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Thesis

Momentum Trading Strategies in the Netherlands: A 'winners only' approach.

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Abstract

Conventional momentum strategies often require investors to buy and sell large quantities of stocks. This in turn can be challenging for an average retail investor due to high trading costs and short-selling constraints. This thesis offers a more practical alternative for retail investors by looking at a 'winners only' momentum strategy in the Netherlands between January 1983 to January 2020. Unlike conventional strategies, portfolios are formed on the best 1-25 stocks on the Dutch market. Four different medium-term strategies are tested, finding all four strategies to significantly outperform the AEX index. The strategies are also found to be robust to the CAPM and the Fama French (1996) three-factor model. In order to strike a balance between portfolio diversification and enjoying significant returns, this thesis suggests that an investor should invest in the 9-stock portfolio or higher.

Contents

1 Introduction

Factor investing in the form of momentum is a field that has been researched extensively over the past few decades. What is intriguing about the momentum anomaly is its persistence through time. In their seminal paper on the winner-loser strategy, De Bondt and Thaler (1985) found that over three to five years, there was a reversal in 'winner' and 'loser' stocks. Since then, there has been vast amounts of literature proving the profitability of momentum strategies on the stock market. Jegadeesh and Titman (1993) were among the first to find a significant strategy in this field. They found that on the US stock market, by going long and short on the best and worst performing stocks respectively from the past three to twelve months, stocks generated significant returns over the next three to twelve months over the period of 1965 to 1989. Rouwenhorst (1998) reinforced these findings, documenting significant returns in an international sphere. The momentum strategies posed by Jegadeesh and Titman (1993) also appeared to be robust to several risk factors. Fama and French (1996) could not explain the phenomena with their three-factor model, and Griffin, Ji, and Martin (2003) found that macroeconomic risk factors could not explain momentum profits in an international context.

However, the practicality of the zero-cost strategy originally posed by Jegadeesh and Titman (1993), is questionable. The strategy requires investors to buy and sell large amounts of stocks, making it challenging for any retail investor to exploit. As well as this, Carhart (1997) documented that after accounting for transaction costs and other various expenses, momentum profits essentially disappeared. This seems plausible, particularly when investors have to handle large amounts of stocks. Furthermore, Grinblatt and Moskowitz (2004) found that a large portion of the profits associated with the strategy come from short positions in small and illiquid stocks. Taking on short positions creates unwanted downside risk, higher trading costs and exposes investors to margin risk. These factors may deter retail investors from implementing the conventional momentum trading strategy.

Nevertheless, what is interesting about conventional momentum investing is its simplicity and apparent persistence through time. Siganos (2010) adapted the traditional approach of Jegadeesh and Titman (1993) by forming the portfolios by buying (short-selling) the best (worst) performing 1-50 stocks in the past twelve months, rather than forming them through a decile or quintile approach. Foltice and Langer (2015) took this one step further, constraining the strategy to only buy stocks. The successful exploration of these strategies in the UK and the US respectively raises questions as to whether this simplified strategy is applicable in an international sphere, leading to the research question: *Can investors exploit a 'winners only' momentum trading strategy in the Netherlands?*

This paper will apply a similar strategy to that of Foltice and Langer (2015) to stocks traded on the Dutch market in order to see whether buying only top performing stocks in the past 6 to 12 months is a viable option for investors in the Netherlands. Additionally, as a robustness check, the CAPM and the Fama and French (1996) three-factor model will be used to see whether alpha can be generated after accounting for systematic risk factors.

This study contributes to the large body of literature in momentum investing in a few ways. Firstly, this paper provides an unconventional momentum strategy where portfolios are formed through buying the best 1-25 stocks, rather than using percentiles to determine portfolios. Secondly, there is minimal literature on momentum strategies in the Netherlands, particularly for retail investors. This study will use data dating back nearly 40 years, providing a comprehensive review of momentum throughout the years and will also shed light on whether a simple 'winners only' strategy can be implemented in the Netherlands.

The remainder of this paper is organized as follows. Section two provides a comprehensive literature review on the efficient market hypothesis, conventional momentum strategies, risk factor models, momentum investing for small investors and momentum strategies in periods of economic downturn. Section three describes the data that is used to perform the research. Section four explains the methodology used in the research. Section five provides the results to the research. Section six provides a comparison of the results obtained in this paper to prior literature, and also sheds light on transaction costs. Finally, section seven gives a conclusion to the paper and provides some limitations and suggestions for future research.

2 Literature Review

2.1 The Efficient Market Hypothesis

The influential papers on the efficient market hypothesis by Fama (1965) and Fama (1970) formed the basis of a large body of literature in academic research in finance. The theory states that in an efficient market, stock prices should fully reflect the information available on the market. This means that prices should not be predictable based on historic returns or information that has already been made public, as this information has already been priced in. In an efficient market, the expected return of a stock should equal to the actual return of a stock, and only when there is inefficiency do these two not equate. When such a situation occurs, anomalies are formed and abnormal returns can be exploited. These anomalies can either be temporary and get arbitraged away, or in the case of the momentum anomaly, appear to persist through time.

2.2 Conventional Momentum Strategies Across Traditional Asset Classes

Amongst the first to explore momentum and relative strength strategies were Jegadeesh and Titman (1993). Their paper analysed stocks on the NYSE and AMEX between the periods of 1965 to 1989. The J-month/K-month strategy they created was to select stocks based on their returns in the past 3, 6, 9, or 12 months (J-months), and hold them for 3, 6, 9, or 12 months (K-months), providing a total of 16 unique strategies. Every month stocks were ranked based on their performance in the past J months, and assigned to one of ten decile portfolios (1 being the best performers, 10 being the worst performers). The strategy then buys the stocks in the best performing decile, and short sells the stocks in the worst performing decile, holding these positions for K months. (Jegadeesh & Titman, 1993) also tested another set of 16 strategies with the only difference being that a week is skipped between the formation and holding period. According to the authors, this prevents some of the bid-ask spread, price pressure and lagged reaction effects that may affect the results. Their most significant strategies found an average excess return of 1%. These findings laid the foundation for further research in the field of momentum strategies.

Rouwenhorst (1998) explored a similar strategy to that of Jegadeesh and Titman (1993) in twelve European countries from 1978 to 1995. The author found that the strategy was significant in all twelve countries and that on average, the 'winner' portfolio (top decile stocks), outperformed the 'loser' portfolio (bottom decile stocks) by approximately 1%. The findings in the twelve European countries showed significant correlation to those of Jegadeesh and Titman (1993) on the U.S. stock market.

Asness, Moskowitz, and Pedersen (2013) investigated momentum in 8 different markets and asset classes. These included global individual stocks, global equity indices, currencies, global government bonds and commodity futures. Through the implementation of the conventional momentum strategy posed by Jegadeesh and Titman (1993), the authors found significant returns across all asset classes.

2.3 Risk-Based Explanations of Momentum Strategies

Fama and French (1996) attempted to provide an explanation for the momentum strategy of Jegadeesh and Titman (1993) using their three-factor model. The model tries to rationalise momentum anomalies through three risk-based factors: (i) the excess return on the market, (ii) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and (iii) the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. Ultimately, the three-factor model was unable to explain the excess return of momentum strategies.

Using a dataset of 40 countries, Griffin et al. (2003) attempted to explain momentum profits with macroeconomic risk factors. Their results found that neither the unconditional model posed by Chen, Roll, and Ross (1986), nor the conditional model of Chordia and Shivakumar (2002) were able to explain the significance of the momentum returns. Griffin et al. (2003) further found that momentum profits were significant in both good and bad economic states, and that there was a reversal over a 1 to 5 year investment horizon, concluding that the phenomenon could not be explained by existing risk-based explanations of momentum and deepening the momentum puzzle further.

Conrad and Kaul (1998) attempted to explain the abnormal profits generated by momentum strategies through bootstrapping and Monte Carlo simulations. The authors tested trading strategies through the periods of 1926 to 1989, using all securities available on the NYSE and AMEX. Of the 120 trading strategies explored, only 55 yielded statistically significant profits, and only 30 of those 55 strategies came from momentum. Profits at medium horizons such as those of Jegadeesh and Titman (1993) were found to be significant in all periods except during 1926 to 1947. The uathors concluded that one of the more important determinants of the profitability of medium-term momentum strategies was that the profits stemmed from cross-sectional variation in the mean return of individual securities. This variation did not have any relation to time-series patterns in return, which typically appears as the foundation of these trading strategies. However, in a paper by (Jegadeesh & Titman, 2002), the authors rejected the explanation made by Conrad and Kaul (1998) on the basis of small sample biases in their bootstrapping and Monte Carlo simulations.

2.4 Practical Implementation of Momentum Strategies

Though momentum strategies have been proven to work in theory, the feasibility of implementing such strategies can be questionable. Rey and Schmid (2007) provided a realistic approach to momentum investing on the Swiss stock market. As a way to simplify the model, the authors restricted the strategy to only Swiss blue-chip stocks which comprised of 17 to 26 stocks from the period of January 1994 to December 2004. The strategy bought the single stock with the highest past return and simultaneously short-sold the stock with the lowest return. The formation and holding periods were similar to those of Jegadeesh and Titman (1993) except the exclusion of the nine month formation and holding period. Depending on the length of the formation and holding period, Rey and Schmid (2007) found that the strategies generated an annualized geometric mean return of 9.19% to 43.79% per year. The 11 year sample period was then also split into two equal sub-periods and found significant returns in both periods. The results indicated that although the second sub-period was classified as a bear market, the returns generated in that period appeared to be higher than that of the former. Furthermore, the strategy proved to be robust to several risk measures, namely the market factor, and a two-factor model (market and a value/growth-factor). Finally, the strategy was still significant after implementing transaction costs.

Lesmond, Schill, and Zhou (2004) found that the returns to momentum trading strategies were not significant when transaction costs were factored in. The reasons they provided included the tendency for the composition of relative strength portfolios to be made up of stocks with high transaction costs. On the other hand, Agyei-Ampomah (2007) investigated the profitability of momentum strategies after accounting for all costs. The paper used all stocks traded on the London Stock Exchange from January 1988 to December 2003. Because the conventional J-month/K-month strategy posed by Jegadeesh and Titman (1993) required an investor to consistently rebalance their portfolio at the end of the holding period, Agyei-Ampomah (2007) factor in portfolio turnover. Furthermore, the author accounted for round trip trading costs using the quoted or effective spread, as well as commissions and stamp duty. The author found that regardless of these additional costs, momentum profits appeared to significantly persist, proving that if momentum profits were indeed illusory as suggested by Lesmond et al. (2004), then the nature of these profits could not be attributed solely to transaction costs.

Siganos (2010) researched the implementation of a momentum strategy for small investors in the United Kingdom (UK). The study used all the listed and delisted UK stocks between January 1988 and December 2006. Rather than employ decile or quintile portfolios to rank stocks, the author created the 'winner' portfolio ('loser' portfolio) by selecting the best (worst) 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50 performing stocks on the market. Siganos (2010) furthermore used non-overlapping 12-month periods to provide more realism for small investors and reduce transaction costs. This meant a 12 month formation period and a 12 month holding period. The total costs of each transaction were accounted for in a similar manner to Lesmond et al. (2004) with an additional cost for short selling. The profitability of the strategy was shown as the difference between the 'winner' and 'loser' portfolio (winner-loser). Most gross momentum returns appeared to come from shorting the 'loser' stocks rather than buying the 'winner' stocks. In order to see what the minimum amount required for such a strategy to work, Siganos (2010) used different starting amounts to simulate the profitability of the strategy based on an investor's starting capital. Because some stocks could be considered 'winners' or 'losers' in consecutive holding periods, the author uses real turnover. Siganos (2010) found that an investor needed at least £15,000 among 20 'winners' and 20 'losers' to achieve significant momentum profits (1.78% per month). The paper also explored the robustness of the strategy by regressing the net momentum returns against different risk factors. This was done by measuring the significance of the alpha in the traditional CAPM, and a two-factor model (market and book-to-market). The results showed that not only did the risk factors fail to explain the alpha, but that there was an increase in the (winner-loser) returns after factoring in risk. Similar results were also found by Siganos (2007) and Fama and French (1996).

Foltice and Langer (2015) researched the profitability of momentum trading strategies for individual investors in the US. The authors looked at all stocks traded on the New York Stock Exchange between July 1991 and December 2010. The paper used a 6 month formation period and ranked stocks based on their return in those 6 months. After the ranking, equally weighted portfolios containing the best 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50 performing stocks were created and held for the next 12 months. Unlike Siganos (2010), this paper only looked at 'winner' stocks and disregarded the 'loser' stocks. The authors' motivations for avoiding short selling was due to the unlimited downside risk associated with short selling stocks in the strategies posed by previous papers. Furthermore, short selling implies trading costs and exposes investors to margin risk, which according to the authors, is not something that is recommended for less knowledgeable investors. The authors found strongly significant gross momentum returns, outperforming the S&P 500 benchmark by as much as 2.44%. Strongly significant returns were also found when accounting for transaction costs and using real turnover. The findings were also robust to the Fama and French (1996) three-factor model. To achieve profitability, the authors found that an initial amount of $5,000 was required.

2.5 Momentum Crashes

Though momentum is seen to be profitable on the whole, there has been evidence of the underperformance of momentum strategies in highly volatile markets or economic downturns. Daniel and Moskowitz (2016) found that on the US market in two of the months in 1932, buying the top decile and shorting the bottom decile generated returns of 32% for past 'winners' and 232% for past 'losers'. This difference was also seen in three of the months in 2009 where past 'losers' rose by 169% and past 'winners' gained only 8%. The authors found that in situations where markets started to recover from multi-year economic downturns, past 'loser' stocks experienced strong gains. However, because the momentum strategy required investors to short these stocks, it caused momentum crashes. They also found that in bear markets, 'loser' stocks performed very strongly due to low market betas. On the other hand, the same could not be said about 'winner' stocks in times of economic prosperity. This created an asymmetric response to momentum strategies in extreme times. The authors created a dynamically weighted momentum strategy through the use of bear market indicators and ex-ante volatility estimates to create their portfolios. Their findings showed that the Sharpe ratio was approximately doubled that of conventional momentum strategies.

Hanauer and Windmüller (2019) applied a similar strategy in an international context, testing it in 49 developed and emerging market countries, finding the strategy to significantly increase the Sharpe ratio. Hanauer and Windmüller (2019) further tested idiosyncratic momentum strategies and found that it outperformed strategies in volatility-scaling, with the Sharpe ratio and t-statistic more than doubling.

Blitz, Hanauer, and Vidojevic (2020) also tested idiosyncratic momentum portfolios and found that volatility was approximately halved compared to conventional momentum strategies. The strategy's success could be explained by the positive returns in both bull and bear markets.

Furthermore, according to the authors, unlike conventional momentum strategies, idiosyncratic momentum strategies can forecast high short-term and long-term returns, while in the former, returns become negative after a year following the portfolio formation.

3 Data

This paper uses monthly return information for all listed and delisted stocks traded in the Netherlands as reported from the Thomson Reuters Datastream database, between January 1983 to January 2020. The inclusion of dead stocks is to ensure that the data is free of survivorship bias. This sample period is selected to provide a comprehensive view of the Dutch stock market and to give insight into which periods the momentum strategy performs strongest. Monthly return information is also retrieved for the AEX index to provide an adequate comparison to the momentum strategies created. The AEX index is composed of the 25 most traded stocks on the Dutch market.

Though the sample period could be extended a further 8 years back, this is not done for two reasons: firstly, the AEX index is used, and it is only formed in 1983, and secondly, after inspection of the earlier data, a lot of data errors and missing data points are found which could potentially cause inaccuracies in the analysis.

The following information is collected for every stock in the mentioned time period:

- The RI data type is used to calculate the monthly return of each stock. This data type assumes the reinvestment of dividends and can be used to represent total returns.
- The MV data type shows the market value of the stock (in € millions).

For the data cleaning process, all data points where all variables are missing or duplicated are dropped. Similar to Foltice and Langer (2015), any stock with a market value less than or equal to the equivalent of €20,000,000 in January 1983 is removed from the sample. This prevents a potential investor willing to invest €1,000,000 or greater from owning 5% of a stock. It also prevents the possibility of illiquid stocks from affecting the results. This is done by retrieving the annual change in the consumer price index of the Netherlands[1]. An inflation index is then created where each year contains the equivalent of €20,000,000 in 1983. All data points with a market value less than or equal to the inflation index are dropped. This totals to 6,792 observations out of 62,410 observations to be deleted.

After cleaning the data, the final sample contained 413 stocks (55,618 observations) throughout the entire time period. On average, the number of stocks per month is approximately 125, ranging from 79 to 194 stocks per month as seem from table 1. Figure 1 also shows the varying number of stocks on the Dutch market per month.

Aside from stock return data, the short-term interest rate of the Netherlands is retrieved from the Organization for Economic Cooperation and Development (OECD) data library, and the size and value factors are retrieved from the Matthias Hanauer and Stefan Windmüller Global Factor Premia data library between the July 1990 and October 2018. This data will be used to model risk factors later in the analysis. Because the risk factors do not cover the entirety of the time period, an additional two-factor model (market and value) using Dutch data retrieved from the Kenneth French data library will be used to affirm the results found.

[1]Retrieved from:
`https://opendata.cbs.nl/statline/#/CBS/en/dataset/70936eng/table?ts=1593621280102`

	Mean	Median	Std. Dev.	Min.	Max.
No. of Stocks	125	123	31	79	194
Market Value	3,449	321	11,129	20	155,134

Table 1: *Descriptive statistics on the number of stocks in the data set and the market value of the stocks.*

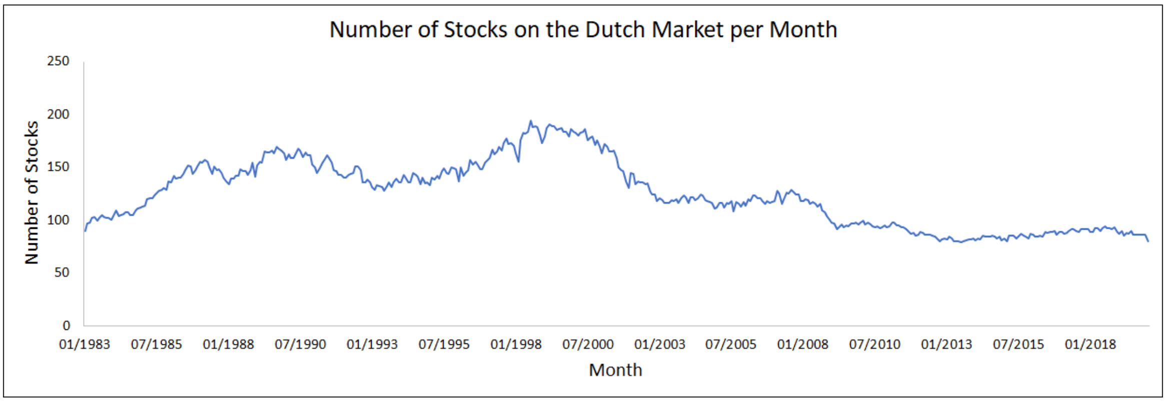

Figure 1: *The number of stocks on the Dutch stock market after the data cleaning process between January 1983 to January 2020.*

4 Methodology

The methodology used in this paper follows a similar framework to that of Jegadeesh and Titman (1993) and Foltice and Langer (2015). Because there is no strong consensus on the optimal formation and holding period, four strategies will be examined. Limiting the number of strategies tested also prevents issues such as data mining. The strategies will have a formation period of 6 or 12 months (J months), and a holding period of 6 or 12 months (K months) creating four unique combinations.

For the purposes of the analysis, overlapping-periods will be used. Though this may potentially increase the value of the returns, this method increases the power of the tests performed. Momentum exposure is also minimal nearing the end of a holding period, hence 'refreshing' the portfolio periodically is essential. Stocks are ranked every month based on their returns in the past J months where the last month of the formation period is skipped. According to Jegadeesh (1990), stocks experience a reversal in the last month which is largely caused by bid-ask spread pressure and the lagged reaction effect.

Using the return index from Datastream, the returns over the formation period (J months) are calculated as follows:

$$R_{i,(t-J,t-1)} = \frac{RI_{i(t-1)} - RI_{i(t-J)}}{RI_{i(t-J)}} \tag{1}$$

Where $R_{i,(t-J,t-1)}$ is the return of stock i during the formation period J (note again that the last month of the formation period is skipped). $RI_{i(t-1)}$ is the return index of stock i at time t and $RI_{i(t-J)}$ is the return index of stock i at time $t-J$. The return of stocks based on equation 1 are then used to rank each stock from best to worst on the basis of their returns at that time.

Equally weighted portfolios are then formed containing the best 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20 or 25 performing stocks, and held for K months. Similar to Foltice and Langer (2015), short selling is not considered due to the extreme downside risk that comes with it, which an average investor may not be prepared to take on. Short selling also comes with extra lending fees, which may be high for stocks that are to be short sold. The reason that the maximum number of stocks held (25) in the holding period is fewer than those of Foltice and Langer (2015) and Siganos (2010) is primarily due the smaller number of total stocks available on the Dutch stock market compared to the UK and US. Finally, if a stock gets delisted during the holding period, the return for that stock will be considered equal to zero.

The calculation of the monthly momentum returns is best described in figure 2. Every tranche represents a portfolio in the holding period. The average of each tranche gets taken to form the average return per tranche. The average between tranches in each month then gets taken to find the average momentum return per month. For example, in 2, for the month of March, there are three portfolios held simultaneously. The average gets taken between the average return of tranche 1, 2 and 3. Because a new tranche is formed every month, at any point in time a series of portfolios are held simultaneously.

In order to see if the strategies generate higher returns than the market, the following hypothesis will be tested:

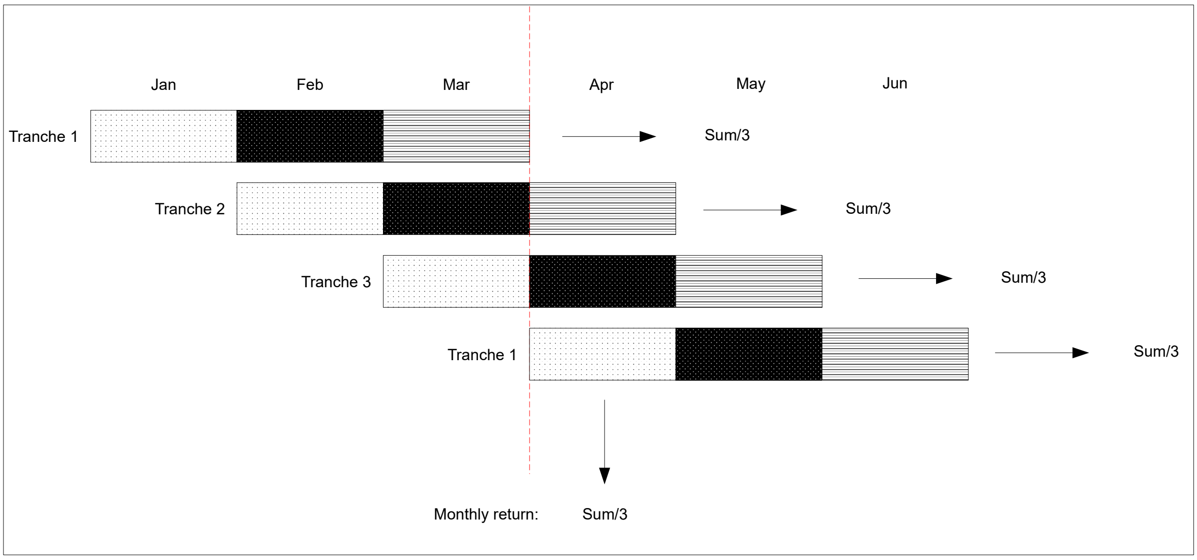

Figure 2: *A visual explanation on how average monthly returns for the portfolios are calculated.*

$$H_0 : Portfolio_i = AEX\ index$$

$$H_\alpha : Portfolio_i > AEX\ index$$

The next step will be to calculate the risk-adjusted returns of the proposed strategies. To test the robustness of the strategy, the analysis will test the significance of Jensen's alpha in the Capital Asset Pricing Model (CAPM). The alpha in this context represents the return in excess of the expected rate of return of the CAPM. The CAPM can be written as follows:

$$E(R_i) - R_f = \beta_i[E(R_m) - R_f] \tag{2}$$

Where $E(R_i)$ is the expected return of a portfolio, R_f is the risk-free rate, β_i gives the systematic risk of the portfolio, and $E(R_m)$ is the expected return of the market portfolio. Jensen's alpha can be seen as the difference between the realized return R_i and the risk adjusted return according to the CAPM model. This can be described as follows:

$$\alpha_i = R_i - [R_f + \beta_i(R_m - R_f)] \tag{3}$$

If α_i is positive and significant, it indicates that the portfolio generates excess returns to the market, meaning that the risk factor on its own is not able to fully explain the momentum returns.

Other risk factors can also be used to test the robustness of the portfolios created. For example the Carhart (1997) four-factor model or the Fama and French (2015) five-factor model. This paper uses the Fama and French (1996) three-factor model, namely the market return, the value factor (high book-to-market ratio minus low book-to-market ratio) and the size factpr (small market capitalisation minus big market capitalisation). Dutch data is collected from the Matthias Hanauer and Stefan Windmüller Global Factor Premia data library. The market return considered is the AEX index. Due to the availability of data on the Global Factor Premia data library, the regressions will only be analysed from July 1990 to October 2018. The following regression will be used to test the significance of alpha:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB + h_i HML + \epsilon_i \tag{4}$$

Where $R_i - R_f$ denotes the risk-adjusted return of the portfolio, α_i is the alpha of the portfolio, β_i gives the coefficient of the exposure the portfolio has to the market factor. s_i gives the coefficient of the exposure the portfolio has to the size factor. h_i gives the coefficient of the exposure the portfolio has to the value factor.

The hypothesis tested for these factor models are as follows:

$$H_0 : \alpha_{portfolio} = 0$$

$$H_\alpha : \alpha_{portfolio} > 0$$

If alpha is positive and significant, it indicates that the portfolios have generated excess returns to the risk factors provided.

5 Results

5.1 Momentum Returns

In this section, the gross returns for the momentum strategies are shown in tables 2, 3, 4, and 5. Each portfolio is compared to the AEX index, which for the purposes of this paper, is considered the benchmark. Each strategy is referred to in brackets where the first number is the number of months in the formation period, and the second number is the number of months in the holding period.

Table 2 shows the average gross return for the (6,6) momentum strategy per month. The standard deviation ranging from the 1-stock portfolio to the 25-stock portfolio appears to steadily decrease from 9.494 to 5.281. A similar trend can also be seen in the minimum and maximum returns of the portfolios where the minimum increases as the portfolio sizes increase and the maximum gradually decreases. The correlation between the portfolios and the AEX index steadily increases as the portfolio size increases. Throughout the entire time period tested, all portfolios outperform the AEX index by the 10% significance level. The test statistic becomes increasingly large as the portfolio size increases though slightly higher returns are more apparent amongst smaller portfolio sizes. Of the portfolios that are significant at the 5% level, the portfolios outperform the AEX index by approximately 0.401 to 0.603 percentage points per month on average.

The portfolios are then split into several different sub-periods. Between the years 1991-2000 and 2011-2020, none of the portfolios significantly outperform the AEX index benchmark. The strongest sub-period performance for the portfolios come in the years 1983-1990. With the exception of the 1-stock portfolio which did not meet the 10% significance threshold, the 2 and 3-stock portfolios are significant at the 5% level, and the 4-stock portfolio and above are significant at the 1% level. The test statistic gets bigger as the portfolio size increases. On average, all portfolios significant at the 5% level outperform the AEX index by approximately 0.997-1.300 percentage points. Between 2001-2010, all portfolio sizes in the (6,6) strategy outperform the AEX index by approximately 0.253-0.931 percentage points on average. However, statistical significance is only present from the 3-stock portfolio and above. Between the portfolios significant at the 5% level, the outperformance of the benchmark ranges between 0.764-0.931 percentage points. The average monthly returns in this sub-period appear to gradually increase as the portfolio size increases. A similar trend can be seen with the test statistic of the portfolios where larger test statistics are seen in the larger portfolio sizes. The years between the financial crisis of 2008 are also measured to give insight into the possibility of momentum crashes. The results show the smaller portfolio sizes (1-stock to 5-stock portfolios) underperform the AEX index by as much as 2.315 percentage points while in the larger portfolio sizes (15-stock to 25-stock portfolios), the portfolios perform nearly on par with the benchmark, varying approximately by -0.042-0.059 percentage points. When the years 2007-2009 are skipped, all portfolios appear to outperform their counterpart where the years of the financial crisis are not skipped. All portfolio sizes are significant at the 1% level with the exception of the 1-stock portfolio which is significant at the 5% level. The average returns of the portfolios show a decreasing trend where smaller portfolio sizes experience larger returns than the larger portfolio sizes. Outperformance of the benchmark ranges between 0.441-0.792 percentage points.

Table 3 shows the average return per month for the (12,12) momentum strategy. The portfolios exhibit similar trends to those of the (6,6) strategy with regards to the standard deviation, minimum and maximum. On average, the smaller portfolio sizes do not show significant returns when compared to the AEX index. Only from the 7-stock portfolio are the strategies statistically significant at the 10% level. The 10-stock portfolio and above are all significant at the 5% level. Between the portfolios that are significant at the 5% level, the average monthly outperformance compared to the benchmark ranges from 0.302-0.338 percentage points. Regardless of significance, the general trend shows that a portfolio's average monthly return increases as the portfolio size gets bigger.

Similar to the (6,6) strategy, between the years 1991-2000 and 2011-2020, none of the portfolios in the (12,12) strategy significantly outperform the AEX index benchmark. In fact, between the years 1991-2000, all portfolios appear to underperform the benchmark. The years 1983-1990 prove again to have the strongest sub-period performance. Similar to the overall performance, in this sub-period, returns tend to increase as the portfolio size increases. A similar trend can be noted for the test statistics of the portfolios - most of the smaller portfolio sizes have small test statistics, leading them to be insignificant even at the 10% level. The 5-stock portfolio shows significance at the 10% level, while the 6-stock portfolio and above show significance at the 5% level, outperforming the benchmark by 0.683 to 0.753 percentage points on average. Only the 25-stock portfolio shows significance at the 1% level averaging a return of 1.756% per month, outperforming the benchmark by 0.736 percentage points. The other significant sub-period is seen between 2001-2010. Although all portfolio sizes outperform the benchmark, statistical significance is not present in the smaller portfolio sizes (1 to 4-stock portfolios). The test statistic gets larger as the portfolio size becomes larger. The 5 and 6-stock portfolios are significant at the 10% level, the 7, 8, and 9-stock portfolios are significant at the 5% level, and the 10-stock portfolio and above are significant at the 1% level. Similar to other periods, the average monthly returns in this sub-period show that returns increase as the portfolio size increases. On average, all portfolios significant at the 5% level in this sub-period outperform the AEX index by approximately 0.826-0.968 percentage points per month. Between the years 2007-2009, most portfolios underperform the AEX index. The strongest losses are experienced in the smaller portfolios where the 1-stock portfolio underperforms the AEX index by as much as 3.077 percentage points. The largest three portfolios perform roughly on par with the AEX index or marginally better, with the difference ranging between -0.082-0.139 percentage points per month. When the years 2007-2009 are skipped, all portfolios appear to outperform the portfolios where the years of the financial crisis are not skipped. The difference in returns between the two portfolios gets smaller as the portfolio size increases. This is made clear by the smaller losses experienced by the larger portfolios in the 2007-2009 sub-period. When the 2007-2009 sub-period is skipped, statistical significance in the portfolio returns is only evident from the 3-stock portfolio and above. The 3, 4, 5, and 6-stock portfolios are significant at the 10% level, while the 7-stock portfolio and above are all significant at the 5% level. Between the portfolios significant at the 5% level, the returns show little variation between smaller and larger portfolios with no clear trend in the returns. On average when the years 2007-2009 are skipped, the portfolios significant at the 5% level outperform the benchmark by 0.267-0.376 percentage points.

Table 4 shows the average monthly gross return for the (6,12) momentum strategy. The standard deviation ranging from the 1-stock portfolio to the 25-stock portfolio shows a steady decrease from 8.376 to 5.253. A sharp decrease is seen in the minimum in smaller portfolio sizes before becoming relatively stable with little variation in the larger portfolio sizes. The maximum also experiences a sharp decrease from the 1-stock portfolio to the 2-stock portfolio, before exhibiting a steady decrease up to the 25-stock portfolio. The correlation between the portfolios and the AEX index steadily increases as the portfolio size increases. Throughout the entire time period tested, all portfolios outperform the AEX index, though statistical significance at the 10% level is only present from the 3-stock portfolio and above. On average the portfolios significant at the 5% level outperform the AEX index by approximately 0.314-0.359 percentage points per month. As can be seen in the table, there is minimal variation between the significant portfolios though the larger portfolio sizes post a bigger test statistic. Only the 25-stock portfolio in this strategy is significant at the 1% level.

Similar to the previous two strategies, between the years 1991-2000 and 2011-2020, none of the portfolios in the (6,12) strategy significantly outperform the AEX index benchmark. The years 1983-1990 show strong performances through all portfolio sizes. With the exception of the 1-stock portfolio, all other portfolios show statistical significance in outperforming the benchmark. The larger the portfolio size the bigger the test statistic. The 3-stock portfolio shows significance at the 5% level, and from the 4-stock portfolio and above, all portfolios show significance at the 1% level. Between the portfolios significant at the 5% level, performances range between 0.899-1.267 percentage points better than the AEX index. The smaller portfolio sizes appear to give slightly higher returns in comparison to the larger portfolio sizes. The years 2001-2010 also exhibit significant returns. The portfolios in this sub-period show a steady increase in returns as the portfolio size increases. This is also evident with the statistical significance of the portfolios. The 3, 4, and 5-stock portfolios are significant at the 10% level, the 6, 7, 8, and 9- stock portfolios are significant at the 5% level, while the 10-stock portfolio and higher are significant at the 1% level. Between the statistically significant portfolios at the 5% level, average monthly returns range between 0.651-0.955 percentage points better than the AEX index benchmark. Between 2007-2009 the (6,12) strategy experiences a similar trend to that of prior strategies. Smaller portfolio sizes experience high underperformance in comparison to the benchmark while larger portfolio sizes perform approximately on par with the AEX index. When the 2007-2009 sub-period is skipped, statistical significance in the portfolio returns is evident in all portfolio sizes where the 1 and 2-stock portfolios are significant at the 10% level, the 3, 4, and 5-stock portfolios are significant at the 5% level, and the 6-stock portfolio and above are significant at the 1% level. As the portfolio size increases the test statistic becomes larger. Compared to the entire time period where the years of the financial crisis are not skipped, all portfolios generate higher returns. The difference in returns however gets smaller as the portfolio size increases. Higher returns are experienced in the smaller portfolios though the difference between small and large portfolios is minimal. On average when the years 2007-2009 are skipped, the portfolios significant at the 5% level outperform the benchmark by 0.339-0.497 percentage points.

Table 5 shows the monthly gross return for the (12,6) momentum strategy. Similar to the other three strategies, the minimum increases as the portfolio size increases, and the maximum decreases as the portfolio size increases. The standard deviation of the portfolios also decreases as the portfolio size increases. Throughout the entire time period tested, all portfolios outperform the AEX index, however statistical significance is only present for the 3-stock portfolio and above. On average the statistically significant portfolios at the 5% level outperform the AEX index by approximately 0.477-0.639 percentage points per month. Between the significant portfolios there is minimal difference between the smaller and larger portfolios, though larger test statistic values are seen in the larger portfolios. In the strategy, the 3 and 4-stock portfolios are significant at the 5% level, while the 5-stock portfolio and above are all significant at the 1% level.

As has been a common theme throughout the results section, none of the portfolios in the (12,6) strategy significantly outperformed the AEX index between the years 1991-2000 and 2011-2020. The years 1983-1990 prove again to be the strongest sub-period. All portfolio sizes are significant at the 1% level with the exception of the 1-stock portfolio which is significant at the 5% level. The average monthly return of the portfolios range between 1.187-1.839 percentage points better than the AEX index, with the smaller portfolio sizes experiencing higher returns. Strong positive returns are also evident between 2001-2010, with the exception of the 1 and 2-stock portfolios, all other portfolio sizes exhibit statistically significant results. The 3-stock portfolio is significant at the 10% level, the 5 and 6-stock portfolios are significant at the 5% level and the 7-stock portfolio and above are significant at the 1% level, showing that the larger the portfolio size the stronger the findings due to the larger test statistics. Between the portfolios significant at the 5% level, the average monthly return ranged between 0.864-1.206 percentage points better than the benchmark. In the years 2007-2009, similar to prior strategies, the (12,6) strategy exhibits strong underperformance in comparison to the AEX index particularly in the smaller portfolios. The 1-stock portfolio underperforms the AEX index by as much as 3.752 percentage points while the 15-stock portfolio and above perform relatively similar if not slightly better than the benchmark. When the years 2007-2009 are skipped, the portfolio returns show statistical significance at the 1% level with the exception of the 2-stock portfolio which is significant at the 5% level, and the 1-stock portfolio which is not statistically significant even at the 10% level. On average the portfolios significant at the 5% level outperform the AEX index by 0.551-0.768 percentage points per month. Larger returns are more evident in the smaller significant portfolios.

The cumulative return of the best portfolios for each respective strategy is shown in figure 3. The natural logarithm for the cumulative return is taken to provide a more adequate comparison of the strategies. As can be seen from the figure, all the portfolios appear to be highly correlated to the AEX index, fluctuating in the same moments as the index. Where the strategies seem to outperform the index the most are between 1983 and 1988, and between 2003 and early 2008. It is evident from the figure that the (12,12) strategy is the weakest strategy of the four, while the (6,6) and (12,6) portfolio interchange as the best performing strategy. The (12,6) strategy then appears to perform best from around 2005 onwards. A €100 investment in the AEX index at the beginning of 1983 would have generated a return of €3,613. In contrast, a similar investment would have generated a return of €31,047, €12,395, €15,537 and €40,823 for the (6,6), (12,12), (6,12), and (12,6) strategies respectively.

The results shown in tables 2, 3, 4 and 5 lead to differing conclusions per strategy. For the (6,6) strategy, at the 5% significance level, the null hypothesis that the portfolios are equal to the AEX index ($H_0 : Portfolio_i = AEX\ index$) can be rejected for the 2-stock portfolio and above. For the (12,12) strategy, at the 5% significance level, the null hypothesis that the portfolios are equal to the AEX index ($H_0 : Portfolio_i = AEX\ index$) can be rejected for the 10-stock portfolio and above. For the (6,12) strategy, at the 5% significance level, the null hypothesis that the portfolios are equal to the AEX index ($H_0 : Portfolio_i = AEX\ index$) can be rejected for the 5-stock portfolio and above. Finally, for the (12,6) strategy, at the 5% significance level, the null hypothesis that the portfolios are equal to the AEX index ($H_0 : Portfolio_i = AEX\ index$) can be rejected for the 3-stock portfolio and above. However it is clear from the results in these tables that with increasing portfolio sizes, the noise in the dataset gets reduced, leading to a stronger isolation of the momentum signal which is shown by the corresponding significance levels in each table.

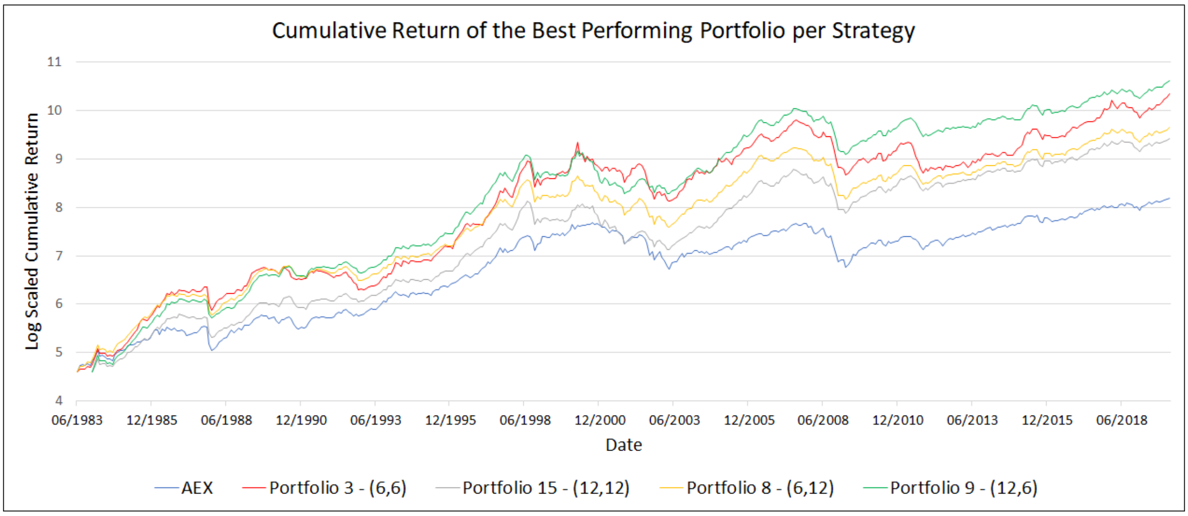

Figure 3: *A time-series plot of the average cumulative return of the best performing portfolio for each respective strategy.*

5.2 Risk-adjusted Return

After the calculation of the momentum returns to the investment strategies, two risk factor models are used to test the robustness of the gross returns to provide risk-adjusted returns. The results of the average alphas throughout the time period tested are shown in table 6. For every regression, the momentum returns are used as the dependent variable, whilst the market returns (the AEX index) are used as the independent variable in panel A, in panel B the value factor

Portfolio size	AEX	1	2	3	4	5	6
Jul. 1983-Jan. 2020	0.987	1.524*	1.492**	1.590***	1.553***	1.569***	1.559***
Max.	15.255	38.689	34.649	31.064	26.368	25.129	19.537
Min.	-29.739	-35.429	-31.934	-27.923	-27.720	-26.590	-26.465
Median	1.576	1.023	1.018	1.347	1.548	1.722	1.649
Std. Dev.	5.683	9.494	8.071	7.388	6.993	6.656	6.454
Correlation	NA	0.562	0.666	0.71	0.747	0.766	0.776
Sub periods							
1983-1990	1.212	1.886	2.443**	2.378**	2.374***	2.457***	2.512***
1991-2000	1.887	2.797	2.253	2.214	2.166	2.158	2.060
2001-2010	0.048	0.464	0.301	0.785*	0.749*	0.804**	0.821**
2007-2009	-0.431	-2.746	-2.262	-1.171	-1.443	-1.220	-0.930
2011-2020	0.840	0.982	1.167	1.128	1.072	1.018	1.020
1983-2006; 2010-2020	1.113	1.905**	1.827***	1.837***	1.820***	1.818***	1.782***
Portfolio size	**7**	**8**	**9**	**10**	**15**	**20**	**25**
Jul. 1983-Jan. 2020	1.537***	1.495***	1.481***	1.461***	1.423***	1.388***	1.408***
Max.	19.994	19.272	18.232	19.099	18.031	17.334	16.954
Min.	-25.725	-25.538	-25.043	-24.710	-23.715	-24.467	-24.995
Median	1.580	1.513	1.522	1.633	1.783	1.681	1.707
Std. Dev.	6.318	6.177	6.032	5.916	5.605	5.443	5.281
Correlation	0.789	0.797	0.806	0.81	0.831	0.849	0.859
Sub periods							
1983-1990	2.489***	2.481***	2.391***	2.312***	2.264***	2.252***	2.209***
1991-2000	2.001	1.961	1.898	1.909	1.764	1.685	1.729
2001-2010	0.861**	0.812**	0.888**	0.877**	0.932***	0.913***	0.979***
2007-2009	-0.761	-0.774	-0.802	-0.737	-0.467	-0.473	-0.372
2011-2020	0.969	0.905	0.912	0.895	0.882	0.859	0.855
1983-2006; 2010-2020	1.742***	1.697***	1.685***	1.657***	1.592***	1.554***	1.567***

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Table 2: *Returns of the (6,6) momentum strategy shown as % per month. Each portfolio size is compared to the AEX index benchmark.*

and size factor are used as additional independent variables. Due to the availability of data, the time period tested is between July 1990 and October 2018.

Panel A of table 6 shows the alphas of the CAPM regression for all four strategies tested. The 1 to 4-stock portfolios in the (6,6) strategy show no statistical significance, while the 5-stock portfolio generates an alpha of 0.457%, significant at the 10% level. The 9-stock portfolio generates an alpha of 0.404%, significant at the 5% level, and the 25-stock portfolio generates an alpha of 0.412%, significant at the 1% level. Higher alphas are generally seen in the smaller portfolio sizes though the test statistic becomes larger as the portfolio size increases.

The (12,12) strategy in panel A shows the alphas in the regression to generally increase as the portfolio size increases. Smaller if not negative alphas are seen in the smaller portfolio sizes while larger alphas are seen in the larger portfolio sizes. The 15-stock portfolio generates an alpha of 0.355%, significant at the 10% level. The 20 and 25-stock portfolios are both significant

Portfolio size	AEX	1	2	3	4	5	6
Jan. 1984-Jan. 2020	0.946	0.804	0.983	1.120	1.141	1.153	1.180
Max.	15.255	60.69	40.187	33.098	27.940	25.224	23.160
Min.	-29.739	-30.818	-29.370	-38.371	-37.954	-34.268	-30.900
Median	1.547	1.181	1.080	1.277	1.212	1.373	1.430
Std. Dev.	5.665	9.585	8.218	7.483	7.071	6.772	6.579
Correlation	NA	0.61	0.693	0.730	0.748	0.754	0.766
Sub periods							
1984-1990	1.020	1.624	1.688	1.599	1.610	1.626*	1.757**
1991-2000	1.887	1.259	1.439	1.602	1.557	1.453	1.355
2001-2010	0.048	0.214	0.309	0.469	0.535	0.689*	0.777*
2007-2009	-0.431	-3.508	-2.874	-2.038	-1.897	-1.540	-1.371
2011-2020	0.840	0.309	0.670	0.933	0.981	0.964	0.980
1983-2006; 2010-2020	1.071	1.195	1.333	1.407*	1.416*	1.397*	1.412*
Portfolio size	**7**	**8**	**9**	**10**	**15**	**20**	**25**
Jan. 1984-Jan. 2020	1.205*	1.241*	1.244*	1.260**	1.284**	1.254**	1.248**
Max.	20.634	20.299	18.671	17.485	16.317	16.332	17.326
Min.	-30.398	-29.668	-28.604	-28.531	-27.330	-27.273	-27.311
Median	1.430	1.677	1.644	1.661	1.618	1.601	1.576
Std. Dev.	6.444	6.329	6.141	6.034	5.677	5.450	5.282
Correlation	0.775	0.780	0.789	0.795	0.817	0.830	0.843
Sub periods							
1984-1990	1.710**	1.773**	1.726**	1.703**	1.750**	1.714**	1.756***
1991-2000	1.465	1.468	1.469	1.542	1.601	1.545	1.491
2001-2010	0.874**	0.966**	0.995**	1.002***	1.016***	1.009***	1.006***
2007-2009	-1.145	-0.955	-0.781	-0.757	-0.513	-0.367	-0.292
2011-2020	0.888	0.876	0.893	0.883	0.863	0.841	0.847
1983-2006; 2010-2020	1.418**	1.441**	1.428**	1.443**	1.447**	1.401**	1.388**

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Table 3: *Returns of the (12,12) momentum strategy shown as % per month. Each portfolio size is compared to the AEX index benchmark.*

at the 5% level, posting alphas of 0.347% and 0.348% respectively. None of the portfolios reach the 1% significance threshold.

A similar trend is seen in the (6,12) strategy where alphas are small or negative in smaller portfolio sizes, but gradually get larger and significant in the larger portfolio sizes. The 15 and 20-stock portfolios show significance at the 10% level with alphas of 0.280% and 0.285% respectively, while the 25-stock portfolio has an alpha of 0.348%, significant at the 5% level.

Just like the (12,12) and (6,12) strategy, the alphas in the (12,6) strategy increase as the portfolio size increases. Negative alphas are seen in portfolio sizes 1 and 2, and significance at the 10% level is seen from the 7-stock portfolio and above where the 7-stock portfolio generates an alpha of 0.453%. The 8-stock portfolio generates an alpha of 0.487%, significant at the 5% level, and the 15-stock alpha generates an alpha of 0.546%, significant at the 1% level.

Panel B of table 6 shows the alphas of the three-factor model regression for the four strategies

Portfolio size	AEX	1	2	3	4	5	6
Jul. 1983-Jan. 2020	0.987	1.159	1.110	1.289*	1.329*	1.308**	1.335**
Max.	15.255	35.027	22.128	20.903	21.762	21.799	21.494
Min.	-29.739	-31.842	-32.189	-24.413	-24.553	-25.100	-25.235
Median	1.576	0.651	0.825	1.129	1.377	1.592	1.675
Std. Dev.	5.683	8.376	7.264	6.885	6.661	6.464	6.343
Correlation	NA	0.590	0.704	0.741	0.760	0.783	0.797
Sub periods							
1983-1990	1.212	2.091	1.967*	2.324**	2.368***	2.446***	2.479***
1991-2000	1.887	1.922	1.475	1.390	1.538	1.469	1.470
2001-2010	0.048	0.296	0.246	0.659*	0.644*	0.636*	0.699**
2007-2009	-0.431	-3.669	-3.215	-1.878	-1.824	-1.652	-1.494
2011-2020	0.840	0.487	0.941	1.003	0.981	0.916	0.927
1983-2006; 2010-2020	1.113	1.591*	1.500*	1.572**	1.610**	1.572**	1.587***
Portfolio size	**7**	**8**	**9**	**10**	**15**	**20**	**25**
Jul. 1983-Jan. 2020	1.343**	1.346**	1.333**	1.341**	1.328**	1.301**	1.325***
Max.	19.937	20.788	19.370	18.999	18.383	17.924	17.599
Min.	-25.436	-25.376	-25.767	-26.038	-25.584	-24.730	-24.573
Median	1.454	1.597	1.567	1.538	1.567	1.529	1.609
Std. Dev.	6.174	6.107	6.003	5.929	5.593	5.357	5.253
Correlation	0.805	0.815	0.819	0.826	0.840	0.853	0.861
Sub periods							
1983-1990	2.423***	2.378***	2.346***	2.326***	2.159***	2.111***	2.130***
1991-2000	1.457	1.493	1.507	1.495	1.518	1.501	1.529
2001-2010	0.768**	0.830**	0.845**	0.892***	0.961***	0.962***	1.003***
2007-2009	-1.282	-1.185	-1.072	-0.918	-0.544	-0.381	-0.300
2011-2020	0.944	0.885	0.828	0.839	0.824	0.774	0.779
1983-2006; 2010-2020	1.577***	1.572***	1.548***	1.543***	1.495***	1.452**	1.471***

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Table 4: *Returns of the (6,12) momentum strategy shown as % per month. Each portfolio size is compared to the AEX index benchmark.*

tested. The alphas of the panel B strategies exhibit a similar trend to their counterparts in panel A. The (6,6) strategy shows for the most part larger alphas in the smaller portfolio sizes, while for the (12,12), (6,12) and (12,6) strategy, the alphas and their respective test statistics increase as the portfolio size increases. All alphas in panel B also appear larger than in panel A.

The (6,6) strategy in panel B shows that the 3 to 8-stock portfolios are all significant at the 5% level where the 3-stock portfolio generates an alpha of 0.547%. The 9, 10, 15, 20 and 25-stock portfolios are all significant at the 1% level where the 9-stock portfolio generates an alpha of 0.486% and the 25-stock portfolio generates an alpha of 0.480%. The (12,12) strategy in panel B shows the 8-stock portfolio to be significant at the 10% level with an alpha of 0.379%. The 9 and 10-stock portfolios are significant at the 5% level where the 9-stock portfolio generates an alpha of 0.401%. The 15, 20 and 25-stock portfolios are significant at the 1% level where the 15-stock portfolio generates an alpha of 0.458%. The (6,12) strategy in panel B shows the

Portfolio size	AEX	1	2	3	4	5	6
Jan. 1984-Jan. 2020	0.946	1.059	1.228	1.423**	1.497**	1.535***	1.562***
Max.	15.255	44.44	34.852	31.187	30.707	26.141	24.104
Min.	-29.739	-32.594	-33.280	-27.971	-31.302	-27.920	-24.971
Median	1.547	0.612	0.660	1.283	1.509	1.622	1.708
Std. Dev.	5.665	10.297	8.677	7.691	7.226	6.837	6.597
Correlation	NA	0.533	0.629	0.664	0.702	0.706	0.724
Sub periods							
1983-1990	1.020	2.678**	2.649***	2.859***	2.621***	2.645***	2.676***
1991-2000	1.887	1.087	1.528	1.606	1.830	1.816	1.783
2001-2010	0.048	0.561	0.582	0.843*	0.912**	1.020**	1.069**
2007-2009	-0.431	-4.183	-3.532	-2.256	-2.052	-1.759	-1.424
2011-2020	0.840	0.308	0.493	0.733	0.895	0.922	0.986
1983-2006; 2010-2020	1.071	1.535	1.659**	1.756***	1.819***	1.834***	1.833***
Portfolio size	**7**	**8**	**9**	**10**	**15**	**20**	**25**
Jan. 1984-Jan. 2020	1.544***	1.585***	1.591***	1.559***	1.555***	1.517***	1.462***
Max.	24.254	22.938	21.127	22.324	21.043	19.911	18.863
Min.	-24.970	-24.870	-24.612	-24.050	-22.500	-22.562	-23.334
Median	1.687	1.756	1.777	1.657	1.836	1.760	1.879
Std. Dev.	6.407	6.316	6.186	6.004	5.680	5.396	5.228
Correlation	0.735	0.742	0.749	0.760	0.782	0.804	0.818
Sub periods							
1983-1990	2.451***	2.592***	2.565***	2.426***	2.363***	2.245***	2.207***
1991-2000	1.783	1.800	1.863	1.842	1.859	1.816	1.707
2001-2010	1.156***	1.248***	1.253***	1.223***	1.221***	1.254***	1.177***
2007-2009	-1.125	-0.812	-0.807	-0.713	-0.466	-0.297	-0.309
2011-2020	0.995	0.928	0.900	0.936	0.951	0.904	0.918
1983-2006; 2010-2020	1.786***	1.802***	1.809***	1.765***	1.738***	1.681***	1.622***

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Table 5: *Returns of the (12,6) momentum strategy shown as % per month. Each portfolio size is compared to the AEX index benchmark.*

7-stock portfolio generates an alpha of 0.294%, significant at the 10% level. The 8, 9, and 10-stock portfolios are significant at the 5% level where the 8-stock portfolio generates an alpha of 0.309%. The 15-stock portfolio and above prove to be significant at the 1% level where the 15-stock portfolio generates an alpha of 0.374%. Finally, the (12,6) portfolio in panel B shows the 5-stock portfolio generates an alpha of 0.481%, significant at the 10% level, the 6-stock portfolio generates an alpha of 0.517%, significant at the 5% level, and the 8-stock portfolio and above to be significant at the 1% level where the 8-stock portfolio generates an alpha of 0.579%.

Although it is not shown in the table, the market coefficient β_i in panel A is significant at the 1% level for all the portfolio sizes in all four strategies. In panel B the market coefficient β_i and the size coefficient s_i are both significant at the 1% level. This shows that both the market factor and the size factor provide strong explanations for the returns of the four different strategies though it does not explain the returns completely as alpha is still significant for a large number of the portfolios. Table 7 in appendix A gives a breakdown of each coefficient and provides an accurate representation of the results seen in the majority of the portfolios.

The results shown in table 6 leads to several conclusions. For the CAPM regression, at the 5% significance level, the null hypothesis ($H_0 : \alpha_{portfolio} = 0$) can be rejected for the 9-stock portfolio and above for the (6,6) strategy, the 20-stock portfolio and above for the (12,12) strategy, the 25-stock portfolio for the (6,12) strategy, and the 8-stock portfolio and above for the (12,6) strategy. For the 3-factor model regression at the 5% significance level, the null hypothesis ($H_0 : \alpha_{portfolio} = 0$) can be rejected for the 3-stock portfolio and above for the (6,6) strategy, the 9-stock portfolio and above for the (12,12) strategy, the 8-stock portfolio and above for the (6,12) strategy, and the 6-stock portfolio and above for the (12,6) strategy.

Panel A: Alpha (%) - CAPM													
Portfolio size	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**15**	**20**	**25**
(6,6)	0.483	0.290	0.460	0.417	0.457*	0.441*	0.419*	0.392*	0.404**	0.407**	0.383**	0.354**	0.412***
(12,12)	-0.365	-0.208	0.059	0.121	0.153	0.171	0.222	0.264	0.287	0.314	0.355*	0.347**	0.348**
(6,12)	-0.033	-0.087	0.078	0.148	0.114	0.149	0.187	0.207	0.213	0.231	0.280*	0.285*	0.325**
(12,6)	-0.213	-0.09	0.156	0.316	0.383	0.418	0.453*	0.487**	0.517**	0.514**	0.546***	0.554***	0.508***
Panel B: Alpha (%) - three-factor model													
Portfolio size	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**15**	**20**	**25**
(6,6)	0.614	0.387	0.547**	0.507**	0.545**	0.531**	0.506**	0.481**	0.486***	0.492***	0.464***	0.428***	0.480***
(12,12)	-0.229	-0.087	0.171	0.234	0.271	0.284	0.336	0.379*	0.401**	0.425**	0.458***	0.444***	0.439***
(6,12)	0.090	0.011	0.180	0.247	0.216	0.255	0.294*	0.309**	0.314**	0.328**	0.374***	0.374***	0.410***
(12,6)	-0.089	0.036	0.260	0.417	0.481*	0.517**	0.546**	0.579***	0.606***	0.600***	0.634***	0.641***	0.592***

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Table 6: *The results from the four strategies are regressed against risk-factors to test the robustness of the findings. The results are only tested between July 1990 to October 2018. Panel A shows the average alpha captured by the CAPM regression given by the equation:* $R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \epsilon_i$. *Panel B shows the average alpha captured by the Fama and French (1996) 3-factor model regression given by the equation:* $R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB + h_i HML + \epsilon_i$.

6 Discussion

In this section the results obtained in this research will be compared to those of prior literature and other analysis performed. Furthermore, a brief discussion on transaction costs will be provided to give insight into the practicality of the strategy.

6.1 Comparison of Results

Foltice and Langer (2015) only analysed the (6,12) strategy, and looked at a period between 1992 and 2010 in the US. They found that their portfolios outperformed the S&P 500 benchmark by 0.52-2.44% per month on average. Using the same strategy, this paper found that the portfolios outperformed the AEX index by only 0.12-0.36 percentage points per month. This is not only a noticeably smaller range in results compared to the findings of Foltice and Langer (2015), but also the outperformance margin is much smaller. A similar pattern can also be noted in the other strategies analysed in this paper. A possible explanation for the difference in results could stem from the number of stocks available in the respective markets. Foltice and Langer (2015), had 2,286 stocks available per month on average when analyzing the US market. In contrast, this paper analyses a much smaller market, with only 125 stocks available on average. Because of this, selecting 25 'winner' stocks on the Dutch market implies buying approximately 20% of all stocks available on the Dutch market. For Foltice and Langer (2015), they maximally buy 50 stocks in their strategy, meaning approximately 2.19% of the U.S. market. Buying the top 2% of stocks makes a significant difference to buying the top 20% of stocks. This line of reasoning can be reinforced by the correlation between the portfolios and their respective benchmarks. For Foltice and Langer (2015), correlation between the portfolios and the market ranges between 0.20-0.65. While for the (6,12) strategy in this paper, the correlation to the AEX index ranges between 0.56-0.86. Such high correlation can provide a possible explanation as to why the portfolios outperform the index by less than those of Foltice and Langer (2015).

Inconsistent again with the findings of Foltice and Langer (2015) is when the strategies are divided into sub periods. In this paper, significant outperformance of the strategies are primarily found in the periods 1983-1990 and 2001-2010. Foltice and Langer (2015) on the other hand found their strategy to consistently outperform the market both in the periods of 1992-2000 and 2001-2009. However, one similarity between the two papers is the underperformance of the strategies during the years of the financial crisis of 2007-2009. Foltice and Langer (2015) found that all portfolios underperformed the market benchmark between 2007-2008, with the 1-stock portfolio underperforming the S&P 500 by 2.74 percentage points and the 50-stock portfolio underperforming by 0.54 percentage points. For the (6,12) strategy, this paper finds the portfolios to underperform the AEX index by as much as 3.24 percentage points for the 1-stock portfolio, and 0.11 percentage points for the 15-stock portfolio. The the 20 and 25-stock portfolio returns are also negative, but marginally outperform the AEX index. Given the consensus by several research papers on the underperformance of momentum strategies in periods of economic downturns, other strategies should be explored in said periods provided there are ex-ante cues to initiate these strategies. As mentioned in section 2, a possible strategy in these periods is the use of idiosynchratic momentum strategies. Blitz et al. (2020) found that these strategies are less affected by time-varying exposure, and as a result are significantly less exposed to crash risk.

Siganos (2010) only analyse the (12,12) momentum strategy, but look at both 'winners' and 'losers'. Though the majority of their portfolios experience strong and significant returns, their 'winners only' portfolio appears to generate minimal, if not negative returns. This is a stark contrast to the findings of this paper. Though the (12,12) strategy only finds significant results from the 7-stock portfolio onwards, all portfolios appear to generate positive return with the exception of the 1-stock portfolio, which underperforms the AEX index. A possible explanation for the difference could be that Siganos (2010) uses non-overlapping periods to test the strategy. Though this method may provide a more accurate description as to what investors could expect if they were to implement the strategy, it significantly reduces the power of the tests. Not only would this be because of fewer observations, but also because after holding a portfolio for 11 months, momentum exposure is minimal. In order to maintain the exposure to momentum, the portfolios need to be rebalanced regularly.

The results in table 6 show alphas only between 1990 and 2018. Unfortunately due to insufficient data, the years between 1983 and 1990 are skipped, which from prior results appears to be the best performing sub-period. For the (6,6) strategy, the alphas of the CAPM do not show clear trends though larger returns are generally seen in the smaller portfolio sizes. On the other hand, for the (12,12), (6,12) and (12,6) strategy, the portfolio sizes of these strategies appear to exhibit similar trends where smaller portfolio sizes (1 to 5-stock portfolios) generate smaller alphas in comparison to larger portfolio sizes (15 to 25-stock portfolios). One similarity between all strategies is that as the portfolio size gets larger, noise surrounding the alpha gets reduced causing the average risk-adjusted returns (alphas) of those portfolios to have larger test statistics.

The alphas in the three-factor model all appear to be larger than their counterparts in the CAPM regression. A possible explanation for this is the negative coefficient of the value factor. This can be seen in table 7 where the full regression of the 25-stock portfolio for the (6,6) strategy is shown. The majority of the value factor coefficients appear negative in the three-factor regressions. Similar patterns also emerge when the CAPM alphas are compared to the alphas of a two-factor model (market and book-to-market) shown in table 8 of Appendix A. Unlike table 6, this (Dutch) data is retrieved from the Kenneth French library where data for the entirety of the time period is available. Table 6 and table 8 show similar findings though the alphas in the latter table are generally larger and are significant in smaller portfolio sizes. Reasons for this could be that the two-factor regression uses data from the whole time period (January 1983 to January 2020) while the three-factor model only uses data from July 1990 to October 2018. From tables 2, 3, 4, and 5, it is evident that the years 1983-1990 are the best performing years for the strategy, hence the omission of these years in the three-factor regression may be hindering results slightly by generating smaller alphas and in turn smaller portfolios experience insignificant results. These findings are also reinforced by the paper from Blitz (2020). The author finds that in global markets excluding the US, the value factor generates negative returns in the years 2010-2019. The findings in table 6 are also consistent with those of Foltice and Langer (2015). Both the papers find slightly higher alphas in the three-factor model regression in comparison to the CAPM. It should however be noted that Foltice and Langer (2015) use net momentum returns and test several overlapping periods, while this paper only uses gross momentum returns. Siganos (2010) also finds the alphas in his two-factor model (market and book-to-market) to be marginally higher compared to the alphas in his CAPM model.

The results gross momentum returns in this paper also suggest that smaller portfolios have very large standard deviations, implying highly volatile returns. This in turn means returns in these portfolio sizes often are not significantly outperforming the AEX index. Larger portfolio sizes on the other hand (15 to 25-stock portfolios) have much lower standard deviations, nearly on par with the AEX index, and the returns of these portfolios in each respective strategy significantly outperform the AEX index either at the 5% level or even at the 1% level. As the portfolio size grows, the correlation of the portfolio with the index is likely to increase. This comes as no surprise due particularly to the smaller number of stocks available on the market in the Netherlands. However, as the correlation increases, one may expect that it becomes more challenging for the momentum portfolio to outperform the benchmark. The results in this paper go against this reasoning and the returns of the portfolios are often larger as the portfolio size increases (with the exception of the (6,6) strategy. If a retail investor were to adopt the 'winners only' strategy, the findings of this paper would suggest the investor to employ at the minimum the 9-stock portfolio. This gives the investor a minimum amount of diversification in their portfolio and reduces the volatility sufficiently to be approximately in line with the AEX index. Furthermore, gross returns at the 9-stock portfolio are significant at the 1% level for the (6,6), (6,12), and (12,6) strategies, and significant at the 10% level for the (12,12) strategy. As well as this, at the 9-stock portfolio size, all strategies are robust to the three-factor model at the 1% level for the (6,6) and (12,6) strategies, and at the 5% level for the (12,12) and (6,12) strategies.

6.2 Trading Costs

In order to test the practicality of implementing the trading strategy in this paper, trading costs have to be accounted for.

In order to minimise hypothetical transaction costs, the online broker DEGIRO is selected to account for all trading costs. Based on the documentation from their website, trading costs are assumed to be fixed at €2+0.02% per transaction[2]. If the strategy were to be implemented by a retail investor, minimising fixed costs plays an important role in executing the trades. For example, if an investor were to use overlapping portfolios for the (6,6) strategy, this would in turn require an investor to rebalance one-sixth of the portfolio each month, increasing fixed costs substantially. Therefore, for the purposes of this brief analysis, non-overlapping periods are considered to minimise the number of transactions, and in turn fixed costs. This assumes that an investor will hold only one portfolio at any given point in time, hence for the (6,6) and

[2]Retrieved from: https://www.degiro.nl/data/pdf/prof feeschedule.pdf

(12,6) strategy, an investor would have to trade twice a year, while for the (12,12) and (6,12) strategy, an investor would only trade once a year. Furthermore, the analysis uses the returns of the 25-stock portfolio as it requires the largest number of transactions.

The average annualised return for the (6,6) strategy was calculated to be approximately 16.34%. Assuming the investor chooses the use the strategy twice a year, there would be 100 different transactions per year. If every transaction costs €2+0.02%, 100 transactions will cost €200+2%. In this case, the minimum investment required to break-even is approximately €1,500. Similarly, a (12,6) strategy will also require the same amount of transactions. The (12,6) strategy generates an average annualised return of 17.14%. To break-even, an investor would need approximately €1,415.

For the (12,12) strategy, the average annualised return was approximately 14.14%. An investor would only need to invest once a year, amounting to 50 transactions. This implies trading costs sum up to €100+1.5%. In order to break-even, an investor needs approximately €792. The (6,12) would also only require 50 transactions per year. The (6,12) strategy generates an average annualised return of approximately 15.23%. To implement this strategy, an investor requires €729 to break-even.

Naturally, this analysis does not give a clear enough indication on what the profitability of the strategy would be if applied in the real world. Bid-ask spreads are not taken into account and only one investment period is used. The returns used to calculate the break-even amount assumed overlapping periods, meaning the annualised returns would be slightly inflated than what is to be expected. Using non-overlapping periods also means exposure to the momentum factor nearing the end of the holding period is minimal, requiring portfolios to be rebalanced to maintain momentum exposure. Furthermore, the analysis assumes full turnover of all stocks. If some stocks persist as 'winners' in consecutive periods, real turnover may be more indicative of the costs. Nevertheless, this provides general insight into a hypothetical situation where transactions would have to be accounted for.

On the other hand, from an institutional investor's persective, fixed costs would not be such a big concern. A €2 cost for a €1 billion portfolio becomes insignificant. However, what would be important is how much a portfolio outperforms the bid-ask spread. If the (6,6) strategy generates an average annualised return of 16.34%, and the AEX index generates an average annualised return of 10.33%, this means the strategy would outperform the market by 6.01 percentage points. By investing in the strategy 12 times a year, meaning the strategy gets bought and rebalanced once a month, the strategy has to outperform the bid-ask spread by approximately 0.50%. Using the same line of reasoning for the (12,12), (6,12) and (12,6) strategies, outperformance of the bid-ask spread would have to be 0.32%, 0.41%, and 0.57% for each respective strategy. This reasoning should however be taken with some caution. Trading costs are often some of the largest for institutional investors. Having to consistently trade with large amounts of money, the market impact of a trade may hinder the potential gains to be made on the strategy. By purchasing a stock, the price of a stock is materially increased, meaning there are less gains to be made in the future. This is often the case for thinly traded stocks where the natural price is impacted. This could raise potential issues if these are the types of stocks that emerge as ‘winners’ based on the strategy.

7 Conclusion

7.1 Conclusion to the Research Question

The persistence of the momentum anomaly coupled with the vast amount of literature in momentum investing over the past few decades, has made it unquestionable that conventional momentum strategies are profitable across various asset classes. This paper approaches the anomaly from a different angle, attempting to answer the research question: *Can investors exploit a 'winners only' momentum trading strategy in the Netherlands?*

This thesis analysed all stocks on the Dutch market with a market capitalisation greater than €20 million from January 1983 to January 2020. Unlike most other papers, this paper looks exclusively at 'winner' stocks, and sorts portfolios on the best 1-25 stocks rather than deciles or quintiles. This paper also provides a much longer time frame relative to other papers testing similar strategies, giving nearly 40 years of perspective. The paper tested four different strategies namely the (6,6), (12,12), (6,12), and (12,6) strategies. All four strategies experienced statistically significant results. At the 5% significance level, the outperformance of the benchmark came from the 2-stock portfolio and higher for the (6,6) strategy, the 10-stock portfolio and higher for the (12,12) strategy, the 5-stock portfolio and higher for the (6,12) strategy, and the 3-stock portfolio and higher for the (12,6) strategy. Two regressions were then performed to see whether the strategies were robust to systematic risk factors. The first regression used the CAPM, while the second used the Fama and French (1996) three-factor model. All four strategies experienced significant results in both regressions with significant results seen mainly in the larger portfolio sizes. The only exception to this was the (6,6) strategy which had larger alphas in smaller portfolio sizes. As well as this, the alphas of the CAPM regression were smaller than those of the three-factor regression, with potential explanations coming from the negative value factor particularly between 2010-2018.

The general consensus found in this paper agrees with prior literature that a 'winners only' momentum strategy paired with portfolios selected on the best 1-25 stocks can be exploited. Generally if a retail investor were to adopt this strategy, the findings of this paper would suggest the investor to employ at the minimum the 9-stock portfolio. This gives the investor a minimum amount of diversification in their portfolio and reduces the volatility sufficiently to avoid extreme peaks and troughs in returns.

7.2 Limitations and Suggestions for Future Research

There are several limitations in this paper that need to be addressed. Firstly, this paper does not account for transaction costs. This is due to the lack of reliable and consistent data on the bid and ask prices on the Dutch stock market, primarily in the earlier years analysed. Nevertheless, a general analysis on the minimum amount required to break-even is presented in section 6. However, implementing transaction costs is a critical element into exploring the feasibility of different momentum strategies, and this paper serves only as a starting point for future research into the implementation of the strategy.

A second limitation of the paper is that the strategy returns are only compared to the AEX index. Another indicative comparison could have been against an equally weighted index composed of all stocks on the Dutch market. This may have been a tougher benchmark to beat but may have provided more insight into the driving factors of the momentum returns.

Another limitation of the paper is the analysis of only cross-sectional momentum strategies. Taking into consideration time-series momentum may provide different insight into the strategies and add more significance to the analysis.

A final limitation of the paper is the use of overlapping test periods. Though this increases the power of the tests, it does not provide a realistic expectation of what investors could generate when implementing the strategy. A suggestion for future research could be to use varying trading frequencies paired with different initial investment amounts to see which would maximize returns.

Another suggestion for future research would be to look at the 'winners only' momentum strategy in Europe. In this day and age, investors are not limited to only one market, accessibility to international markets could potentially make the strategy even stronger due to the larger amount of stocks available. The strategy could also explore 'loser stocks' as the paper from (Siganos, 2010) finds momentum profits to largely be driven shorting prior losers. Furthermore, as could be seen from the results of the paper, the momentum strategy proposed appeared to generate negative returns in bear markets. Reinforced by the findings of Daniel and Moskowitz (2016), implementing a dynamically weighted momentum strategy could improve the returns of the strategy.

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A Appendix

The 25-stock portfolio for the (6,6) strategy					
Panel A - CAPM	α_i	β_i			R^2
Coefficient	0.412	0.798			0.718
Test statistic	(2.71)	(29.30)			
Panel B - 3-factor model	α_i	β_i	s_i	h_i	R^2
Coefficient	0.480	0.910	0.514	-0.026	0.811
Test statistic	(3.83)	(37.64)	(12.83)	(-0.83)	

Table 7: *The 25-stock portfolio regression results for the (6,6) strategy. Panel A shows the values of each coefficient in the CAPM regression given by the by the equation:* $R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \epsilon_i$. *Panel B shows the values of each coefficient in the Fama and French (1996) 3-factor model regression given by the equation:* $R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB + h_i HML + \epsilon_i$.

Panel A: Alpha (%) - CAPM													
Portfolio size	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**15**	**20**	**25**
(6,6)	0.581	0.544*	0.658***	0.624***	0.656***	0.656***	0.636***	0.603***	0.596***	0.584***	0.563***	0.532***	0.563***
(12,12)	-0.161	0.034	0.198	0.239	0.272	0.308	0.338*	0.381**	0.394**	0.415**	0.458***	0.441***	0.444***
(6,12)	0.265	0.193	0.374*	0.419**	0.399**	0.426**	0.444**	0.447***	0.441***	0.452***	0.462***	0.451***	0.481***
(12,6)	0.137	0.308	0.544*	0.622**	0.689***	0.721***	0.711***	0.755***	0.768***	0.743***	0.753***	0.727***	0.678***
Panel B: Alpha (%) - three-factor model													
Portfolio size	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**15**	**20**	**25**
(6,6)	0.584	0.550*	0.663***	0.628***	0.660***	0.661***	0.641***	0.607***	0.601***	0.588***	0.566***	0.536***	0.566***
(12,12)	-0.148	0.044	0.207	0.246	0.279	0.314	0.344*	0.387**	0.399**	0.420**	0.462***	0.445***	0.447***
(6,12)	0.279	0.206	0.384*	0.428**	0.406**	0.434**	0.451**	0.454***	0.448***	0.459**	0.468***	0.457***	0.486***
(12,6)	0.146	0.316	0.550**	0.627**	0.693***	0.724***	0.714***	0.757***	0.770***	0.746***	0.754***	0.728***	0.680***

* Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level

Table 8: *The results from the four strategies are regressed against risk-factors to test the robustness of the findings. The results are tested throughout the entire time period. Panel A shows the average alpha captured by the CAPM regression given by the equation:* $R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \epsilon_i$. *Panel B shows the average alpha captured by an adjusted two-factor model (market and value factors) regression given by the equation:* $R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + h_i HML + \epsilon_i$.