	0.54%	4.81%	0.09	5.66$	3.22%	1.73	5.13%	4.29%	71.32%
8	0.02%	5.19%	0.08	5.74%	3.17%	1.78	5.65%	4.46%	71.87%
9	- 0.67%	5.92%	- 0.125	5.28%	3.31%	1.57	5.95%	4.92%	70.78%
10	- 2.28%	7.18%	- 0.32	4.62%	3.53%	1.28	6.90%	5.38%	69.23%

Table 2

The table below reports the regression results of the Fama and French 3-factors regressed on the low volatility portfolio returns. The portfolios are updated monthly and based on their 3-years historical daily volatility. The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	0.29***	0.72***	0.80***	0.84***	0.89***	0.90***	0.92***	0.92***	0.89***	0.81***
	(34.16)	(115.4)	(114.3)	(169.5)	(183.5)	(165.6)	(145.7)	(107.5)	(63.32)	(37.79)
βSMB	-0.04***	0.02	0.13***	0.31***	0.43***	0.55***	0.67***	0.74***	0.75***	0.66***
	(-2.588)	(1.631)	(9.528)	(31.25)	(44.77)	(51.03)	(54.00)	(43.71)	(27.03)	(15.69)
βHML	-0.04**	0.02	0.07***	0.17***	0.21***	0.23***	0.22***	0.20***	0.17***	0.01
	(-2.412)	(1.557)	(5.124)	(17.57)	(22.08)	(21.64)	(17.80)	(11.86)	(5.955)	(0.267)
α	0.35	-0.05	-0.20	-0.16	-0.303**	-0.46***	-0.44**	-0.76***	-1.55***	-2.94***
	(1.454)	(-0.306)	(-1.028)	(-1.142)	(-2.245)	(-3.025)	(-2.502)	(-3.170)	(-3.930)	(-4.921)
Adjusted R-squared	0.559	0.940	0.943	0.976	0.980	0.978	0.973	0.952	0.875	0.707

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

Table 3

The table below reports the regression results of the Fama and French 3-factors regressed on the low volatility portfolio returns. The portfolios are updated monthly and based on their 3-years historical monthly volatility. The alphas are reported in monthly percentages. The sample period is from January 2007 to December 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	0.28***	0.65***	0.78***	0.82***	0.86***	0.95***	1.02***	1.09***	1.16***	1.46***
	(184.6)	(568.3)	(776.9)	(842.8)	(962.5)	(995.1)	(824.2)	(561.1)	(348.3)	(259.9)
βSMB	-0.11***	0.01***	0.12***	0.24***	0.36***	0.47***	0.54***	0.69***	0.80***	1.11***
	(-42.65)	(4.727)	(72.77)	(156.9)	(247.8)	(306.0)	(271.1)	(220.4)	(149.6)	(122.4)
βHML	-0.16***	-0.07***	0.01***	0.06***	0.18***	0.19***	0.23***	0.25***	0.30***	0.24***
	(-64.92)	(-34.80)	(7.756)	(41.93)	(126.5)	(121.7)	(119.5)	(81.41)	(57.45)	(27.28)
α	0.32***	0.20***	0.13***	0.11***	0.06***	-0.09***	-0.21***	-0.41***	-0.71***	0.02
	(58.24)	(49.79)	(37.46)	(32.06)	(19.46)	(-26.04)	(-48.72)	(-59.57)	(-60.15)	(0.816)
Adjusted R-squared	0.432	0.891	0.944	0.956	0.969	0.973	0.962	0.926	0.835	0.741

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

Table 4

The table below shows the summary statistics for the 1-20 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(20) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.53%	1.66%	0.26	1.21%	1.18%	0.94	0.68%	1.01%	66.85%
2	0.77%	2.91%	0.23	2.58%	2.27%	1.09	1.81%	2.20%	65.04%
3	0.79%	3.34%	0.21	3.11%	2.14%	1.41	2.32%	2.49%	66.65%
4	0.85%	3.71%	0.20	3.37%	2.30%	1.42	2.51%	2.84%	65.54%
5	0.75%	4.09%	0.16	3.25%	2.56%	1.23	2.49%	3.09%	64.38%
6	0.56%	4.36%	0.11	3.86%	2.72%	1.38	3.28%	3.54%	64.98%
7	0.54%	4.81%	0.09	4.04%	2.91%	1.35	3.48%	3.66%	65.12%
8	0.02%	5.19%	0.08	3.91%	2.81%	1.36	3.40%	3.90%	65.75%
9	- 0.67%	5.92%	- 0.125	3.67%	3.03%	1.18	4.31$	4.47%	66.26%
10	- 2.28%	7.18%	- 0.32	3.17%	3.63%	0.85	5.39%	5.36%	64.51%

Table 5

The table below shows the summary statistics for the 1-50 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(50) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.53%	1.66%	0.26	0.76%	1.11%	0.59	0.23%	1.09%	62.28%
2	0.77%	2.91%	0.23	1.86%	2.36%	0.75	1.08%	1.86%	60.98%
3	0.79%	3.34%	0.21	1.94%	1.97%	0.93	1.15%	2.29%	60.94%
4	0.85%	3.71%	0.20	2.34%	2.30%	0.97	1.49%	2.23%	60.84%
5	0.75%	4.09%	0.16	1.95%	2.33%	0.79	1.20%	2.76%	58.84%
6	0.56%	4.36%	0.11	2.23%	2.30%	0.93	1.70%	2.86%	59.63%
7	0.54%	4.81%	0.09	2.38%	2.74%	0.83	1.85%	2.99%	59.55%
8	0.02%	5.19%	0.08	2.34%	2.67%	0.84	2.31%	3.45%	60.35%
9	- 0.67%	5.92%	- 0.125	1.97%	2.94%	0.64	2.64%	4.22%	60.93%
10	- 2.28%	7.18%	- 0.32	1.51%	3.81%	0.37	3.79%	5.20%	58.68%

Table 6

The table below shows the summary statistics for the 1-100 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(100) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.53%	1.66%	0.26	0.49%	1.01%	0.39	- 0.04%	1.28%	59.49%
2	0.77%	2.91%	0.23	1.41%	2.31%	0.57	0.64%	1.92%	58.32%
3	0.79%	3.34%	0.21	1.39%	1.71%	0.75	0.57%	2.66%	58.86%
4	0.85%	3.71%	0.20	1.64%	2.12%	0.73	0.79%	2.43%	57.97%
5	0.75%	4.09%	0.16	1.43%	2.01%	0.66	0.68%	3.13%	57.19%
6	0.56%	4.36%	0.11	1.64%	2.43%	0.63	1.10%	3.01%	57.52%
7	0.54%	4.81%	0.09	1.58%	2.61%	0.57	1.05%	3.43%	56.96%
8	0.02%	5.19%	0.08	1.36%	2.43%	0.52	1.33%	3.69%	56.95%
9	- 0.67%	5.92%	- 0.125	1.23%	2.84%	0.40	1.90%	4.44%	59.29%
10	- 2.28%	7.18%	- 0.32	0.63%	3.71%	0.14	2.91%	5.54%	56.45%

Table 7

The table below shows the summary statistics for the 1-200 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(200) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.53%	1.66%	0.26	0.43%	0.96%	0.34	- 0.11%	1.30%	59.09%
2	0.77%	2.91%	0.23	1.15%	2.04%	0.51	0.38%	1.73%	57.56%
3	0.79%	3.34%	0.21	1.06%	1.56%	0.62	0.27%	2.48%	58.13%
4	0.85%	3.71%	0.20	1.37%	2.20%	0.58	0.52%	2.55%	57.25%
5	0.75%	4.09%	0.16	1.15%	2.09%	0.50	0.40%	3.00%	56.32%
6	0.56%	4.36%	0.11	1.13%	2.36%	0.44	0.57%	3.11%	56.00%
7	0.54%	4.81%	0.09	1.02%	2.37%	0.39	0.49%	3.45%	55.83%
8	0.02%	5.19%	0.08	0.87%	2.30%	0.33	0.85%	3.96%	55.90%
9	- 0.67%	5.92%	- 0.125	0.56%	2.53%	0.18	1.24%	4.70%	57.66%
10	- 2.28%	7.18%	- 0.32	0.27%	3.15%	0.05	2.55%	5.93%	56.44%

Table 8

The table below shows the summary statistics for the 50-200 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(50-200) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.53%	1.66%	0.26	0.21%	1.06%	0.10	-0.32%	1.28%	57.32%
2	0.77%	2.91%	0.23	0.73%	1.80%	0.35	-0.04%	1.99%	56.52%
3	0.79%	3.34%	0.21	0.36%	1.57%	0.17	-0.42%	2.76%	54.92%
4	0.85%	3.71%	0.20	0.67%	2.13%	0.27	-0.18%	2.85%	55.48%
5	0.75%	4.09%	0.16	0.49%	2.49%	0.16	-0.26%	2.99%	54.69%
6	0.56%	4.36%	0.11	0.51%	2.32%	0.18	-0.05%	3.21%	54.81%
7	0.54%	4.81%	0.09	0.07%	2.97%	-0.01	-0.47%	3.28%	53.56%
8	0.02%	5.19%	0.08	0.26%	2.50%	0.06	0.24%	4.05%	53.70%
9	- 0.67%	5.92%	- 0.125	-0.06%	2.82%	-0.06	0.62%	4.78%	56.04%
10	- 2.28%	7.18%	- 0.32	-1.13%	4.06%	-0.30	1.15%	5.71%	52.19%

Tabel 9

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-10 portfolio returns. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.19***	-0.40***	-0.49***	-0.54***	-0.56***	-0.56***	-0.59***	-0.60***	-0.59***	-0.59***
	(-701.2)	(-960.1)	(-1,075)	(-1,116)	(-1,054)	(-1,038)	(-1,045)	(-986.0)	(-867.6)	(-767.9)
βSMB	0.05***	0.02***	-0.01***	-0.06***	-0.14***	-0.20***	-0.28***	-0.33***	-0.38***	-0.39***
	(104.0)	(24.21)	(-14.63)	(-65.38)	(-144.5)	(-201.9)	(-266.7)	(-291.5)	(-296.9)	(-267.7)
βHML	0.03***	0.02***	-0.01***	-0.04***	-0.04***	-0.10***	-0.07***	-0.04***	-0.05***	0.06***
	(51.11)	(19.04)	(-10.47)	(-45.73)	(-40.26)	(-90.21)	(-63.15)	(-31.04)	(-37.09)	(39.70)
α	1.95***	4.59***	5.55***	6.27***	6.93***	7.68***	8.31***	9.09***	9.57***	10.95***
	(272.6)	(410.7)	(447.0)	(483.8)	(486.7)	(524.9)	(544.8)	(554.6)	(516.3)	(524.0)
Adjusted R-squared	0.361	0.537	0.602	0.632	0.620	0.630	0.644	0.623	0.575	0.511

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

Table 10

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-20 portfolio returns. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.19***	-0.44***	-0.52***	-0.56***	-0.58***	-0.61***	-0.64***	-0.62***	-0.64***	-0.61***
	(-29.92)	(-44.02)	(-47.42)	(-48.99)	(-44.27)	(-46.76)	(-47.07)	(-42.06)	(-39.06)	(-33.14)
βSMB	0.04***	0.03	0.03	-0.04*	-0.11***	-0.12***	-0.26***	-0.33***	-0.37***	-0.37***
	(3.584)	(1.497)	(1.427)	(-1.765)	(-4.438)	(-8.188)	(-10.48)	(-11.93)	(-12.34)	(-10.73)
βHML	0.01	0.02	0.01	0.00	-0.02	-0.05**	-0.05*	-0.01	-0.01	0.06*
	(0.985)	(0.923)	(0.501)	(-0.0899)	(-0.844)	(-1.998)	(-1.752)	(-0.170)	(-0.311)	(1.782)
α	1.28***	3.27***	4.14***	4.53***	4.53***	5.76***	6.06***	6.63***	7.35***	8.91***
	(7.364)	(12.09)	(13.99)	(14.53)	(12.90)	(16.41)	(16.64)	(16.74)	(16.66)	(17.87)
Adjusted R-squared	0.369	0.574	0.612	0.640	0.606	0.649	0.662	0.621	0.594	0.511

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

Table 11

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-50 portfolio returns. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.21***	-0.44***	-0.54***	-0.55***	-0.58***	-0.64***	-0.63***	-0.62***	-0.65***	-0.62***
	(-749.2)	(-1,040)	(-1,175)	(-1,127)	(-1,060)	(-1,183)	(-1,112)	(-1,010)	(-936.4)	(-778.7)
βSMB	0.04***	0.04***	0.06***	-0.04***	-0.10***	-0.20***	-0.23***	-0.31***	-0.32***	-0.35***
	(73.04)	(51.81)	(69.45)	(-46.50)	(-101.5)	(-192.2)	(-222.0)	(-275.1)	(-249.5)	(-234.9)
βHML	0.02***	0.01***	0.02***	-0.02***	-0.08***	-0.07***	-0.07***	-0.05***	-0.05***	0.06***
	(34.30)	(7.899)	(21.44)	(-23.37)	(-70.38)	(-69.62)	(-60.40)	(-37.52)	(-40.30)	(41.28)
α	0.66***	2.26***	2.51***	3.06***	2.70***	3.48***	3.72***	4.38***	4.95***	6.60***
	(89.39)	(198.8)	(202.8)	(230.4)	(182.7)	(239.6)	(245.0)	(267.1)	(264.8)	(306.9)
Adjusted R-squared	0.404	0.576	0.633	0.634	0.620	0.682	0.662	0.633	0.597	0.509

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

Table12

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-100 portfolio returns. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.21***	-0.41***	-0.55***	-0.51***	-0.56***	-0.59***	-0.58***	-0.58***	-0.62***	-0.61***
	(-32.18)	(-42.11)	(-51.85)	(-43.51)	(-43.35)	(-47.55)	(-45.60)	(-41.55)	(-38.92)	(-32.18)
βSMB	0.04***	0.03*	0.02	-0.07***	-0.14***	-0.21***	-0.28***	-0.35***	-0.41***	-0.39***
	(3.509)	(1.722)	(1.191)	(-3.194)	(-5.757)	(-8.996)	(-12.01)	(-13.53)	(-13.87)	(-11.17)
βHML	0.02	-0.01	0.01	-0.05**	-0.09***	-0.11***	-0.11***	-0.11***	-0.12***	0.06
	(1.488)	(-0.588)	(0.406)	(-2.194)	(-3.715)	(-4.653)	(-4.361)	(-3.770)	(-3.793)	(1.491)
α	0.33*	1.68***	1.79***	2.10***	2.04***	2.71***	2.65***	3.06***	4.02***	5.52***
	(1.918)	(6.348)	(6.200)	(6.648)	(5.849)	(8.043)	(7.683)	(8.138)	(9.287)	(10.77)
Adjusted R-squared	0.411	0.561	0.660	0.602	0.616	0.671	0.667	0.638	0.616	0.510

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

Table 13

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-200 portfolio returns. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.19***	-0.33***	-0.54***	-0.47***	-0.52***	-0.53***	-0.56***	-0.59***	-0.63***	-0.62***
	(-30.87)	(-36.61)	(-52.85)	(-42.82)	(-42.07)	(-44.64)	(-49.81)	(-46.52)	(-41.91)	(-32.36)
βSMB	0.05***	0.02	0.02	-0.07***	-0.12***	-0.20***	-0.31***	-0.38***	-0.39***	-0.40***
	(3.962)	(1.390)	(0.829)	(-3.218)	(-5.263)	(-9.205)	(-14.98)	(-16.21)	(-13.90)	(-11.07)
βHML	0.02	0.01	0.01	-0.07***	-0.09***	-0.13***	-0.13***	-0.13***	-0.19***	0.01
	(1.582)	(0.0452)	(0.0690)	(-3.325)	(-3.826)	(-5.547)	(-5.750)	(-5.371)	(-6.265)	(0.267)
α	0.25	1.17***	1.37***	1.629***	1.54***	1.81***	1.75***	2.32***	2.93***	4.83***
	(1.473)	(4.853)	(5.003)	(5.613)	(4.662)	(5.747)	(5.862)	(6.893)	(7.282)	(9.417)
Adjusted R-squared	0.391	0.492	0.672	0.597	0.599	0.647	0.713	0.695	0.647	0.516

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

Table 14

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 50-200 portfolio returns. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.15***	-0.35***	-0.49***	-0.45***	-0.43***	-0.50***	-0.43***	-0.57***	-0.61***	-0.56***
	(-25.54)	(-40.01)	(-49.69)	(-40.20)	(-36.71)	(-42.15)	(-37.60)	(-44.87)	(-41.53)	(-30.78)
βSMB	0.02**	0.0120	-0.09***	-0.13***	-0.20***	-0.25***	-0.38***	-0.40***	-0.41***	-0.40***
	(1.997)	(0.734)	(-4.698)	(-6.473)	(-9.123)	(-11.13)	(-17.88)	(-17.11)	(-14.85)	(-11.73)
βHML	0.03**	-0.03*	-0.06***	-0.14***	-0.14***	-0.17***	-0.17***	-0.18***	-0.20***	-0.07*
	(2.324)	(-1.891)	(-2.865)	(-6.343)	(-6.113)	(-7.352)	(-7.611)	(-7.087)	(-6.993)	(-1.946)
α	-0.16	0.57**	0.24	0.55*	0.40	0.83***	0.09	1.37***	1.96***	2.57***
	(-1.074)	(2.421)	(0.910)	(1.853)	(1.287)	(2.627)	(0.301)	(4.026)	(4.973)	(5.262)
Adjusted R-squared	0.310	0.543	0.668	0.591	0.567	0.637	0.634	0.689	0.650	0.504

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

low-priced stocks are omitted

Table 15

The table below shows the summary statistics for the 1-10 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Stocks priced lower than $5 are omitted from the dataset. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Volatility Decile portfolios			Panel B MA (10) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.49%	1.59%	0.25	1.43%	1.13%	1.18	0.94%	1.17%	72.41%
2	0.78%	2.65%	0.26	3.06%	2.22%	1.33	2.28%	2.63%	69.72%
3	0.77%	3.13%	0.21	3.89%	2.67%	1.42	3.12%	3.10%	71.51%
4	0.91%	3.46%	0.23	4.49%	2.70%	1.63	3.58%	3.20%	72.80%
5	0.94%	3.75%	0.22	4.63%	2.64%	1.72	3.70%	3.40%	70.99%
6	0.84%	4.07%	0.18	5.05%	3.05%	1.62	4.21%	3.47%	71.66%
7	0.79%	4.37%	0.16	5.16%	3.10%	1.63	4.38%	3.69%	70.30%
8	0.89%	4.61%	0.17	5.53%	3.27%	1.66	4.64%	4.10%	70.73%
9	0.84%	5.15%	0.14	6.80%	3.63%	1.85	5.25%	4.57%	70.93%
10	1.44%	5.45%	0.25	5.93%	3.77%	1.55	4.49%	4.54%	72.10%

Table 16

The table below reports the regression results of the Fama and French 3-factors regressed on the low volatility portfolio returns. The portfolios are updated monthly and based on their 3-years historical daily volatility. Stocks that are priced lower than $5 are omitted from the dataset. The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	0.23***	0.68***	0.78***	0.83***	0.85***	0.90***	0.93***	0.96***	1.02***	1.03***
	(25.58)	(106.1)	(112.7)	(139.1)	(177.8)	(179.7)	(172.0)	(160.6)	(135.4)	(79.01)
βSMB	-0.05***	-0.01	0.07***	0.22***	0.35***	0.46***	0.58***	0.70***	0.83***	0.87***
	(-2.762)	(-0.896)	(5.651)	(18.40)	(37.36)	(46.35)	(54.53)	(59.47)	(55.69)	(33.79)
βHML	-0.06***	0.00	0.04***	0.12***	0.19***	0.22***	0.24***	0.25***	0.26***	0.14***
	(-3.108)	(0.086)	(3.031)	(10.37)	(19.91)	(21.96)	(22.44)	(21.02)	(17.24)	(5.451)
α	0.44*	0.05	-0.19	-0.05	-0.06	-0.21	-0.34**	-0.15	-0.28	0.95***
	(1.768)	(0.272)	(-0.975)	(-0.285)	(-0.469)	(-1.482)	(-2.276)	(-0.875)	(-1.325)	(2.620)
Adjusted R-squared	0.408	0.929	0.940	0.963	0.979	0.980	0.979	0.977	0.970	0.916

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

Table 17

The table below shows the summary statistics for the 1-20 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Stocks priced lower than $5 are omitted from the dataset. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Volatility Decile portfolios			Panel B MA (20) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.49%	1.59%	0.25	1.08%	1.15%	0.85	0.59%	1.04%	66.83%
2	0.78%	2.65%	0.26	2.41%	2.09%	1.11	1.63%	1.62%	66.15%
3	0.77%	3.13%	0.21	2.85%	2.11%	1.30	2.08%	2.08%	65.89%
4	0.91%	3.46%	0.23	3.14%	2.38%	1.27	2.23%	2.22%	65.74%
5	0.94%	3.75%	0.22	3.47%	2.33%	1.45	2.53%	2.55%	65.59%
6	0.84%	4.07%	0.18	3.67%	2.70%	1.32	2.83%	2.83%	65.10%
7	0.79%	4.37%	0.16	3.85%	2.93%	1.28	3.06%	3.07%	65.26%
8	0.89%	4.61%	0.17	4.00%	2.89%	1.35	3.11%	3.11%	65.91%
9	0.84%	5.15%	0.14	4.15%	3.36%	1.21	3.32%	3.32%	65.20%
10	1.44%	5.45%	0.25	4.72%	3.64%	1.27	3.28%	3.30%	69.21%

Table 18

The table below shows the summary statistics for the 1-50 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Stocks priced lower than $5 are omitted from the dataset. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(50) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.49%	1.59%	0.25	0.66%	1.15%	0.49	0.17%	1.08%	63.01%
2	0.78%	2.65%	0.26	1.57%	1.91%	0.77	0.78%	1.79%	61.07%
3	0.77%	3.13%	0.21	1.96%	2.27%	0.82	1.18%	2.08%	60.67%
4	0.91%	3.46%	0.23	2.09%	2.32%	0.86	1.18%	2.12%	60.50%
5	0.94%	3.75%	0.22	2.30%	2.17%	1.01	1.37%	2.56%	60.35%
6	0.84%	4.07%	0.18	2.19%	2.53%	0.83	1.35%	2.67%	59.03%
7	0.79%	4.37%	0.16	2.52%	3.00%	0.81	1.73%	2.55%	59.90%
8	0.89%	4.61%	0.17	2.26%	2.91%	0.74	1.37%	3.21%	59.57%
9	0.84%	5.15%	0.14	2.62%	2.91%	0.87	1.79%	3.53%	60.73%
10	1.44%	5.45%	0.25	3.12%	3.39%	0.89	1.69%	3.77%	64.86%

Table 19

The table below shows the summary statistics for the 1-100 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Stocks priced lower than $5 are omitted from the dataset. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(100) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.49%	1.59%	0.25	0.39%	1.08%	0.27	- 0.11%	1.20%	59.06%
2	0.78%	2.65%	0.26	1.05%	1.77%	0.54	0.26%	1.89%	58.46%
3	0.77%	3.13%	0.21	1.32%	2.24%	0.55	0.54%	2.34%	57.59%
4	0.91%	3.46%	0.23	1.58%	2.07%	0.71	0.67%	2.43%	59.29%
5	0.94%	3.75%	0.22	1.55%	1.92%	0.76	0.62%	2.72%	57.63%
6	0.84%	4.07%	0.18	1.58%	2.28%	0.65	0.74%	2.86%	57.14%
7	0.79%	4.37%	0.16	1.80%	2.57%	0.66	1.02%	2.80%	57.85%
8	0.89%	4.61%	0.17	1.63%	2.66%	0.58	0.74%	3.14%	57.25%
9	0.84%	5.15%	0.14	1.87%	2.37%	0.75	1.04%	4.30%	58.22%
10	1.44%	5.45%	0.25	2.39%	3.11%	0.74	0.96%	4.07%	62.85%

Table 20

The table below shows the summary statistics for the 1-200 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Stocks priced lower than $5 are omitted from the dataset. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(200) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.49%	1.59%	0.25	0.30%	0.98%	0.20	-0.20%	1.17%	57.92%
2	0.78%	2.65%	0.26	1.01%	1.67%	0.54	0.22%	1.78%	58.50%
3	0.77%	3.13%	0.21	0.95%	2.28%	0.37	0.18%	1.99%	56.44%
4	0.91%	3.46%	0.23	1.28%	2.00%	0.59	0.37%	2.37%	57.71%
5	0.94%	3.75%	0.22	1.28%	1.94%	0.61	0.35%	2.65%	56.60%
6	0.84%	4.07%	0.18	1.22%	2.12%	0.53	0.38%	2.88%	56.60%
7	0.79%	4.37%	0.16	1.40%	2.58%	0.50	0.62%	2.96%	57.09%
8	0.89%	4.61%	0.17	0.95%	2.61%	0.33	0.06%	3.00%	56.21%
9	0.84%	5.15%	0.14	1.19%	2.35%	0.46	0.37%	4.16%	56.52%
10	1.44%	5.45%	0.25	1.76%	3.00%	0.55	0.33%	4.52%	62.65%

Table 21

The table below shows the summary statistics for the 50-200 day Moving Average timing strategy used on portfolios sorted on their 3-year historical daily volatility. Stocks priced lower than $5 are omitted from the dataset. Panel A reports the average returns, standard deviation and Sharpe ratio of the low volatility portfolios. Panel B reports the same statistics Moving Average timing strategy. Panel C reports the average return, standard deviation and success rate of the MAP portfolio. The statistics are reported in monthly percentages. Success is defined as the percentage of buy signals that the return was higher than the risk free rate. The sample period is from January 1st 2007 to December 30th 2016.

	Panel A Voltaility Decile Portfolios			Panel B MA(50-200) Timing Strategy			Panel C Moving Average Portfolio (MAP)		
	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Sharpe Ratio	Avg. Ret.	Std. Dev.	Succes
Decile Portfolio									
1	0.49%	1.59%	0.25	0.20%	1.09%	0.09	-0.29%	1.13%	56.63%
2	0.78%	2.65%	0.26	0.47%	1.42%	0.26	-0.32%	1.96%	55.56%
3	0.77%	3.13%	0.21	0.45%	1.93%	0.18	-0.33%	2.16%	55.50%
4	0.91%	3.46%	0.23	0.53%	2.06%	0.21	-0.38%	2.59%	55.50%
5	0.94%	3.75%	0.22	0.63%	2.08%	0.25	-0.29%	2.87%	54.58%
6	0.84%	4.07%	0.18	0.36%	2.47%	0.11	-0.48%	3.05%	53.89%
7	0.79%	4.37%	0.16	0.73%	2.79%	0.23	-0.05%	2.89%	55.56%
8	0.89%	4.61%	0.17	0.40%	3.13%	0.10	-0.49%	2.82%	54.82%
9	0.84%	5.15%	0.14	0.58%	2.68%	0.18	-0.25%	4.01%	55.11%
10	1.44%	5.45%	0.25	0.51%	3.67%	0.73	-0.92%	4.26%	58.10%

Table 22

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-10 portfolio returns. Stocks priced lower than $5 are omitted from the dataset. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.15***	-0.40***	-0.46***	-0.51***	-0.54***	-0.57***	-0.56***	-0.57***	-0.64***	-0.66***
	(-23.63)	(-42.73)	(-44.04)	(-46.17)	(-46.00)	(-46.43)	(-41.63)	(-40.46)	(-41.67)	(-37.41)
βSMB	0.04***	0.04**	0.00	-0.01	-0.07***	-0.17***	-0.17***	-0.31***	-0.37***	-0.44***
	(3.577)	(2.095)	(-0.0496)	(-0.254)	(-3.182)	(-7.418)	(-6.695)	(-11.83)	(-12.94)	(-13.32)
βHML	0.03***	0.01	-0.01	-0.03	-0.05**	-0.07***	-0.09***	-0.08***	-0.06**	-0.02
	(2.612)	(0.626)	(-0.516)	(-1.373)	(-2.040)	(-2.746)	(-3.219)	(-2.809)	(-2.075)	(-0.506)
α	1.58***	3.90***	5.22***	5.97***	6.24***	7.05***	7.26***	7.71***	8.70***	7.62***
	(9.519)	(15.59)	(18.52)	(20.25)	(19.80)	(21.20)	(20.01)	(20.07)	(20.92)	(15.96)
Adjusted R-squared	0.258	0.557	0.583	0.608	0.620	0.644	0.594	0.609	0.626	0.582

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

Table 23

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-20 portfolio returns. Stocks priced lower than $5 are omitted from the dataset. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.15***	-0.40***	-0.48***	-0.54***	-0.57***	-0.59***	-0.61***	-0.62***	-0.70***	-0.70***
	(-23.15)	(-43.15)	(-44.96)	(-48.09)	(-47.90)	(-46.07)	(-45.52)	(-43.54)	(-44.76)	(-39.26)
βSMB	0.04***	0.04**	0.03*	0.01	-0.07***	-0.18***	-0.16***	-0.29***	-0.34***	-0.44***
	(3.062)	(2.257)	(1.649)	(0.318)	(-3.336)	(-7.659)	(-6.496)	(-10.94)	(-11.49)	(-13.24)
βHML	0.02*	-0.01	0.02	-0.01	-0.01	-0.05**	-0.055**	-0.058**	-0.04	0.02
	(1.900)	(-0.591)	(1.128)	(-0.628)	(-0.399)	(-2.077)	(-2.061)	(-2.059)	(-1.163)	(0.692)
α	1.07***	2.96***	3.75***	4.08***	4.59***	5.10***	5.46***	5.58***	6.00***	5.94***
	(6.280)	(11.72)	(13.00)	(13.50)	(14.37)	(14.78)	(15.01)	(14.51)	(14.20)	(12.32)
Adjusted R-squared	0.254	0.565	0.584	0.625	0.636	0.641	0.630	0.633	0.646	0.600

t-statistics in parentheses

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

Table 24

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-50 portfolio returns. Stocks priced lower than $5 are omitted from the dataset. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.16***	-0.42***	-0.47***	-0.53***	-0.56***	-0.61***	-0.62***	-0.65***	-0.71***	-0.74***
	(-24.93)	(-45.24)	(-44.83)	(-47.54)	(-47.84)	(-47.58)	(-46.13)	(-47.48)	(-46.60)	(-41.36)
βSMB	0.04***	0.04**	0.06***	-0.01	-0.05***	-0.16***	-0.14***	-0.30***	-0.35***	-0.47***
	(3.223)	(2.439)	(3.071)	(-0.331)	(-2.591)	(-6.650)	(-5.772)	(-12.02)	(-12.25)	(-14.16)
βHML	0.03**	0.01	0.04*	-0.02	-0.05**	-0.07***	-0.07**	-0.11***	-0.09***	-0.03
	(2.212)	(0.335)	(1.696)	(-0.833)	(-2.029)	(-2.681)	(-2.515)	(-4.143)	(-3.125)	(-0.898)
α	0.50***	1.81***	2.48***	2.59***	2.94***	3.00***	3.54***	3.15***	3.84***	3.75***
	(2.983)	(7.218)	(8.710)	(8.675)	(9.261)	(8.763)	(9.854)	(8.564)	(9.325)	(7.791)
Adjusted R-squared	0.286	0.587	0.578	0.624	0.638	0.653	0.636	0.678	0.670	0.631

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

Table 25

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-100 portfolio returns. Stocks priced lower than $5 are omitted from the dataset. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.15***	-0.41***	-0.44***	-0.52***	-0.54***	-0.58***	-0.59***	-0.62***	-0.70***	-0.74***
	(-25.25)	(-46.16)	(-41.89)	(-48.61)	(-46.33)	(-46.21)	(-45.39)	(-48.13)	(-47.14)	(-42.24)
βSMB	0.05***	0.02	0.03	-0.00	-0.01***	-0.14***	-0.16***	-0.33***	-0.42***	-0.49***
	(4.207)	(1.106)	(1.539)	(-0.303)	(-4.595)	(-6.034)	(-6.567)	(-13.66)	(-15.22)	(-15.10)
βHML	0.03**	-0.01	0.01	0.00	-0.07***	-0.07***	-0.12***	-0.16***	-0.13***	-0.10***
	(2.537)	(-0.511)	(0.597)	(0.0493)	(-3.210)	(-2.782)	(-4.516)	(-6.494)	(-4.402)	(-2.899)
α	0.14	1.13***	1.61***	1.93***	1.90***	2.217***	2.62***	2.29***	2.88***	2.89***
	(0.821)	(4.642)	(5.671)	(6.678)	(6.026)	(6.448)	(7.428)	(6.590)	(7.144)	(6.067)
Adjusted R-squared	0.290	0.608	0.556	0.637	0.638	0.642	0.641	0.698	0.694	0.652

t-statistics in parentheses

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

Table 26

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 1-200 portfolio returns. Stocks priced lower than $5 are omitted from the dataset. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
βMKP	-0.15***	-0.41***	-0.41***	-0.49***	-0.51***	-0.58***	-0.55***	-0.56***	-0.69***	-0.77***
	(-25.20)	(-48.09)	(-40.52)	(-46.69)	(-45.66)	(-46.99)	(-43.49)	(-45.39)	(-47.87)	(-45.50)
βSMB	0.05***	0.02	0.04*	-0.04*	-0.11***	-0.14***	-0.18***	-0.37***	-0.43***	-0.53***
	(4.084)	(1.418)	(1.961)	(-1.875)	(-5.168)	(-6.315)	(-7.591)	(-15.97)	(-15.86)	(-16.85)
βHML	0.02*	0.01	0.01	-0.02	-0.09***	-0.10***	-0.11***	-0.14***	-0.18***	-0.13***
	(1.680)	(0.469)	(0.587)	(-1.163)	(-4.132)	(-4.075)	(-4.500)	(-5.542)	(-6.396)	(-3.748)
α	0.09	1.00***	1.32***	1.62***	1.65***	1.79***	2.26***	1.36***	2.11***	2.08***
	(0.574)	(4.364)	(4.866)	(5.718)	(5.452)	(5.404)	(6.609)	(4.078)	(5.409)	(4.544)
Adjusted R-squared	0.292	0.624	0.537	0.625	0.634	0.651	0.625	0.684	0.703	0.687

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

Table 27

The table below reports the regression results of the Fama and French 3-factors regressed on the MAP 50-200 portfolio returns. Stocks priced lower than $5 are omitted from the dataset. The portfolios are updated monthly and based on the sorted portfolios.The alphas are reported in monthly percentages. The sample period is from January 1st 2007 to December 30th 2016.

Fama-French regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
mktrf	-0.09***	-0.40***	-0.29***	-0.44***	-0.47***	-0.43***	-0.47***	-0.40***	-0.62***	-0.69***
	(-17.76)	(-49.97)	(-32.12)	(-42.01)	(-42.20)	(-37.77)	(-39.06)	(-37.45)	(-43.99)	(-40.78)
smb	0.04***	0.01	0.01	-0.09***	-0.15***	-0.24***	-0.19***	-0.34***	-0.45***	-0.54***
	(3.694)	(0.329)	(0.281)	(-4.457)	(-7.103)	(-11.52)	(-8.608)	(-17.30)	(-17.16)	(-17.06)
hml	0.04***	-0.01	-0.03	-0.09***	-0.15***	-0.14***	-0.13***	-0.16***	-0.22***	-0.18***
	(3.453)	(-0.897)	(-1.630)	(-4.204)	(-6.893)	(-6.259)	(-5.514)	(-7.662)	(-7.997)	(-5.396)
α	-0.22	0.23	0.05	0.27	0.43	0.10	0.80**	0.06	0.82**	-0.05
	(-1.610)	(1.068)	(0.199)	(0.972)	(1.446)	(0.330)	(2.523)	(0.196)	(2.166)	(-0.118)
Adjusted R-squared	0.167	0.650	0.436	0.596	0.616	0.593	0.588	0.629	0.684	0.653

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