

ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Master Specialisation Financial Economics

Master Thesis

Do Several Forms of Momentum Anomalies in the US Still Exist?

Abstract

Investigating monthly US data from January 1965 to March 2017 we find that the best possible asset pricing model consists of the Fama and French three-factor model with the momentum factor, the short-term reversal factor and the long-term reversal factor. We draw this conclusion based on several tests of model performances. These tests also show that single-sorted portfolios performed better than double-sorted portfolios for the period investigated in the US. For the momentum and reversal factors we find that the factors are only significant if they correspond with some single-sorted dependent variables. This means that the model only works for particular sorts of portfolios.

Keywords — Asset Pricing, CAPM, Momentum Anomalies, GRS

JEL Classification — G10, G11, G12, G31, G41

Author: L.H.C. Tan
Student number: 362064
Thesis Supervisor: Dr. J.J.G. Lemmen
Second reader: Dr. A. Breaban
Finish Date: 16-01-2020

Preface and Acknowledgements

I would like to thank my supervisors M. Montone and J.J.G. Lemmen for helping me with this thesis.

NON-PLAGIARISM STATEMENT

By submitting this thesis the author declares to have written this thesis completely by himself/herself, and not to have used sources or resources other than the ones mentioned. All sources used, quotes and citations that were literally taken from publications, or that were in close accordance with the meaning of those publications, are indicated as such.

COPYRIGHT STATEMENT

The author has copyright of this thesis, but also acknowledges the intellectual copyright of contributions made by the thesis supervisor, which may include important research ideas and data. Author and thesis supervisor will have made clear agreements about issues such as confidentiality.

Electronic versions of the thesis are in principle available for inclusion in any EUR thesis database and repository, such as the Master Thesis Repository of the Erasmus University Rotterdam

Contents

Abstract	
Preface and Acknowledgements	
Contents	
List of Tables	4
I Introduction	5
II Literature Review	10
2.1 CAPM.....	10
2.2 Three Factor Model	11
2.3 Momentum	13
2.4 Momentum Reversals.....	15
2.5 Model Performances	18
III Data	19
3.1 Factor formation.....	19
CAPM.....	20
Size Factor	20
Value Factor.....	21
Momentum Factor	21
Short-term Reversal Factor	22
Long-term Reversal Factor	22
3.2 Dependent variable portfolio formation	23
IV Methodology	33
4.1 Model Performance.....	33
4.2 Regression analysis	34
V Results	36
5.1 Model Performance.....	36
5.2 Regression Details.....	43
VI Conclusion & Limitations.....	50
References	53
Tables	57
Appendix.....	68

List of Tables

Table 1 - Construction of Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal factors.....	23
Table 2 - Average monthly excess returns for portfolios formed on Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal	26
Table 3 - Summary statistics for monthly factor returns.....	30
Table 4 - Correlation Matrices.....	31
Table 5 - Summary statistics for tests of four-, five- and six-factor models.....	41
Table 6 - Regressions for 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios	46

I Introduction

It was generally believed that securities markets were extremely efficient in reflecting information about individual stocks. The accepted view was that as soon as information arises, the news spread so quickly that all the information is incorporated into the prices of securities without delay (Malkiel, 2003). This so called efficient-market hypothesis (EMH) states that stocks always trade at their fair value on stock exchanges. Fair value means that the market price of the stock is equal to the fundamental price of the stock, which basically states that future prices cannot be predicted by analyzing prices from the past (Fama, 1970). However, there is much evidence that asset pricing models can describe stock returns. It all started with the capital asset pricing model (CAPM) of William Sharpe (1964) and John Lintner (1965). CAPM often is the only asset pricing model taught in courses (Fama & French, 2003). An asset pricing model that expands on the CAPM by adding size and value factor to the market risk factor is the Fama and French three-factor model. In the modern financial world, it is widely accepted that the three-factor model of Fama and French (1992) has made a huge contribution to the development of the prediction of stock returns. Even today, many firms use the asset pricing model derived from Fama and French. Eugene Fama and Kenneth French found that value stocks outperform growth stocks. Similarly, small-cap stocks tend to outperform large-cap stocks. In 2015 Fama and French extended their own three-factor model to five. They added a profitability and an investment factor. Where the profitability factor is defined as the difference between stock returns on diversified portfolios on robust minus weak profitability. And the investment factor is the difference between the returns on diversified portfolios of stocks of low minus high investment firms. They also found that the addition of the two factors resulted into the value factor being redundant for describing average returns in their sample. The new model still ignores momentum, while this factor is widely accepted within academia and has been around for more than twenty years. However this model still ignores momentum, while this factor is widely accepted within academia and has been around for more than twenty years. The same Fama that claimed that analyzing historical prices cannot predict future prices (1970) found that momentum appears to be the strongest and most pervasive anomaly (Fama

and French, 2008). In 1997 Carhart constructed a four-factor model which was an extension of the three-factor model of Fama and French (1993). The four-factor model included an additional factor capturing Jegadeesh and Titman's (1993) one-year momentum anomaly. The momentum effect is a popular return predictor which is nothing more than a stock's recent performance history. There is a vast academic literature documenting the success of momentum strategies both in the US and globally (Griffin, Ji and Martin, 2005). Although the evidence favors the profitability of momentum strategies, some studies do not support this phenomenon or even find contrary evidence. In 2001 Liu and Lee document price reversal rather than price momentum in the Japanese stock market from 1975 to 1997. In 2000 Lee and Swaminathan show that trading volume is a useful variable in technical analysis as it provides information about continuations in reversals in returns. For example, Chan et al. (2000) show that price momentum for international stock market indices is stronger after a rise in volume turnover. In their sample of NYSE and AMEX stocks from 1965 to 1995, Lee and Swaminathan (2000) find that high volume winners and low volume losers experience faster reversals. They also find that price momentum is stronger among high volume stocks, but low volume stocks tend to outperform high volume stocks once controlled for price momentum. In 2008 Ji confirms the positive relation between trading volume and momentum profitability in his sample of 40 countries between 1962 and 2000. In contrast to Lee and Swaminathan (2000), Jiang et al. (2008) found that high-volume stocks earn significantly higher returns than low-volume stocks over the 30 trading days after portfolio creation in the Chinese stock market from 1997 to 2005. Another test of the relation between trading volume and price momentum is conducted by Drew et al. (2007) for the Australian stock market. Similar to Lee and Swaminathan (2000), for portfolios based on three and six month returns, price momentum is stronger among high volume stocks. However, for portfolios based on nine and twelve month returns, price momentum is stronger among low volume stocks. Price overreactions are defined by the notion that investors are subject to waves of optimism (and pessimism) and thus create momentum that causes prices to temporarily swing away from their fundamental values [see, e.g., DeBondt and Thaler (1985, 1987), Poterba and Summers (1988)]. Investor overconfidence about private signals causes stock price overreaction, whereas investors underestimate public

signals. In addition, biased self-attribution increases investors' confidence even further since confirming new public information is too strongly attributed to investors' own ability, which stimulates the initial overreaction and thus leads to short-run momentum. Prices eventually revert to fundamentals as warranted by the public information. This overreaction view is consistent with De Long et al. (1990a) who argue that the positive feedback trading strategies followed by noise traders can lead to overreaction. Since rational speculators anticipate the noise traders' positive feedback reaction to news, the price change in response to news is temporarily bigger than is justified by the news itself. In line with findings of many studies over the past several years, it is safe to say that stock returns appear to find (reverse-) momentum in the short, medium and long run (Cakici and Topyan, 2014). The momentum anomaly is an empirically observed trend for stocks that performed well in the past to keep outperforming the stock market and stocks that performed poorly to underperform compared to the market. Two of the most prominent financial market anomalies are momentum and reversal (Vayanos and Woolley, 2013). Several researchers have also found short-term return reversals of momentum in the stock market. This phenomenon has been shown to be robust and economically significant for more than 40 years Fama (1965). In line with business accounting measures we classify a period of time of less than 12 months as short-term, where a period of time larger than 12 months is classified as long-term. A short-term reversal is defined as a time series momentum strategy where you buy last weeks (or month) losing stocks and sell last week's winning stocks. Where the exact opposite happens for a short-term momentum strategy; i.e. buy last week's winning stocks and sell last week's losing stocks.

In 1990 Jegadeesh, for example, found a significant return of approximately 2% per month between 1934-1987 using the reversal strategy that buys losing stocks and sells winning stocks of the last month and holds them for one month. Possible explanations for short-term reversal profits have received a lot of attention in prior literature Shiller (1984), Black (1986), Chordia et al. (2005) and Summers and Summers (1989) example claim that these reversal profits show that market prices may reflect investors' overreaction to information. Economists label this as the sentiment-based explanation. Another explanation by Grossman and Miller (1988),

Jegadeesh and Titman (1995) is based on the price pressure that occurs when short-term demand curve of a stock is downward sloping while the supply curve is upward sloping. A similar phenomenon to the short-term reversal anomaly is the long-term reversal anomaly. DeBondt and Thaler (1985) were one of the first who document return reversals over relatively longer horizons. Losing firms over the past three- to five- years earn higher average returns than firms that were winning throughout the same period. Regarding to stocks, Jegadeesh and Titman (1993) also found that return performance of momentum strategies tends to be negative, on average, over the past 13 to 60 months. What causes these effects is still a matter of debate. Several researchers have claimed that the effect occurs due to mispricing. In short, profits due to momentum strategies have generated consistently positive returns throughout most of the 20th century. However, little research has been conducted about these phenomena combined with the Fama and French three-factor model in the past twenty years. The purpose of this study is to identify whether the momentum anomaly in the United States still exist. Therefore, the research question I will try to answer is:

“Do various forms of momentum anomalies in the United States still exist?”

Answering this research question will provide more empirical evidence on the momentum effect in combination with the existent three-factor model. A topic that is relevant not only for academic studies, but it might also be useful for practitioners of the subject. The goal of this paper is to look if several forms of momentum anomalies improve the three-factor model. Prior studies have shown that adding variables cause problems for the three-factor factor, so it is normal to ask why we choose various momentum factors to augment the model. The answer is that findings of Carhart (1997) helped to the investigation of portfolio or individual stock performance, although this model was initially formed to find persistence in mutual fund performance. The purpose of this study is to get a more in depth look at the added value of momentum factors in asset pricing models. To the best of my knowledge, no other study has tried to detect the momentum anomalies in the United States over recent years. Moreover, also no research has combined the Fama and French three-factor model with reversal factors.

With help of various model performance predictors we desire to detect which form of asset pricing model works best for our research. We run these tests for both our dependent as independent variables to eventually show most representative results of our data. We find that the best possible asset pricing model consists of the Fama and French three-factor model with momentum factor, short-term reversal factor and the long-term reversal factor. We draw this conclusion based on several tests of model performances. These tests also show that single-sorted portfolios were more representative than double-sorted portfolios for the period investigated in the US. For the momentum and reversal factors we find that the factors are mainly significant if they correspond with the single-sorted dependent variable. This means that the model only works for particular sorts of portfolios.

The remainder of the paper is organized as follows, Section 2 will cover existing literature about the Factor models and the momentum anomalies. Furthermore, it describes which method will be used to test the model performances. Section 3 provides information about the data & methodology that is used to answer the research question. It goes in depth about how the factors and portfolios are formed. In Chapter 4 we discuss the results of which model performs best based on the gathered data. The best performing model is used to gather results in order to accurately answer the research question. Finally, Chapter 5 will conclude and show limitations of my research. It will also recommend possible ideas for future research. After Chapter 5 a summary of all the tables will be presented. For convenient purposes all the Tables will also be shown throughout the text.

II Literature Review

Standard asset pricing models work forward, from assumptions about investor preferences and portfolio opportunities to predictions about how risk should be measured and the relation between risk and expected return. Whereas, empirical asset pricing models work backward they analyze the patterns in average returns, and propose models to capture them. This section presents a literature overview that concerns the topic of this paper. First, we will look at the studies of the beginning of the empirical asset pricing models, which can be tracked back to the CAPM of William Sharpe in 1964. Second, we will elaborate on the phenomenon called the momentum anomaly. This paper will extend the Fama and French three-factor model by adding different forms of this anomaly. The most widely recognized anomalies are the size, book-to-market and the momentum anomaly. Hence these anomalies are the core factors of the asset pricing model we desire to construct. The development of the field of asset pricing developed along the way and even today researchers are trying to find ways to improve the models by extending the existent one. We will do that by adding reversal factors to Carhart's four-factor model. By investigating how these factors work combined with the existing model we desire to find a model that captures more variation of stock returns than the current existing models.

2.1 CAPM

The capital asset pricing model (CAPM) of William Sharpe (1964) and John Lintner (1965) marks the birth of asset pricing theory. The attraction of the CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk (Fama and French, 2003). The following formula expresses the CAPM,

$$E(R_i) = R_f + \beta_i \cdot E(R_m - R_f) + e_{it}$$

where $E(R_i)$ is the expected return on any asset i , the risk-free interest rate R_f represents the constant of this formula, the market beta (systematic risk) β_i is the covariance of the return of asset i divided by the variance of the market return $\beta_i = \frac{Cov(R_m, R_i)}{Var(\sigma_m^2)}$. Since the market beta of

asset i represents the slope of the excess return on the market, a correct interpretation of beta is that it measures the sensitivity of the asset's return to variation in the market return. This means that a beta of 1 indicates that stock prices perfectly correlate with the market. A beta lower than 1 indicates that stocks are relatively less volatile than the market. A beta higher than 1 means that stock prices are more volatile than the market. If the CAPM holds, then, average stock return patterns should be explained by the equation. Whenever stock returns cannot be explained by the model, they are classified as anomalies. Due to several assumptions the CAPM fails to explain stock returns in many samples. It assumes that investors seek return tempered by risk, can borrow and lend at a risk-free rate and the model neglects market frictions such as transaction costs, taxes, or short-sell restrictions. Despite the sometimes-unrealistic assumptions, it has been, and still is, a widely accepted model for estimating an asset's required rate of return. To construct our asset pricing model we use CAPM as the basis of our model.

2.2 Three Factor Model

In 1981 Banz examined the empirical relationship between return and the total market value of NYSE common stocks. He found a negative correlation between average returns of stocks and firm size. Relatively smaller firms quoted on the NYSE between 1926 and 1975 showed higher risk adjusted returns, on average, than larger firms. This so called 'size effect' has been around the financial world for forty years and provides evidence of the misspecifications of the CAPM. Further research into this 'size effect' led to the statement of Fama and French (1993) that this can be a result of smaller firms being exposed to higher betas. Investigating several other empirical determinants as leverage, earnings-to-price (E/P) and book-to-market equity (B/M) resulted into the discovery of the 'value effect'. The effect can be explained as the phenomenon, where stocks of firms with a relatively high ratio of book value of equity to market value of equity outperform stocks of firms with a relatively low book-to-market ratio price (DeBondt and Thaler, 1985; Lakonishok, Shleifer, and Vishny, 1994). In other words: value stocks outperform growth stocks. Fama and French (1992, 1993, 1996) state that several anomalies under the CAPM framework disappear when adding these two additional factors (size and value). Their sample included data from non-financial firms listed on the NYSE, AMEX

and NASDAQ between 1962 and 1991. This resulted into the introduction of a three-factor model which incorporates the additional two factors. In this model, the expected return of the asset depends on the sensitivity of its return to the market (beta) and the return on two portfolios which mimic the two additional risk factors. The three-factor model is constructed the following way:

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + e_{it}$$

where α_i represents the intercept which desirably shows a value of (or close to) zero. The regression coefficients b_i, s_i and h_i reflect sensitivities of returns on asset i to the risk factor mimicking portfolio returns. Note that the coefficient b_i simply represents the CAPM beta. The market risk premium is formulated as $(R_{Mt} - R_{ft})$. SMB_t is the difference between the returns on diversified portfolios of small stocks and big stocks, and HML_t is the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. In addition, the SMB factor represents the returns of a portfolio holding a long position in relatively small firms and a short position in relatively larger firms. Similarly, the HML factor represents the returns of a portfolio of stocks that goes long in firms with high B/M ratios and short low B/M stocks. However, the abnormal returns obtained by these models are potentially driven by a so called “bad-model problem”. For example, when the CAPM fails to explain expected returns on small companies, the Fama and French three-factor model could successfully explain the returns depending on the sample. Fama (1998) also pointed out that many researchers use equally-weighted returns when conducting their analyses. However, a vast amount of the anomalies occur around small companies, he shows that using equally-weighted data instead of value-weighted returns overstates the occurrence of potential abnormal returns. Due to the use of value-weighted returns the appearance of abnormal returns fades away. In short, aforementioned analyzed anomalies after adjusting the underlying methodologies. By adding these factors to the CAPM we now form a basis of three factors we use for our asset pricing model.

2.3 Momentum

One of few anomalies that still exists despite changes in methodology and out-of-sample tests, according to Fama (1998), is the continuation of returns called momentum. In finance momentum is defined as the rate of change on price movements for particular assets – that is, the speed at which the price is changing. We distinguish two types of momentum trading strategies. Positive-feedback trading strategy is one with which an investor buys past winners and sells past losers. In contrast, a negative-feedback (or contrarian) trading strategy does the exact opposite: an investor buys past losers and sells past winners. Throughout the years several portfolio managers and stock analysts found that momentum strategies provide significant profits. This phenomenon was addressed by Fama and French (1996) as the ‘main embarrassment of the three-factor model’. Jegadeesh and Titman (1993) even argue that the momentum effect represents the strongest evidence against the Efficient Markets Hypothesis (EMH). One of the reasons that this effect occurs is the irrationality of investors who underemphasize short-term news while they overreact on earlier news. It can also be a result of confirmation bias, where investors overemphasize the news which supports their view in the potential of an investment. In 1989 Grinblatt and Titman found that huge numbers of successful mutual funds appear to have a preference for stocks of which the price has risen in the previous quarter. The occurrence that the best- and worst-performing stocks of the past three to twelve months continue to realize, respectively, high and low returns over the next three to twelve months, is called price momentum. Between 1965 and 1985 Jegadeesh and Titman (1993) found abnormal returns in the U.S. for an investment strategy of roughly 1% per month. In a follow-up study, Jegadeesh and Titman (2001) found that the performance of momentum strategies in the U.S. continued to exist from 1990 to 1998 and was about the same size as in the prior investigated period. Grundy and Martin (2001) showed that the high returns could not be explained by the three-factor model of Fama and French (1996) in case the dynamics of the factor betas of the momentum strategy were taken into account. In 1997 Carhart came with a four-factor model which was an extension of the three-factor model of Fama and French (1993). The four-factor model included an additional factor capturing Jegadeesh and Titman’s (1993) one-year momentum anomaly. Results of Carhart indicate that

the four-factor model performs better than the CAPM in explaining mutual fund returns. Although this model was initially formed to find persistence in mutual fund performance, it can also be used to explain portfolio or individual stock performance. Between 1963 and 1993 buying the top ten percent mutual funds of last year and shorting the bottom ten percent yields an average return of 8 percent per year. Of this percentage, the momentum effect explains around 4.6 percent. These findings are in line with the momentum effect in U.S. stock returns found by Jegadeesh and Titman (1993). Investigating a period from 1962 to 2000, Connolly and Stivers (2005) find substantial momentum on equity indices, index future and individual stocks in the US, Japan and UK. They found momentum effects on weekly stock returns when the past week had an abnormally high turnover. While substantial reversals occurred, in consecutive weekly returns when the past week has abnormally low turnover. They imply that funds performed well last year are expected to show positive returns the next year and that one should avoid funds that persistently underperform. One of the possible explanations is that momentum patterns occur is that it can result from extrapolative expectations about prices, from stop-loss orders. This phenomenon is described as automatically selling when the price falls below a certain threshold and buying when it exceeds a certain threshold. Whenever investors sell when the market is declining and buy when it is rising is an example of the aggregate effects of positive feedback. In other words, positive feedback trading is one of the main reasons that market declines often lead to further market declines, while increases often lead to further increases, rather than returning to their “normal” level. We expect that portfolios underperform during the financial crisis. We also expect that the momentum phenomena disappears. However, investigating recessionary and non-recessionary periods from 1962 to 2005 Arshanapalli et al. (2006) that the momentum strategy performs well under all economic conditions. More recently, in 2012 Fama and French investigated size, value and momentum in international stock returns in North America, Europe, Japan and Asia Pacific. They found strong momentum returns in all regions except for Japan, which is in line with prior studies. In 2010 Chui, Titman, and Wei confirmed the absence of momentum returns in Japan due to low individualism. In line with Carhart’s 1997 model we add the momentum factor to our three-factor model.

2.4 Momentum Reversals

In the past years, numerous researchers have shown evidence that cross-sectional stock returns are predictably based on past returns. Two of the most prominent financial market anomalies are momentum and reversal (Vayanos and Wooley, 2013). Several economists use different time horizons to determine what they consider as short-term. In line with business accounting measures we classify a period of time of less than 12 months as short-term, where a period of time larger than 12 months is classified as long-term. The reversal variable for each stock in month t is defined as the return of the same stock over the previous month.

Over time economists like Bachelier & Cootner (1964) and Fama (1965) have been aware that individual stock returns tend to show negative serial correlation over short horizons. By investigating daily observations of equity securities listed on the New York and American Stock Exchanges on CRSP from 1962 to 1990 Lehman (1990) finds that portfolios of securities that had positive returns in one week typically had negative returns in the next week, while those with negative returns in one week showed positive returns in the next week. Research by Jegadeesh (1990) finds that these contrarian strategies on the NYSE from 1963 to 1979 showed return reversals of about 2% per month. Jegadeesh (1990) sorted portfolios based on lagged-returns regression predictions as well as previous 1 to 12 months performance, while Lehman (1990) used a relative-weight contrarian sorting technique to study 1-week reversals. They both found statically significant short-term mean reversion. At the same time Jegadeesh (1990) initially found the hypothetical short-horizon reversal profits to be stronger in magnitude than the well-known momentum. The notable paper by Wang and Yu (2004) was the pioneer that investigated short horizon contrarian profits in futures (financial and non-financial) by using the ranking methodology of long/short weight by Lehmann (1990). They found strong one-week return reversals. However, they found no similar effect for longer horizons. The magnitude seems mostly to be explained by lagged change of open interest and trading volume. Open interest is the total number of outstanding unsettled derivative contracts. Therefore, short-term reversal momentum can occur due to the fact that certain transactions have not been

finalized yet. Open interest is sometimes confused with trading volume, but the two terms represent different measures. If a trader who holds an option contract decides to sell it to a new trader entering the market, the amount of option contracts in the market remains unchanged. While the trading volume rises, n is now $n+1$. Another research was done by Bremer and Sweeney (1991) who analyzed significant daily stock price declines of large companies. Even after controlling for some additional liquidity issues their findings confirmed that the abnormal returns were positive in the first couple of days following a large negative one-day return. Bremer and Sweeney define negative returns of a minimum of 10% as a large negative event. They found that the return after a 10% fall were followed by a significantly positive average returns of 2% on following days. Aside from these articles there does not seem to be a lot of existing literature which studies short horizon reversals of stocks. In 1985 De Bondt and Thaler pointed out that empirical studies on individual choice behavior provided clear indications for the existence of an overreaction to information. They gathered monthly data of NYSE stocks on CRSP for the period between January 1926 and December 1982. Consistent with the predictions of the overreaction hypothesis, portfolios of losers are found to outperform winners. Three years after the formation, losing stocks tend to gain about 25% more than the winners. The effect still occurred as late as five years after portfolio formation. However several aspects of these findings remain without adequate explanation. For example, the large positive excess returns earned by the losing portfolio were mostly found in January. Also they did not implement the possible effects of transaction costs. Whenever a one buys/sell stocks they have to pay transactions costs. Therefore constantly rebalancing your portfolio results in more costs.

In line with De Bondt and Thaler (1995), Chopra, Lakonishok and Ritter (1992) find long-term reversal in cross-sectional stock returns over 1- to 5-year horizons. Jegadeesh and Titman (1993) found that return performance of momentum strategies to be negative, on average, over the months 13 up to 60. However, they also find that during the period of 1965 to 1981, the evidence of return reversals is substantially weaker in the 1982 to 1998 period. This is noteworthy because there is no distinguishable difference between either the magnitude or the

significance of the momentum profits in the two subperiods. In 1999 Hong and Stein found that Market prices show short-term momentum and long-term reversal, because uninformed traders act as trend-chasers, causing prices to overreact to information, and then reverse that overreaction. According to Vayanos and Wooley (2013) momentum and reversal are viewed as anomalies because they are hard to explain within the standard asset-pricing paradigm with a rational representative agent. The prevalent explanations of these phenomena are behavioral. In their paper they show that momentum and reversal can result from flows between investment funds in markets. Lee and Swaminathan (2000) show that the price momentum effect reported by Jegadeesh and Titman (1993) eventually reverses and that the timing of this reversal can be predicted based on past trading volume. They show that it is possible to create Jegadeesh and Titman-type momentum portfolios that exhibit long-horizon return reversals of the type first documented by DeBondt and Thaler (1985). This finding represents an important conceptual shift in the literature. Previous researchers have generally viewed intermediate-horizon momentum and long-horizon price reversal as two separate phenomena. Our results show that trading volume provides an important link between these two effects. In 2008 Du shows that long-term reversals occur when past performance is measured based on nearness to the 52-week high in international stock markets. So, the initial underreaction is followed by an overreaction in the adjustment process that results into long-term reversal.

Institutions like Pension funds, SWFs etc. have the tendency to pick recent winners when they decide to deviate from an index. These incentives to chase relative returns can lead to an overreaction, which is supported by the examined trading behavior of institutions and the long-run reversal of relative-return momentum that only occurs for the most bought winner stocks and the most sold loser stocks. Some researchers looked into behavioral theories suggesting that investor psychological biases in the reaction to information may be causing systematic underreaction, resulting in the continuation of short-term returns. However they also found that the persistence of momentum returns long after the anomaly has been widely disseminated. This suggests that behavioral theories may not provide the full picture.

Chordia & Shivakumar (2002) show that profits to momentum strategies are explained by a parsimonious set of macroeconomic variables that are related to the business cycle.

2.5 Model Performances

More recently, Fama and French (2015) extended the three-factor model by two factors creating a five-factor model that incorporates profitability and investment (hence, drops momentum). They found that on average, firms with robust profitability generate significantly higher returns than firms with weak profitability. The mathematical methodology behind the two factors will not be discussed in this paper. However, it is interesting to pay attention to the method of comparing model performances Fama and French use. To test whether their five-factor model can better explain average stock returns compared to their previous three-factor model they examine the alpha of both models and the Gibbons, Ross, and Schanken (1989) (hereafter: GRS) statistics. The F-test of GRS checks the hypothesis whether intercepts are jointly equal to zero. If intercepts of a regression are statistically significantly equal to zero then the factors included in the model capture all the variation in stock returns and the model is a good predictor of its asset performance. If the intercepts statistically significantly differ from zero it means that some risk factors have been omitted and the model is incomplete. This paper will elaborate on the GRS test in the section of model performance. In line with Fama and French (2015) the GRS test will be an important indicator of model performance in the remainder of the thesis. Another measure of model performance we look at is the adjusted R-squared. The adjusted R-squared is a modified version of the R-squared that has been adjusted for the numbers of explanatory variables in the model. The higher the value of the adjusted R-squared the better our independent variables explain the dependent variable. This also means that omitted variable bias decreases. Thirdly, we look at the average absolute intercept represented by $A|a_i|$. This value basically determines the absolute deviation of the intercept. The closer this value is to zero the better our factors capture the variation (i.e. the better the model). The last performance indicator we look at is the standard error of the mean (SE_{μ}). It is defined as the standard deviation of the distribution of sample means taken from a population. The smaller the value of the error, the more representative the sample of the overall data.

III Data

The goal of this paper is to extend the evidence of momentum to more recent periods. The methodology will be used similar to the paper of Fama and French (2015). For comparability with prior studies monthly returns of portfolios from January 1965 to March 2017 will be gathered from CRSP firms incorporated in the United States and listed on the NYSE, AMEX, or NASDAQ. This results into 627 investigated months. For the factor and portfolio formation we retrieve data from the Fama and French Dartmouth website. Data needs to be gathered for both dependent and independent variables. The following sections start with the formation of the factors. It goes in depth about where we gathered the data and how the factors are constructed. After the factor formation we explain how the investigated portfolios are formed. A total amount of 50 single-sorted and 24 double-sorted portfolios are constructed which adds up to 74 portfolios. First insights will be given about summary statistics of the portfolios and their performance relative to the risk-free rate. Correlation matrices of both factor and portfolios will also be discussed in this section. Furthermore we explain which method we are using to test the performance of our proposed models. After these model performance tests we select our best performing model to run regressions on. In the regression analysis we show results of a combination of the best performing dependent and independent variables. Extending the Fama and French 3-factor model with our selected momentum anomalies results in 7 regression possibilities. The statistical software used for the data analysis are E-views and STATA. For convenience purposes two different software's were used. For example, E-views is more convenient to gain summary statistics we show at the tables. On the other side, performing GRS-test is not possible on E-views. Therefore we run the model performance tests on STATA.

3.1 Factor formation

We firstly show how we construct the independent variables for our asset pricing model. Table 1 provides insight about the construction of the investigated factors. Note that all of the factors besides the CAPM are assigned to two size groups and three of their own. In line with Fama and

French we use breakpoints which are determined by NYSE median/percentiles. Value-weighted portfolios defined by the intersections of the groups are the building blocks for the factors.

CAPM

To determine the influence of systematic risk on expected return of the market the CAPM model is used. The market risk premium is calculated by the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ at the beginning of month t , shares and available price data at the beginning of t , and return data for t minus the one-month Treasury bill rate.

Size Factor

The Fama and French factors are constructed by using six value weighted portfolios formed on size and book-to-market. SMB (Small minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios.

$$SMB = 1/3 (Small\ High + Small\ Neutral + Small\ Low) - 1/3 (Big\ High + Big\ Neutral + Big\ Low)$$

The portfolios are intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). It is the average of small and big value factors constructed with portfolios of only small stocks and portfolios of only big stocks. The size breakpoint for year t is the median NYSE market equity at the end of June of year t . BE/ME for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. The final portfolios, which represent the 'SMB factor' in our model, are the six intersections of the two ME and three BE/ME groups (S/L, S/M, S/H, B/L, B/M and B/H). Monthly value-weighted returns for these portfolios are calculated from July _{t} to June _{$t+1$} , then the portfolios are also reformed. In line with the Fama and French Dartmouth website, we include Size in all of the portfolios for the factor formation.

Value Factor

$$HML = \frac{1}{2} (Small\ High + Big\ High) - \frac{1}{2} (Small\ Low + Big\ Low)$$

The third factor HML (High Minus Low) is meant to copy the risk factor in returns related to book-to-market equity. It is constructed by the difference of each month between the average returns on two high-B/M ratios SH and BH, (Small High and Big High) and the average returns on two low-B/M portfolios SL and BL (Small Low and Big Low). The two components of HML are returns on high and low-B/M portfolios with roughly similar weighted average size. Therefore the difference between these portfolios should be mainly free of size factor in returns, focusing instead on different return behaviors of high- and low-B/M firms. Using value-weighted components results into minimizing variance, since return variances are negatively related to size (Fama and French, 1993). In this paper HML is defined as the average return on the two value portfolios minus the average return on the growth portfolios.

Momentum Factor

$$Mom = \frac{1}{2} (Small\ Up + Big\ Up) - \frac{1}{2} (Small\ Down + Big\ Down)$$

Following the Fama and French Dartmouth website we construct the momentum factor by forming four portfolios based on size and momentum. These portfolios include NYSE, AMEX and NASDAQ stocks with prior return data. The requirement to be included in a portfolio for month t , which is formed at the end of month $t-1$, a stock must have a price for the end of month $t-13$ and a “good” return for $t-2$. Six portfolios are formed on size and prior (2-12 months) returns to construct the fourth factor. Similar to the Size Value portfolios, the monthly formed portfolios are the intersections of two portfolios formed on size and three portfolios formed on prior return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. Momentum is the average return on two high prior return portfolios minus the average return on the two lower prior return portfolios.

Short-term Reversal Factor

$$ST_Rev = \frac{1}{2} (Small\ Down + Big\ Down) - \frac{1}{2} (Small\ Up + Big\ Up).$$

In line with the literature we determine the short-term reversal factor (ST_Rev) by looking at the return of the prior (t-1) month. Six value-weighted portfolios are formed in combination with the size factor to construct ST_Rev. The portfolios, which are constructed monthly, are the intersections of two portfolios formed on size and three formed on prior (t-1) return. The monthly size breakpoint is the median NYSE market equity, whereas the monthly prior return breakpoints are the 30th and 70th NYSE per centiles. Slightly different to the momentum factor ST_Rev is calculated by taking the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios.

Long-term Reversal Factor

$$LT_Rev = \frac{1}{2} (Small\ Down + Big\ Down) - \frac{1}{2}(Small\ Up + Big\ Up)$$

Another six value-weighted portfolios are formed on size and prior returns in the past 13 to 60 months to construct the long-term reversal factor (LT_Rev). In this case the monthly portfolios are the intersections of 2 portfolios formed on size and 3 portfolios formed on the prior 13 to 60 months. Again the monthly size breakpoint is the median NYSE market equity, whereas the monthly prior return breakpoints are the 30th and 70th NYSE percentiles. In line with the ST_Rev factor the LT_Rev factor is formed by taking the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios.

Table 1 provides a brief summary about the aforementioned construction of the factors used in this paper. Notice that we use independent sorts to assign stocks to two size groups, and three B/M, Momentum, Short-Term Reversal and Long-Term Reversal groups.

Table 1– Construction of Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal factors

We use independent sorts to assign stocks to two *Size* groups, and three *B/M*, Momentum (*MOM*), Short-Term Reversal (*ST REV*) and Long-Term Reversal (*LT REV*) groups. The value-weighted portfolios defined by the intersections of the groups are the building blocks for the factors. We label these portfolios with two or four letters. The first always describes the *Size* group, small (*S*) or big (*B*). The second describes the *B/M* group, high (*H*), neutral (*N*), or Low (*L*), or the *MOM*, *ST REV* and *LT REV* group, up (*U*) or down (*D*). The factors are *SMB* (small minus big), *HML* (high minus low *B/M*), *MOM* (up minus down), *ST REV* (down minus up) and *LT REV* (down minus up).

Sort	Breakpoints	Factors and their components
2x3 sorts on Size and B/M	<i>Size</i> : NYSE Median	$SMB = (SH+SN+SL)/3 - (BH+BN+BL)/3$
2x3 sorts on Size and B/M	<i>B/M</i> : 30th & 70th NYSE percentiles	$HML = (SH+BH)/2 - (SL+BL)/2$
2x3 sorts on Size and Mom	<i>MOM</i> : 30th & 70th NYSE percentiles	$MOM = (SU+BU)/2 - (SD+BD)/2$
2x3 sorts on Size and ST Rev	<i>ST REV</i> : 30th & 70th NYSE Percentiles	$ST REV = (SD+BD)/2 - (SU+BU)/2$
2x3 sorts on Size and LT Rev	<i>LT REV</i> : 30th & 70th NYSE Percentiles	$LT REV = (SD+BD)/2 - (SU+BU)/2$

3.2 Dependent variable portfolio formation

To test the factors several portfolios will be constructed by formulating them following the method of Fama and French. Firstly, we will investigate single portfolios on Size, Value, Momentum, Short-term reversal and Long-term reversal. Each of the factors will be sorted in 10 deciles to analyze the factors in greater detail. This will result in 50 investigated single-sorted portfolios which will represent the dependent variable R_{it} . Second, 2x3 portfolios will be formed on Size-Value, Size-Momentum, Size-ST_Rev and Size-LT_Rev. If we add the 24 double-sorted portfolios to the single-sorted portfolios we will investigate a total of 74 portfolios over a period of 627 months.

The single-sorted portfolios of Size and Value are constructed relatively easy by sorting them in ten deciles by respectively their Market Equity and book-to-market ratio. The portfolios of momentum, short-term reversal and long-term reversal are constructed using monthly NYSE return decile breakpoints. This results into 50 single-sorted portfolios. It includes NYSE, AMEX and NASDAQ stocks with prior return data. To be included in a portfolio for month t (formed at the end of month $t-1$), a stock must contain a price for the end of month $t-13$ and a good return for $t-2$. For the short-term reversal the stock must have a price for the end of month $t-2$ and a

good return for t-1. Whereas, the long-term reversal required an end of the month price at t-61 and a good return for t-13.

The double-sorted portfolios are constructed quite similar to the factors. Six portfolios are constructed monthly with intersections of 2 portfolios formed on size and 3 portfolios formed on book-to-market ratio. The six momentum portfolios are all constructed monthly with intersections of 2 portfolios formed on size and 3 portfolios formed on prior (2-12) return. Six short-term reversal portfolios are all constructed monthly with intersections of 2 portfolios formed on size and 3 portfolios formed on prior (t-1) return. Lastly, The six long-term reversal portfolios are all constructed monthly with intersections of 2 portfolios formed on size and 3 portfolios formed on prior (13-60) return. This results into 24 double-sorted portfolios.

At Table 2, Panels A to E show average monthly excess returns in excess of the one-month U.S. Treasury bill rate for ten single-sorted portfolios per factor. Panel A shows the portfolio formed on size have a higher average return on the lowest decile compared to the highest.

Since small size firms perform better than large size firms.

An average monthly excess return of respectively 0.35 versus a slightly positive return of 0.04. In contrast, Panel B shows that the highest deciles have higher monthly returns on average versus the lowest value formed portfolios. An average monthly excess return of respectively 0.49 in the highest decile versus a slightly positive return of 0.02 in the lowest decile. This statistic is not surprising since we expect firms with higher B/M ratios to perform better than firms with relatively low B/M ratios.

In line with Panel B it can be seen that the portfolios formed on momentum (Panel C) have relatively high average returns on their top deciles. The top decile shows an average monthly excess return of 0.69 versus a negative return of -0.59 in the lowest decile. For the Short-term reversal portfolio in Panel D we see that the lowest decile earns a positive excess return of 0.20 while the highest decile earns a negative return of 0.13. The last single-sorted portfolio shows that the long-term reversal portfolios in Panel E shows an average monthly return of

respectively 0.51 in the lowest decile versus a slightly positive return of 0.05 in the top decile. These insights of average monthly excess returns on single-sorted portfolios are broadly in line with our expectations.

Panel F shows average excess returns of for six value weighted portfolios from independent sorts of stocks into two size and three B/M groups. The way these 2x3 portfolios are formed was explained earlier at the dependent variable portfolio formation section.

Almost similar to the construction of the Size-B/M portfolio the Size-Momentum portfolio of

Panel G is formed by 2 portfolios of size, but 3 portfolios formed on prior (2-12) returns. The monthly size breakpoint is the median market equity. The monthly prior (2-12) return breakpoints are the 30th and the 70th NYSE percentiles. In contrast with our expectations it can be seen that the average monthly excess return decreases as the momentum group increases. However, the size effect holds for the low and medium group of momentum since the excess returns for the smaller groups are relatively higher. Panel H shows portfolios which are formed on 2 portfolios on size and 3 portfolios formed on prior (t-1) return. Again, the monthly size breakpoint is the median NYSE market equity while the monthly prior (t-1) return breakpoints are the 30th and 70th NYSE percentiles.

The results of Panel H are more in line with our expectations in comparison with the size-momentum portfolio. The highest excess return is shown by the group with the smallest size and the lowest ST-rev. It is also satisfying to see that the excess return decreases as the ST-rev goes higher or the size becomes bigger. The portfolios formed on Panel I are almost identical to the portfolios formed on Size-ST Rev. Two portfolios formed on size are now formed with 3 portfolios formed on prior (13-60) return. The monthly prior (13-60) return breakpoints are again the 30th and 70th NYSE percentiles. Panel I also shows results in line with our expectations. The highest excess return is once again the small-low value of the portfolio and the return decreases when the LT Rev group increases. In short, Panel F to I show that the size effect dominates the 2x3 portfolios since it holds for all groups. It shows that the average return typically falls from small stocks to big stocks.

Table 2 – Average monthly excess returns for portfolios formed on Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal; January 1965 - March 2017, 627 months

At the end of June each year, stocks are allocated to ten Size, B/M, Momentum, ST Rev, LT Rev and two Size groups (Small and Big) using NYSE market cap breakpoints. To construct double-sorted portfolios stocks are allocated independently to three B/M, ST Rev and LT rev (low to high), again using NYSE breakpoints. In the sort for June of year t, B is book equity at the end of the fiscal year ending in year t-1 and M is market cap at the end of December of year t-1, adjusted for changes in shares outstanding between the measurement of B and the end of December. The Size-Mom, Size-ST Rev and Size-LT Rev are formed in the same way, except that the second sort variable is respectively Momentum, Short-Term Reversal and Long-Term Reversal.

	Lo 10	2-Dec	3-Dec	4-Dec	5-Dec	6-Dec	7-Dec	8-Dec	9-Dec	Hi 10
Panel A: Size	0,35	0,33	0,39	0,33	0,37	0,29	0,29	0,25	0,19	0,04
Panel B: Value	0,02	0,12	0,18	0,13	0,13	0,25	0,21	0,29	0,45	0,49
Panel C: Mom	-0,59	-0,09	0,06	0,10	0,04	0,09	0,13	0,27	0,33	0,69
Panel D: St_Rev	0,20	0,36	0,33	0,23	0,19	0,09	0,07	0,08	-0,05	-0,13
Panel E: Lt_Rev	0,51	0,31	0,31	0,24	0,23	0,22	0,20	0,17	0,05	0,05
	Low	Med	High				Low	Med	High	
Panel F: Size-B/M							Panel G: Size-Mom			
Small	0,12	0,48	0,62				0,78	0,41	-0,11	
Big	0,08	0,12	0,29				0,35	0,03	-0,08	
Panel H: Size-ST Rev							Panel I: Size-LT Rev			
Small	0,64	0,41	-0,03				0,59	0,50	0,29	
Big	0,26	0,12	-0,05				0,31	0,18	0,06	

Table 3 provides information about summary statistics for the factors and different versions of the portfolios. Panels A to E show the mean of all 50 single-sorted portfolios and their standard deviation of monthly dataset between January 1965 and March 2017. Note that the returns are roughly 0.40% higher than the values of Table 2. This is because of the fact that the one-month Treasury bill rate is deducted from the means to calculate the excess returns in Table 2. It is also noteworthy that the highest standard deviations per single-sorted portfolio are shown in the lowest deciles.

For example, Panel A shows that the standard deviations of the portfolios range from 6.39% to 4.25%. The lowest decile shows a standard deviation of 6.39% which decreases to 4.25% in the highest decile. We also see that the portfolios of the lowest decile generate average returns of 0.75. As we go up from the lowest decile to the highest, we notice that the average returns

slightly decrease to an average return of 0.44 in the highest decile. This is in line with the risk-return principle which states that the potential return rises with an increase in volatility.

Panel B shows similar findings regarding this principle. The lowest decile shows an average return of 0.42 which increases to an average return of 0.89 in the highest decile. We also see the standard deviation rising from 5.11% in the lowest decile to 6.15% in the highest decile.

Panel C shows a standard deviation of 8.16% corresponding to a negative return of -0.19% in the lowest decile. This finding is inconsistent with the risk-return principle since a relatively high standard deviation shows a negative average return. But we do see an average return of 1.09 in combination with a standard deviation of 6.21% in the highest decile.

However Panel C seems to be the only exception out of the five single-sorted portfolios, since Panels D and E on average show positive correlation between the standard deviation and their mean.

At Panels F to I it is clear to see that the Small sized portfolios have higher standard deviations than the relatively large sized portfolios. This can be explained by the higher volatility relatively new firms (and thus small firms) have when entering the market. However the principle of higher returns for higher volatility also holds on average for all of the four panels. Once again, the portfolio including Momentum shows inconsistent findings. The reason why it is inconsistent is because we expect average returns to increase as soon as the portfolios on positive momentum increase.

At Panel G we see that a standard deviation of 7.20% connects to a mean of 0.29% in a Small-Up portfolio, while a standard deviation of 6.22% and a mean of 1.18% correspond to a Small-Down portfolio. This is not in line with our expectations since we predict a better performance of the Small-Up portfolio versus the Small-down portfolio. For the remaining portfolios (Panels F, H and I) the portfolio which we expect to perform best, actually have the best performance. For example, the best performing portfolio of Panel H is the Small-Down portfolio which has a positive mean of 1.04% and a standard deviation of 7.11%. The Small-Down portfolio is also performing the best in Panel I with a monthly mean of 0.99% and a standard deviation of 6.49%.

Panel J shows summary statistics for the six different factors. The standard deviation of the CAPM factor is 4.47% with a positive mean of 0.50% on average which shows that investing would have provided a higher return than leaving your money on a risk-free rate. The momentum factor shows the highest mean and the highest standard deviation. A mean of 0.66% and a standard deviation of 4.28% is however in line with the risk and reward principle. In short, Panel J shows positive means for all the factors which means that these factors are constructed in a way where excess returns are visible.

Panel K shows the correlation matrix of the single-sorted portfolios. It can be seen that all portfolios highly correlate with each other. However, a pattern occurs that the correlation decreases/increases as the decile increases/decreases. For example, if we look at the lowest decile of Size we see that it correlates from 0.96 with the second decile and it goes down to a correlation of 0.65 with the top decile. This pattern that comes forward in all five of the factors which makes sense since the characteristics of these single-sorted portfolios differ more from each other as their decile rank changes. The relatively high positive correlation of the single-sorted portfolios may potentially undermine the results of the research.

An almost similar pattern is shown in Panel L. There is a clear view in the distinction of the breakpoints size in the 2x3 portfolios. The portfolios which are categorized as small highly correlate with each other, while they correlate less with the 'bigger' portfolios. The somewhat more interesting view is the correlation matrix of the factors. Panel L shows that the value, momentum and long-term reversal factors are negatively correlated with the market factor. While size and short-term reversal factors are positively correlated with the market factor. This is partly in line with the original articles by Fama and French (1996) and Carhart (1997) where they also find positive relationship between size and market risk premium and a negative relation between size and value. Since small stocks and short-term reversal tend to have relatively higher market betas it is rational that these factors are positively correlated with the excess market return. It also makes sense that the momentum factor is negatively correlated

with the short-term reversal and long-term reversal factor, -0.29 and -0.07. Since these three don't correlate with each other it is interesting to zoom in on the different factors of momentum. In short, none of the factors highly correlate with each other which is what we obviously desire.

|

Table 3 – Summary statistics for monthly factor returns; January 1965 - March 2017, 627 months

At the end of June each year, stocks are allocated to two Size groups (Small and Big) using NYSE market cap breakpoints. The LHS variables are the monthly excess returns on the 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios. $R_m - R_f$ is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. At the end of each June, stocks are assigned to two Size groups using the NYSE median market cap as breakpoint. Stocks are also assigned independently to three book-to-market equity (B/M), momentum, short-term reversal and long-term reversal groups, using NYSE medians of B/M, MOM, ST REV and LT REV or the 30th and 70th percentiles.

	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Panel A: Size										
Mean	0.75	0.73	0.79	0.73	0.77	0.69	0.69	0.65	0.59	0.44
Std Dev	6.39	6.41	6.09	5.86	5.66	5.31	5.21	5.07	4.63	4.25
Panel B: B/M										
Mean	0.42	0.52	0.58	0.53	0.53	0.65	0.61	0.69	0.85	0.89
Std Dev	5.11	4.67	4.65	4.68	4.49	4.39	4.61	4.66	5.00	6.15
Panel C: Momentum										
Mean	-0.19	0.31	0.46	0.50	0.44	0.49	0.53	0.67	0.73	1.09
Std Dev	8.16	6.26	5.36	4.81	4.49	4.52	4.38	4.47	4.83	6.21
Panel D: ST Rev										
Mean	0.60	0.76	0.73	0.63	0.59	0.49	0.47	0.48	0.35	0.27
Std Dev	7.33	5.79	5.15	4.74	4.51	4.35	4.32	4.47	4.78	5.53
Panel E: LT Rev										
Mean	0.91	0.71	0.71	0.64	0.63	0.62	0.60	0.57	0.45	0.45
Std Dev	6.72	5.32	4.82	4.53	4.43	4.29	4.39	4.42	4.80	5.95
Panel F: Size-B/M										
	SL	SN	SH	BL	BN	BH				
Mean	0.52	0.88	1.02	0.48	0.52	0.69				
Std Dev	6.90	5.46	5.63	4.63	4.31	4.87				
Panel G: Size-MOM										
	SD	SM	SU	BD	BM	BU				
Mean	1.18	0.81	0.29	0.75	0.43	0.32				
Std Dev	6.22	5.26	7.20	4.86	4.28	5.91				
Panel H: Size ST Rev										
Mean	1.04	0.81	0.37	0.66	0.52	0.35				
Std Dev	7.11	5.46	6.02	5.56	4.26	4.61				
Panel I: Size LT Rev										
Mean	0.99	0.90	0.69	0.71	0.58	0.46				
Std Dev	6.49	5.17	5.99	4.98	4.16	4.87				
Panel J: Six Factors										
	$R_m - R_f$	SMB	HML	MOM	ST	LT				
Mean	0.50	0.24	0.35	0.66	0.49	0.27				
Std Dev	4.47	3.12	2.85	4.28	3.15	2.52				

Table 4 - Correlation Matrices

Panel K: Correlations between different deciles of the single-sorted portfolios

	Size									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.96	0.94	0.91	0.89	0.86	0.85	0.82	0.78	0.65
20	0.96	1.00	0.98	0.97	0.95	0.93	0.91	0.89	0.84	0.73
30	0.94	0.98	1.00	0.98	0.97	0.96	0.94	0.92	0.88	0.77
40	0.91	0.97	0.98	1.00	0.98	0.97	0.95	0.93	0.90	0.79
50	0.89	0.95	0.97	0.98	1.00	0.98	0.97	0.96	0.92	0.82
60	0.86	0.93	0.96	0.97	0.98	1.00	0.98	0.97	0.94	0.85
70	0.85	0.91	0.94	0.95	0.97	0.98	1.00	0.98	0.96	0.87
80	0.82	0.89	0.92	0.93	0.96	0.97	0.98	1.00	0.97	0.89
90	0.78	0.84	0.88	0.90	0.92	0.94	0.96	0.97	1.00	0.92
Hi 10	0.65	0.73	0.77	0.79	0.82	0.85	0.87	0.89	0.92	1.00

	Value									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.90	0.86	0.81	0.77	0.74	0.73	0.71	0.71	0.66
20	0.90	1.00	0.93	0.90	0.86	0.84	0.82	0.80	0.81	0.75
30	0.86	0.93	1.00	0.93	0.90	0.89	0.86	0.84	0.85	0.78
40	0.81	0.90	0.93	1.00	0.92	0.91	0.88	0.86	0.85	0.80
50	0.77	0.86	0.90	0.92	1.00	0.91	0.89	0.86	0.86	0.80
60	0.74	0.84	0.89	0.91	0.91	1.00	0.91	0.88	0.87	0.80
70	0.73	0.82	0.86	0.88	0.89	0.91	1.00	0.90	0.88	0.84
80	0.71	0.80	0.84	0.86	0.86	0.88	0.90	1.00	0.91	0.87
90	0.71	0.81	0.85	0.85	0.86	0.87	0.88	0.91	1.00	0.90
Hi 10	0.66	0.75	0.78	0.80	0.80	0.80	0.84	0.87	0.90	1.00

	Momentum									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.91	0.86	0.82	0.78	0.73	0.67	0.63	0.59	0.54
20	0.91	1.00	0.93	0.90	0.86	0.81	0.74	0.69	0.64	0.55
30	0.86	0.93	1.00	0.92	0.89	0.85	0.78	0.72	0.68	0.55
40	0.82	0.90	0.92	1.00	0.91	0.89	0.84	0.80	0.75	0.61
50	0.78	0.86	0.89	0.91	1.00	0.91	0.87	0.84	0.80	0.67
60	0.73	0.81	0.85	0.89	0.91	1.00	0.91	0.88	0.86	0.73
70	0.67	0.74	0.78	0.84	0.87	0.91	1.00	0.91	0.90	0.76
80	0.63	0.69	0.72	0.80	0.84	0.88	0.91	1.00	0.93	0.84
90	0.59	0.64	0.68	0.75	0.80	0.86	0.90	0.93	1.00	0.88
Hi 10	0.54	0.55	0.55	0.61	0.67	0.73	0.76	0.84	0.88	1.00

	ST Rev									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.93	0.88	0.84	0.83	0.80	0.77	0.76	0.72	0.69
20	0.93	1.00	0.92	0.89	0.88	0.86	0.81	0.79	0.75	0.69
30	0.88	0.92	1.00	0.90	0.90	0.88	0.85	0.81	0.76	0.70
40	0.84	0.89	0.90	1.00	0.92	0.91	0.88	0.86	0.82	0.75
50	0.83	0.88	0.90	0.92	1.00	0.92	0.90	0.87	0.84	0.77
60	0.80	0.86	0.88	0.91	0.92	1.00	0.91	0.89	0.85	0.78
70	0.77	0.81	0.85	0.88	0.90	0.91	1.00	0.92	0.90	0.81
80	0.76	0.79	0.81	0.86	0.87	0.89	0.92	1.00	0.91	0.84
90	0.72	0.75	0.76	0.82	0.84	0.85	0.90	0.91	1.00	0.90
Hi 10	0.69	0.69	0.70	0.75	0.77	0.78	0.81	0.84	0.90	1.00

	LT Rev									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.89	0.84	0.81	0.77	0.74	0.69	0.67	0.67	0.68
20	0.89	1.00	0.90	0.87	0.84	0.83	0.79	0.76	0.77	0.74
30	0.84	0.90	1.00	0.89	0.87	0.84	0.81	0.77	0.78	0.74
40	0.81	0.87	0.89	1.00	0.90	0.88	0.86	0.82	0.82	0.77
50	0.77	0.84	0.87	0.90	1.00	0.89	0.89	0.87	0.85	0.78
60	0.74	0.83	0.84	0.88	0.89	1.00	0.90	0.89	0.87	0.80
70	0.69	0.79	0.81	0.86	0.89	0.90	1.00	0.91	0.90	0.82
80	0.67	0.76	0.77	0.82	0.87	0.89	0.91	1.00	0.92	0.86
90	0.67	0.77	0.78	0.82	0.85	0.87	0.90	0.92	1.00	0.90
Hi 10	0.68	0.74	0.74	0.77	0.78	0.80	0.82	0.86	0.90	1.00

Panel L: Correlations between double-sorted portfolios and between different factors

Size-B/M

	SH	SM	SL	BH	BM	BL
SH	1.00	0.94	0.89	0.82	0.73	0.73
SM	0.94	1.00	0.97	0.79	0.82	0.83
SL	0.89	0.97	1.00	0.74	0.80	0.85
BH	0.82	0.79	0.74	1.00	0.86	0.78
BM	0.73	0.82	0.80	0.86	1.00	0.90
BL	0.73	0.83	0.85	0.78	0.90	1.00

Size-Momentum 2x3

	SU	SM	SD	BU	BM	BD
SU	1.00	0.93	0.81	0.86	0.78	0.65
SM	0.93	1.00	0.91	0.79	0.84	0.78
SD	0.81	0.91	1.00	0.64	0.75	0.86
BU	0.86	0.79	0.64	1.00	0.87	0.63
BM	0.78	0.84	0.75	0.87	1.00	0.83
BD	0.65	0.78	0.86	0.63	0.83	1.00

Size-ST_REV 2x3

	SD	SM	SU	BD	BM	BU
SD	1.00	0.95	0.90	0.87	0.80	0.74
SM	0.95	1.00	0.94	0.83	0.84	0.79
SU	0.90	0.94	1.00	0.76	0.80	0.84
BD	0.87	0.83	0.76	1.00	0.90	0.76
BM	0.80	0.84	0.80	0.90	1.00	0.89
BU	0.74	0.79	0.84	0.76	0.89	1.00

Size-LT_REV 2x3

	SD	SM	SU	BD	BM	BU
SD	1.00	0.96	0.93	0.85	0.78	0.73
SM	0.96	1.00	0.96	0.85	0.85	0.79
SU	0.93	0.96	1.00	0.81	0.82	0.84
BD	0.85	0.85	0.81	1.00	0.88	0.79
BM	0.78	0.85	0.82	0.88	1.00	0.89
BU	0.73	0.79	0.84	0.79	0.89	1.00

Factors

	MKT_RF	SMB	HML	MOM	ST	LT
MKT_RF	1.00	0.30	-0.26	-0.13	0.29	-0.02
SMB	0.30	1.00	-0.20	0.00	0.16	0.26
HML	-0.26	-0.20	1.00	-0.19	0.00	0.45
MOM	-0.13	0.00	-0.19	1.00	-0.29	-0.07
ST	0.29	0.16	0.00	-0.29	1.00	0.08
LT	-0.02	0.26	0.45	-0.07	0.08	1.00

IV Methodology

4.1 Model Performance

As mentioned before a model performance test is conducted to look at returns left unexplained by the OLS time-series regressions. The Gibbons Ross Shanken (GRS) test is a financial F-test for the hypothesis that all the intercepts for a set of time-series regressions are zero. Each alpha is the intercept in a time-series regression of excess returns on factors. The F-statistic allows to identify whether variability in dependent variable is fully explained by the regression inputs.

The GRS test is formulated as follows:

$$\frac{T - N - K}{N} * \left(1 + E(f)' * \widehat{\Omega}^{-1} * E(f) \right)^{-1} * \widehat{a}' \widehat{\Sigma}^{-1} \widehat{a} \sim F(N, T - N - K)$$

Where, the first part represents the scale of the test $\left(\frac{T-N-K}{N}\right)$, T stands for the number of time period observations, which is deducted by the numbers of portfolios N, which is deducted by the number of factors represented by K. To complete the scale of the test this number is divided by N. The next part focusses on the returns explained by the factors, where $E(f)$ represents the expected returns of the risk factors and stands as a vector of the average returns of the risk factors. This is then multiplied by $\widehat{\Omega}^{-1}$ which is the inverse of the covariance matrix of risk factor returns. This result is then multiplied by the transposed vector of average factor returns, denoted by $E(f)'$. The whole second part is then summed by one and inversed. The last part of the equation focusses on the explained returns of the model. The vector \widehat{a} and transposed vector of the intercepts \widehat{a}' are multiplied by the inverse residual covariance matrix $\widehat{\Sigma}^{-1}$. After the multiplication of the three parts the GRS-statistic is subjected to an F-distribution with N number of degrees of freedom in the numerator and T-N-K number of degrees of freedom in the denominator. If the GRS holds it means that there are no returns left unexplained after the risk factors are added to the model. When the hypothesis is rejected it means that all the combined estimated alphas are significant, and the model is incomplete. In depth, there are portfolios with returns whose variation remains unexplained by the model's risk factors. To use the GRS test to our data STATA is being used. In short, the alphas and GRS statistics for our proposed model serve as an examination of the performance of the multi-factor models. It is safe to say that the lower the value of the GRS statistic the better the

performance of our model. This is obviously the case since we desire to construct a model where all our factors explain the dependent variable. We also checked for heteroskedasticity with Breusch-Pagan-Godfrey tests.

4.2 Regression analysis

To evaluate the performance of our portfolios various extensions of the three-factor model are used. The estimation for portfolio i is,

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + m_iMOM_t + e_{it} \quad (1)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + s_iST_REV_t + e_{it} \quad (2)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + l_iLT_REV_t + e_{it} \quad (3)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + m_iMOM_t + s_iST_REV_t + e_{it} \quad (4)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + s_iST_REV_t + l_iLT_REV_t + e_{it} \quad (5)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + m_iMOM_t + l_iLT_REV_t + e_{it} \quad (6)$$

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + m_iMOM_t + r_iST_REV_t + l_iLT_REV_t + e_{it} \quad (7)$$

where $R_{it} - R_{ft}$ represents the return on portfolio i in month t in excess of the risk-free rate (the one-month U.S. Treasury bill rate from Ibbotson and Associates Inc.), $R_{Mt} - R_{ft}$ represents the market risk premium which is calculated by the value-weighted return of all CRSP firms minus the one-month Treasury bill rate, the size factor SMB_t measures the difference between the return on portfolio of small stocks and that of big stocks, the book-to-market factor (B/M) HML_t measures the difference in return performance of portfolios with high B/M stocks and low B/M stocks, MOM_t represents the momentum factor which measures the difference between the best performing portfolios of the past 12 months with the worst performing portfolios, α_i is the average return left unexplained by the model and indicates a positive excess returns for portfolio i if it is positive and statistically significant, e_{it} is the regression residual. SMB, HML and MOM are value-weighted, zero investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns. In equation (2) MOM_t is replaced by ST_REV_t which represents the Short-Term Reversal factor which measures the difference between the worst performing portfolios of the past month with best performing portfolios. The only difference between (2) and (3) is that equation (3) replaces the Short-Term Reversal factor with LT_REV_t which represents the difference of the worst

performing portfolios of the past 13 to 60 months with the best performing portfolios. Equations (4) to (6) show different forms of combinations where the Fama and French three-factor model is extended by two momentum factors. Lastly, equation (7) is formed to identify whether all the investigated factors together explain the excess return the best. As can be seen all of the proposed regressions are extensions of the Fama and French three-factor model. The goal of this paper is to look if several forms of momentum anomalies improve the three-factor model. Note that equation (1) is similar to Carhart's (1997) four-factor model that includes one-year momentum to the Fama and French three-factor model. When we perform the model performance test we want to determine not only which asset pricing model performs best, but also which dependent variable is best. We make a distinction between two dependent variables: single-sorted or double-sorted and the seven asset pricing models. We run regressions on the winning combination to desirably get the most accurate results.

V Results

5.1 Model Performance

To determine which of the suggested regressions performs best we run the GRS test on all of prior mentioned models. We will also look at the Adjusted R-squared and average intercept of the models. Serial correlation will be tested through a Breush-Pagan-Godfrey test, homoscedasticity through a White test, a correlation matrix is used to detect possible multicollinearity. Whenever we solely observe heteroscedasticity a White correction is applied. If we solely observe serial correlation or both serial correlation and heteroscedasticity a Newey-West correction is applied. Ideally the test shows us which asset pricing model completely captures expected returns. We are interested in the improvements in the description of average returns provided by adding the momentum factors to the original three-factor model. We do this by looking at the earlier mentioned model performance indicators. The Gibbons Ross Shanken (GRS) test is a financial F-test for the hypothesis that all the intercepts for a set of time-series regressions are zero. Each alpha is the intercept in a time-series regression of excess returns on factors. The F-statistic allows to identify whether variability in dependent variable is fully explained by the regression inputs. The adjusted R-squared is a modified version of the R-squared that has been adjusted for the numbers of explanatory variables in the model. The higher the value of the adjusted R-squared the better our independent variables explain the dependent variable. This also means that omitted variable bias decreases. Another value shown in Table 5 is the average absolute intercept represented by $A|\alpha_i|$. This value basically determines the absolute deviation of the intercept. The closer this value is to zero the better our factors capture the variation (i.e. the better the model). We consider seven asset pricing models, namely: 1) three four-factor models that combine $(R_M - R_f)$, *SMB* and *HML* with *MOM*, *ST_REV* and *LT_REV* individually; 2) three five-factor models that combine $(R_M - R_f)$, *SMB* and *HML* with pairs of *MOM*, *ST_REV* and *LT_REV*; and 3) the six-factor model that combines all the factors together. It is rational to mainly focus attention to the models that fare relatively well in the model performance tests. Since so many literatures supports the Fama and French three-factor model we use this model as our basis. To see whether the models improve after adding single/several of the momentum factors we show all of the model

performance results in the tables. This way we can judge improvements provided by the momentum factors. If the intercept of the regression is not equal to zero it means that the model does not completely capture the expected returns. This means that we desire the model to be significantly combined with an intercept of zero.

The results of the GRS test are shown in table 5, it tests for combinations of the portfolios and the investigated factors. Since it is hard to judge which model performs best we look at a combination of measures that help us. For comparison purposes we make a distinction between the model performance of the single-sorted portfolios (Panels A to F) and the double-sorted portfolios (Panels G to J). Panels A to F show several outputs for model performance test we ran. First column shows the GRS value, this statistic basically determines the likelihood of the intercept being zero. However, if the GRS value is significant it means that the intercept is not equal to zero which then means that our model is incomplete. We found significant P-values on GRS tests for almost all of our models. More detailed output of the GRS test including the accompanied P-values can be found in the Appendix. However, we want to determine which model has the best story for excess returns on portfolios formed in different ways. Another value shown in table 5 is the average absolute intercept represented by $A|a_i|$. This value basically determines the absolute deviation of the intercept. The closer this value is to zero the better our factors capture the variation (i.e. the better the model). The third value in the column is the adjusted R squared represented by R_{adj}^2 . The adjusted R-squared is a modified version of the R-squared that has been adjusted for the numbers of explanatory variables in the model. There is a reason we use the adjusted R-squared instead of the 'normal R-squared'. One of the major problems regarding the R-squared is that its value increases every time you add a variable to the model. Consequently, whenever the model with more terms appears to have a better fit because it has more terms. On the other side, the adjusted R-squared only increases if the added variable increases the explanatory power of the model more than would be expected by chance. Its value also decreases whenever a performance measure is improving the model by less than expected by chance. It is also a fact that the adjusted R-squared can be negative and never be higher than the R-squared. The purpose of

the adjusted R-squared in this paper is that it compares the descriptive power of the seven asset pricing models that contains several risk factors (number of predictors). The standard error of the mean SE_{μ} is defined as the standard deviation of the distribution of sample means taken from a population. The smaller the value of the error, the more representative the sample of the overall data. We are mainly interested in the improvements in the description of average returns provided by adding reversal factors to Carhart's four-factor model. To interpret the T-statistics of the GRS tests it is important to state that we desire to see low values in Table 5. The reason behind this is that this implies that the intercept does not significantly differ from zero which can mean that the model captures most of the variation in returns.

While the 10-Size portfolios in Panel A show almost equal values we see that the 10-B/M portfolios clearly differ. The best performing models from Panel B are (4) and (7) with t-statistics of respectively 1.51 and 1.52. For these models it means that we cannot reject the hypothesis that their intercepts are jointly equal to zero at a 95% significance level. In Panel C we see that all of the models for the 10-momentum portfolios produce high GRS test statistic, which means that average alfa's in the regression are significantly different from zero. It is interesting to see that low GRS values are found for asset pricing models which do not include the ST Rev factor(1), (3) and (5) in Panel D.

For the 10-LT Rev portfolios in Panel E we see that all of the models have intercepts that do not significantly differ from zero. The 6-factor model (7) and 5-factor model (4) contain the relatively lowest vales of respectively 59.0 basis points. For the 50 pooled decile portfolios in Panel F we see insignificant values for (1) and (5) which is similar to the results shown in Panel D. For the double-sorted portfolios we solely see significant GRS statistics which means that the intercepts are significantly different from zero. We notice that the value of GRS generally decreases as soon as we add variables to the models but stay significant. It seems that the single-sorted portfolios work better as dependent variable than the double-sorted portfolios if we only observe GRS statistics. Also we can say that the best performing model is the one with most of the variables, namely the 6-factor model is formed by the traditional 3 factor model including the momentum, short-term reversal and long-term reversal factor (7).

We notice that the average absolute intercepts $A|a_i|$ in Table 5 show the relatively lowest values for the four-factor model with momentum (1) and the six-factor model (7). For convenient purposes we therefore mainly analyze equation (1) vs (7). For the 10-Size portfolios at Panel A all factor models show no improvements (4.4 vs 4.4 basis points) in the average absolute intercept. The same can be concluded for the 10-B/M portfolios at Panel B which contains an average absolute intercept of 6.2 basis points in both four and six-factor model. In

Panel C we can see that despite the relatively low values the average absolute value of the 10-Momentum portfolio increases from the 4-factor momentum model to the 6-factor model with respectively 0.9 basis points (11.5 vs 12.4). The improvement of single-sorted portfolios is the largest for the 10-st rev portfolios which improve by 2.6 basis points (11.7 vs 8.1). For the remaining single-sorted portfolios we see slight improvements of 10-LT Rev portfolios (5.1 vs 4.7) and 50-decile portfolios (7.8 vs 7.2) at respectively Panels E and F. Therefore we can conclude that the average absolute intercept of 5 out of six single-sorted portfolios stays equal or improves if we compare the asset pricing models (1) vs (7). For the double-sorted portfolios at Panels G to K we see improvements for all of the portfolios. Continue to compare the models (1) to (7) we see improvements for the 6 Size-B/M portfolios (9.1 vs 8.5 basis points), the 6 Size-Momentum portfolios (11.2 vs 10.8 basis points), the 6 Size-ST Rev portfolios (18.4 vs 9.6 basis points), the 6 Size-LT Rev portfolios (6.8 vs 5.6 basis points) and the 24 pooled(2x3) portfolios (11.4 vs 8.6). Note that the biggest improvements in the average absolute intercept are produced by the six-factor model when applied to the 6 Size-ST Rev portfolio. In short, these results indicate that the original four-factor model (1) is likely to fare poorly when applied to portfolios that include strong tilts toward various combinations of momentum and reversal factors.

As mentioned before the adjusted R-squared solely increases if the added variable increases the explanatory power of the model more than would be expected by chance. This means that its value also decreases if a predictor is improving the model by less than expected by chance. In contrast to the prior mentioned predictors, we now desire the values to be high. Looking at Panel A and B we notice that the 10-Size and the 10-B/M portfolios almost show identical

adjusted R-squared values for all of the models (1) to (7). However, the 10-Size portfolios do show a higher value of basis points than the 10-B/M portfolios (96.1 vs 89.9 basis points). The adjusted R-squared values for the 10-Momentum portfolios in Panel C range from 80.7 to 89.8 basis points with the 6-factor model (7) containing the highest explanatory power. Note that it is not always the case that more variables is followed by higher values of adjusted R-squared. For example, Panel D shows that a 4-factor model (2) for the 10-ST Rev portfolios has more explanatory power than a 5-factor model (5) of respectively 91.2 vs 86.0 basis points. Yet, it is the 6-factor model that provides the highest adjusted R-squared of 91.3 basis points. The highest adjusted R-squared for the 10-LT Rev portfolios and 50- decile portfolios in Panel E and F are once again given by the 6-factor model of respectively 89.1 and 91.3 basis points. It is interesting to see that similar patterns are visible for the double-sorted portfolios from Panel G to Panel K. The 6 Size-B/M portfolios show equal adjusted R-squared values for all of the models. Furthermore the largest adjusted R-squared values are shown by the 6-factor models (7) for the 6 Size-Momentum portfolios (96.0 basis points), the 6 Size-ST Rev portfolios (96.8 basis points), Size-LT Rev (96.0 basis points) and the 24 pooled-2x3 portfolios (96.4 basis points). For the adjusted R-squared it can be concluded by the results given by Panel A to K that the 6-factor model contains the relatively largest explanatory power. Our findings are in line with Fama and French (1996) and Ferson and Harvey (1999) which found adjusted R-squared values between 70.0 and 95.0 basis points. For the standard error of the mean (SE_{μ}) a rule of thumb states that the smaller the value of the error, the more representative the sample of the overall data. To calculate the t-values of the coefficients we use the OLS standard errors. Similar to the prior predictors of model performances it is safe to say that the 6-factor model performs best according to the values given by the standard error of the mean in Table 5 for Panel A to J. Note that the standard error of the mean is not the absolute lowest for the 6-factor model at each of the Panels. For example, for the 10-Size portfolios at Panel A it can be seen that the value for the 6-factor model (7) is higher than a 4-factor model (3) of respectively 4.5 vs 4.3 basis points. However, analyzing each of the Panels of table 5 it is clear to see that the 6-factor model generally contains the lowest standard error of the mean.

Table 5 – Summary statistics for tests of four-, five- and six-factor models; January 1965 - March 2017, 627 months

The table tests the ability of four-, five- and six-factor models to explain monthly excess returns on 10 Size portfolios (Panel A), 10 B/M portfolios (Panel B), 10 Momentum portfolios (Panel C), 10 ST Rev portfolios (Panel D), 10 LT Rev portfolios (Panel E), 50 single-sorted portfolios (Panel F), 6 Size-B/M portfolios (Panel G), 6 Size-Momentum portfolios (Panel H), 6 Size-ST Rev portfolios (Panel I), 6 Size-LT Rev portfolios (Panel J) and 24 double-sorted portfolios (Panel K). For each set of 6, 10, 24 or 50 regressions, the table shows the factors that augment $R_m - R_f$, SMB and HML in the regression model, the GRS statistic testing whether the expected values of all 6, 10, 24 or 50 intercepts estimates are zero, the average absolute value of the intercepts, $A|a_i|$, the adjusted R-squared comparing the explanatory power of the models that contain different number of predictors, R_{adj}^2 and SE_μ which is the standard error of the mean.

	GRS	$A a_i $	Adj R2	SE_μ		GRS	$A a_i $	Adj R2	SE_μ
Panel A: 10-Size portfolios					Panel B: 10-B/M portfolios				
(1) MOM	2.780	0.044	0.961	0.044	(1) MOM	1.700	0.062	0.898	0.064
(2) ST	2.336	0.042	0.961	0.044	(2) ST	2.105	0.076	0.898	0.063
(3) LT	2.419	0.042	0.961	0.043	(3) LT	2.204	0.075	0.899	0.062
(4) MOM ST	2.677	0.044	0.961	0.045	(4) MOM ST	1.509	0.062	0.898	0.065
(5) MOM LT	2.770	0.044	0.961	0.044	(5) MOM LT	1.724	0.062	0.899	0.063
(6) ST LT	2.320	0.042	0.961	0.043	(6) ST LT	2.123	0.076	0.899	0.063
(7) MOM ST LT	2.673	0.044	0.961	0.045	(7) MOM ST LT	1.516	0.062	0.899	0.064
Panel C: 10-Momentum portfolios					Panel D: 10-ST Rev portfolios				
(1) MOM	3.511	0.115	0.897	0.071	(1) MOM	1.619	0.117	0.860	0.080
(2) ST	6.638	0.340	0.806	0.098	(2) ST	4.613	0.091	0.912	0.062
(3) LT	5.306	0.294	0.801	0.099	(3) LT	1.995	0.104	0.856	0.080
(4) MOM ST	3.987	0.124	0.897	0.071	(4) MOM ST	3.616	0.081	0.913	0.063
(5) MOM LT	3.501	0.114	0.898	0.070	(5) MOM LT	1.611	0.116	0.860	0.080
(6) ST LT	6.614	0.340	0.807	0.098	(6) ST LT	4.598	0.091	0.912	0.062
(7) MOM ST LT	3.998	0.124	0.898	0.071	(7) MOM ST LT	3.614	0.081	0.913	0.063
Panel E: 10-LT Rev portfolios					Panel F: 50-decile portfolios				
(1) MOM	0.691	0.051	0.857	0.078	(1) MOM	1.918	0.078	0.895	0.067
(2) ST	0.799	0.063	0.856	0.078	(2) ST	2.715	0.123	0.887	0.069
(3) LT	1.101	0.062	0.889	0.067	(3) LT	2.213	0.116	0.881	0.070
(4) MOM ST	0.589	0.048	0.857	0.079	(4) MOM ST	2.367	0.072	0.905	0.065
(5) MOM LT	0.687	0.046	0.891	0.067	(5) MOM LT	1.927	0.077	0.902	0.065
(6) ST LT	1.222	0.070	0.890	0.067	(6) ST LT	2.708	0.124	0.894	0.067
(7) MOM ST LT	0.590	0.047	0.891	0.068	(7) MOM ST LT	2.363	0.072	0.913	0.062

Table 5 – (continued) double-sorted portfolios

	<i>GRS</i>	$A a_i $	Adj <i>R</i> ²	SE_{μ}
Panel G: 6 Size-B/M portfolios				
(1) <i>MOM</i>	6.065	0.091	0.967	0.037
(2) <i>ST</i>	6.823	0.100	0.967	0.036
(3) <i>LT</i>	7.053	0.102	0.967	0.036
(4) <i>MOM ST</i>	5.605	0.085	0.967	0.037
(5) <i>MOM LT</i>	6.060	0.091	0.967	0.037
(6) <i>ST LT</i>	6.809	0.100	0.967	0.036
(7) <i>MOM ST LT</i>	5.600	0.085	0.967	0.037
Panel I: 6 Size-ST Rev portfolios				
(1) <i>MOM</i>	7.659	0.184	0.921	0.062
(2) <i>ST</i>	6.774	0.097	0.965	0.042
(3) <i>LT</i>	8.017	0.121	0.917	0.063
(4) <i>MOM ST</i>	4.821	0.096	0.967	0.042
(5) <i>MOM LT</i>	7.658	0.185	0.922	0.062
(6) <i>ST LT</i>	6.750	0.096	0.966	0.042
(7) <i>MOM ST LT</i>	4.838	0.096	0.968	0.041
Panel K: 24 (2x3) portfolios				
(1) <i>MOM</i>	5.392	0.114	0.945	0.050
(2) <i>ST</i>	6.220	0.152	0.935	0.053
(3) <i>LT</i>	6.585	0.146	0.928	0.056
(4) <i>MOM ST</i>	4.611	0.086	0.956	0.045
(5) <i>MOM LT</i>	5.398	0.114	0.952	0.047
(6) <i>ST LT</i>	6.231	0.151	0.942	0.050
(7) <i>MOM ST LT</i>	4.623	0.086	0.964	0.042

	<i>GRS</i>	$A a_i $	Adj <i>R</i> ²	SE_{μ}
Panel H: 6 Size Momentum portfolios				
(1) <i>MOM</i>	6.366	0.112	0.959	0.046
(2) <i>ST</i>	11.822	0.344	0.879	0.078
(3) <i>LT</i>	10.730	0.305	0.874	0.079
(4) <i>MOM ST</i>	5.680	0.108	0.959	0.047
(5) <i>MOM LT</i>	6.345	0.112	0.960	0.046
(6) <i>ST LT</i>	11.785	0.343	0.880	0.078
(7) <i>MOM ST LT</i>	5.675	0.108	0.960	0.046
Panel J: 6 Size-LT Rev portfolios				
(1) <i>MOM</i>	3.009	0.068	0.931	0.055
(2) <i>ST</i>	3.695	0.067	0.928	0.056
(3) <i>LT</i>	3.360	0.055	0.956	0.044
(4) <i>MOM ST</i>	2.224	0.056	0.931	0.056
(5) <i>MOM LT</i>	3.013	0.067	0.960	0.043
(6) <i>ST LT</i>	3.703	0.065	0.957	0.044
(7) <i>MOM ST LT</i>	2.236	0.056	0.960	0.043

5.2 Regression Details

To get more in depth on model performance we examine details of regression results, particularly, intercepts and pertinent slopes. After analyzing several predictors for model performances in we continue with one of the seven investigated models (1) to (7) defined in the regression analysis section. These results are shown in Table 5. Based on our four indicators of model performance and to keep the presentation manageable we only continue to work with the 6-factor model (7) for our regressions. Since we also noticed that the single-sorted portfolios mainly perform better we continue to use these as dependent variables. Also because they show similar results to the single-sorted portfolios. Table 6 shows values of independent variables combined with their t-statistic right below them. We use a confidence interval of 95% to determine which variables are significant. This means that every coefficient with a T-value lower than -1.96 or higher 1.96 than is significant.

Firstly, we see that the intercept in Panel A, represented by alpha, is mainly insignificant. If there are significant intercepts they can be found in the lower deciles. For example, for the single-sorted portfolios on size we see that lo20 has a significant value of -0.12% per month ($t = -2.66$). Consistent with Fama and French (1993, 2012) we see negative intercepts for relatively small stocks. They found that portfolios for small extreme growth stock produce negative three-factor intercepts. Yet, we do not see negative intercepts for low B/M portfolios. By itself, the intercept for the ST reversal portfolio in Lo10 of -0.34% ($t = -3.32$) is enough to doubt this model as a description of expected returns on 50 single-sorted portfolios. For the momentum portfolios, we see significant values for the four lowest deciles (Lo10 to Lo40) with respectively, -0.30%, 0.19%, 0.28% and 0.20%. This indicates that for these portfolios the intercept significantly differ from zero, which is obviously undesirable.

Panel B of table 7 shows the market risk slopes for the six-factor model of the 50 single-sorted portfolios. It is clear to see that all the slopes are highly significant. Consistent with findings of Fama and French we find that all the market slopes are always close to 1.0. This indicates that the volatility/systematic risk of our portfolios positively correlates with the market risk as a whole.

Panel C of Table 7 provide insights to the SMB slopes for our asset pricing model. We notice that for Size, B/M and Momentum we once again see all significant slopes. However, for the ST and LT rev portfolios we see that some of the deciles are not significant. Looking at the Size portfolios we see that the slopes are strongly positive for small stocks and decrease to an even negative slope for the top decile ranging from 1.22% to -0.28%. The exact opposite occurs for the B/M portfolios where negative slopes are visible for the lowest decile (-0.11%) increasing to slightly positive slopes for the top decile (0.41%). For the momentum portfolios, we notice that the lowest and top deciles have positive slopes of respectively 0.42% and 0.38% while the middle deciles have slightly negative slopes around -0.05%. Similar patterns are found for the ST and LT portfolios. The lowest deciles of these portfolios have positive slopes of 0.38% and 0.48% while the top deciles have slopes of 0.35% and 0.14%. However as mentioned before not all the slopes are significant in the ST and LT deciles.

Panel D of table 7 completes the classic three-factor model of Fama and French. In line with our expectations we see positive coefficients for the lowest deciles of the Size portfolios which decrease further in the deciles ending with a negative value of -0.28% ($t=-40.77$) at the largest decile. The B/M portfolios show significantly positive slopes for the highest deciles and negative slopes for the lowest deciles. These results are consistent with our expectations on growth vs value stocks. Unlike the size and b/m portfolios we notice that the momentum, ST-rev and LT-rev portfolios show insignificant values for some of the deciles. However, mainly the middle deciles contain desirable T-statistics. We find that the momentum portfolios show positive slopes with a max of 0.21% ($t=3.99$) for the HML factor. The largest significant positive slope for the ST-rev portfolios has a value of 0.12% ($t=3.55$). The LT-rev portfolios contain relatively large significant slopes for the HML factor ranging from 0.23 ($t=4.75$) to -0.19 ($t=-4.93$). Note that the negative slope in the top decile is not in line with our expectations.

Panel E of table 7 extends the three-factor model with the momentum factor which corresponds to the Carhart (1997) 4-factor model. We immediately notice that the slopes for size and B/M are relatively small (ranging from -0.10% to 0.03%). The only significant slope is the second largest decile of the B/M portfolios with a negative slope of -0.04 ($t=-2.81$). We see significant negative slopes for the 5 lowest deciles of momentum portfolios. The lowest decile

even shows a value of -0.94% ($t=-21.16$). From lowest to highest decile we see the slopes increasing to a significant positive slope of 0.55 ($t=14.11$) in the top decile. This means that the momentum factor is positive for portfolios ranked on relatively large momentum. Despite some negative slopes in the lowest deciles for the ST-rev and LT-rev of -0.14% ($t=-2.70$) and -0.16% ($t=4.92$) portfolios we mainly see insignificant slopes. It is therefore safe to say that the momentum factor does not work properly for these portfolios.

Panel F of table 7 shows the values of single-sorted portfolios on the ST-rev factor. Consistent with the momentum factor we see that the Size and B/M portfolios show insignificant slopes for all the deciles. The momentum portfolios show similar significance for their deciles of the ST-rev factor. Just as Panel E we see that the significant slopes are mainly the portfolios of the investigated factor. For 9 out of 10 deciles we see significant slopes for the ST-rev portfolios in Panel F. Ranging from 0.79 ($t=16.85$) to -0.66 ($t=-18.72$) we see the slopes decreasing from the lowest to the largest decile. Just like that pattern of the momentum factor this is in line with our expectations.

Lastly Panel G of table 7 shows the slopes of the LT-rev factor for our single-sorted portfolios. Once again we notice that the significant values mainly come from the portfolios which is equal to the investigated factor. The Size, B/M, Mom and ST-rev portfolios show insignificant values. It is safe to say that this factor is only relevant if LT-rev portfolios are examined. Yet the LT-rev portfolios range decrease with a positive slope from the lowest decile of 0.97 ($t=17.35$) to a negative slope of -0.49 ($t=10.96$) in the highest decile. This is another finding consistent with our expectations.

Daniel et al. (1998) show that overconfidence implies negative long-lag autocorrelations. They define an overconfident investor as one who overestimates the precision of his private information signal, but not of information signals publicly received by all. They show that this overreaction-correction pattern is consistent with long-run negative autocorrelation in stock returns (long-term Reversal). However, momentum may still be the result of mispricing, but transaction costs may be the binding costs that limit arbitrage. This argument is supported by the findings of Lesmond et al. (2004), who show that there is cross-sectional relation between transaction costs and momentum profits.

Table 6 – Regressions for 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios; January 1965 - March 2017, 627 months

At the end of June each year, stocks are allocated to five Size groups (Small to Big) using NYSE market cap breakpoints. The LHS variables are the monthly excess returns on the 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios. The RHS variables are the excess market return, RM-RF, the Size factor, SMB, the value factor, HML, the momentum factor, MOM, the short-term reversal factor, ST, and the long-term reversal factor, LT, constructed using independent 2x3 sorts on Size and each of B/M, MOM, ST and LT. The first two rows of Panel A show the six-factor models intercepts and their t-statistics. The remainder of Panel A shows the six-factor models slopes for SMB, HML, MOM, ST and LT, and their t-statistics using the factors from the 2x3 sorts.

$$R_t - R_{ft} = \alpha + \beta(R_{M_t} - R_{ft}) + \gamma SMB_t + \delta HML_t + \varepsilon MOM_t + \zeta ST_t + \eta LT_t + e_t$$

	Lo10	20	30	40	50	60	70	80	90	Hi10
Panel A: Mkt SMB HML MOM ST LT										
	α									
Size	-0.07	-0.12	-0.01	-0.03	0.05	0.01	0.04	0.04	0.03	0.04
B/M	0.12	0.09	0.07	-0.04	-0.03	0.02	-0.06	-0.06	0.07	-0.06
Mom	-0.30	0.19	0.28	0.20	0.01	-0.01	-0.04	-0.04	-0.08	0.09
ST	-0.34	-0.08	-0.04	0.01	0.04	0.00	0.07	0.14	0.08	-0.02
LT	0.05	-0.02	0.04	0.04	0.06	0.05	0.06	0.10	-0.03	0.02
	$t(\alpha)$									
Size	-1.00	-2.66	-0.17	-0.75	1.21	0.21	0.84	0.76	0.81	1.76
B/M	2.20	1.59	1.25	-0.58	-0.41	0.29	-0.84	-0.77	1.20	-0.61
Mom	-2.46	2.25	3.50	2.88	0.17	-0.08	-0.50	-0.53	-0.08	0.88
ST	-3.32	-1.23	-0.51	0.11	0.58	-0.07	1.08	2.54	1.19	-0.30
LT	0.61	-0.29	0.63	0.65	0.82	0.66	0.90	1.45	-0.39	0.24
Panel B: Mkt SMB HML MOM ST LT										
	β									
Size	0.90	1.02	1.04	1.03	1.05	1.03	1.05	1.05	1.01	0.98
B/M	1.00	0.98	1.01	1.01	0.98	0.96	0.99	0.99	1.05	1.19
Mom	1.20	1.08	0.98	0.96	0.94	0.97	0.96	0.98	1.04	1.16
ST	1.17	1.03	0.99	0.99	0.97	0.94	0.98	1.00	1.06	1.12
LT	1.11	1.03	0.98	0.96	0.97	0.94	0.96	0.95	1.03	1.16

	$t(\beta)$									
Size	50.4	93.1	117.1	105.4	105.0	89.9	93.4	94.3	100.7	206.1
B/M	76.3	75.9	72.3	46.1	35.2	59.2	47.5	42.5	73.3	47.8
Mom	27.4	53.2	54.0	54.5	44.5	42.2	39.0	59.2	43.1	40.1
ST	32.3	60.0	55.1	43.6	53.2	70.3	73.5	67.3	64.4	40.8
LT	34.2	60.6	53.3	49.1	46.8	41.4	38.2	47.3	64.5	61.1

Panel C: Mkt SMB HML MOM ST LT

	γ									
Size	1.22	1.09	0.94	0.84	0.69	0.52	0.37	0.27	0.08	-0.28
B/M	-0.11	-0.05	-0.03	0.00	-0.05	0.00	0.00	0.17	0.20	0.41
Mom	0.42	0.13	0.00	-0.03	-0.05	-0.04	-0.09	-0.03	0.01	0.38
ST	0.38	0.12	-0.02	-0.05	-0.06	-0.05	-0.09	-0.03	0.06	0.35
LT	0.48	0.08	-0.02	0.02	-0.08	-0.08	-0.08	-0.06	-0.03	0.14

	$t(\gamma)$									
Size	46.70	67.80	71.95	58.67	47.32	31.05	22.59	16.22	5.76	-40.77
B/M	76.26	75.95	72.33	46.08	35.19	59.19	47.50	42.50	73.26	47.75
Mom	27.39	53.22	54.01	54.50	44.52	42.18	39.03	59.25	1.04	40.13
ST	10.87	5.10	-0.74	-1.63	-2.68	-2.60	-2.95	-1.31	2.32	9.33
LT	11.32	2.07	-0.63	0.60	-2.57	-2.67	-2.65	-1.76	-0.98	4.39

Panel D: Mkt SMB HML MOM ST LT

	δ									
Size	0.25	0.20	0.22	0.19	0.17	0.17	0.11	0.09	0.11	-0.07
B/M	-0.49	-0.15	0.04	0.24	0.33	0.44	0.54	0.68	0.70	0.85
Mom	-0.09	0.05	0.10	0.16	0.18	0.21	0.19	0.20	0.21	-0.08
ST	-0.07	0.05	0.04	0.09	0.08	0.07	0.12	0.03	0.04	0.00
LT	0.05	0.05	0.05	0.23	0.24	0.25	0.22	0.20	0.14	-0.19

	$t(\delta)$									
Size	8.03	10.54	14.03	11.24	9.54	8.39	5.50	4.83	6.50	-7.90
B/M	-21.29	-6.48	1.71	3.54	6.41	15.29	9.48	12.09	27.90	22.04
Mom	-1.27	1.08	1.98	2.65	3.52	3.99	3.39	3.90	0.21	-1.64
ST	-1.37	1.26	1.32	2.33	2.06	2.96	3.55	1.32	1.09	0.06
LT	0.93	1.08	1.04	4.75	4.52	4.91	4.15	3.43	2.16	-4.93

Panel E: Mkt SMB HML MOM ST LT

	ε									
Size	-0.01	0.00	-0.02	-0.01	-0.02	-0.01	0.00	-0.02	-0.01	0.00
B/M	0.00	0.00	0.00	0.00	-0.03	0.03	-0.02	-0.01	-0.04	-0.10
Mom	-0.94	-0.69	-0.53	-0.31	-0.15	-0.04	0.09	0.25	0.35	0.55
ST	-0.14	-0.03	0.04	0.01	0.02	0.01	-0.03	-0.04	-0.06	-0.04
LT	-0.16	-0.06	-0.01	-0.04	0.00	0.04	0.07	0.03	0.06	0.01
	$t(\varepsilon)$									
Size	-0.40	-0.31	-2.55	-0.60	-2.35	-0.67	0.08	-1.68	-0.68	-0.58
B/M	-0.38	-0.19	-0.27	-0.12	-0.78	2.08	-0.80	-0.67	-2.81	-2.08
Mom	-21.16	-27.16	-12.08	-10.51	-4.04	-1.05	3.02	8.08	0.35	14.11
ST	-2.70	-1.89	1.32	0.62	0.75	0.89	-1.30	-2.19	-2.48	-1.56
LT	-4.92	-2.87	-0.18	-1.60	0.12	1.21	2.02	0.93	1.83	0.25

Panel F: Mkt SMB HML MOM ST LT

	ζ									
Size	0.00	0.00	0.01	-0.02	-0.03	0.02	0.00	0.00	0.01	0.00
B/M	0.00	0.02	-0.02	0.02	0.01	-0.03	0.03	-0.04	-0.01	-0.05
Mom	0.10	-0.01	-0.03	0.00	0.03	-0.01	0.01	0.04	0.05	-0.01
ST	0.79	0.61	0.46	0.17	0.09	0.01	-0.16	-0.29	-0.49	-0.66
LT	0.00	0.05	-0.02	-0.01	-0.02	0.01	0.00	0.02	-0.02	0.01
	$t(\zeta)$									
Size	0.19	0.31	0.95	-1.66	-2.11	1.49	-0.13	0.13	0.66	-0.34
B/M	0.19	1.04	-0.84	0.46	0.21	-1.13	1.20	-1.26	-0.66	-1.00
Mom	1.62	-0.44	-0.67	0.01	0.66	-0.15	0.23	1.25	0.05	-0.22
ST	16.85	22.66	11.10	3.61	2.47	0.55	-4.61	-7.89	-14.27	-18.71
LT	0.11	1.47	-0.46	-0.37	-0.61	0.31	0.11	0.57	-0.56	0.49

Panel G: Mkt SMB HML MOM ST LT

	η									
Size	-0.01	0.01	-0.06	-0.06	-0.03	-0.08	0.00	0.01	-0.05	0.02
B/M	-0.03	-0.02	0.00	-0.10	-0.09	-0.04	-0.07	-0.03	-0.04	0.16
Mom	0.04	-0.03	0.05	-0.09	-0.03	-0.11	-0.11	-0.13	-0.14	0.00
ST	-0.05	0.01	0.03	0.02	-0.01	-0.03	-0.04	0.00	-0.07	-0.02
LT	0.97	0.70	0.64	0.23	0.10	-0.01	-0.18	-0.34	-0.41	-0.49
	$t(\eta)$									
Size	-0.15	0.40	-3.36	-3.14	-1.50	-3.78	-0.22	0.48	-2.53	2.16
BM	-1.13	-0.62	-0.02	-1.86	-1.62	-1.30	-1.38	-0.76	-1.31	3.41
Mom	0.56	-0.68	1.22	-2.04	-0.75	-2.21	-1.77	-2.62	-0.14	0.01
ST	-1.20	0.20	1.05	0.78	-0.42	-1.22	-0.97	-0.16	-1.68	-0.48
LT	17.35	17.33	16.44	5.55	2.21	-0.16	-3.33	-7.14	-8.93	-10.96

VI Conclusion & Limitations

The purpose of this study was to identify whether the momentum anomaly in the United States still exist. We tried to answer this research question by providing more empirical evidence on the momentum effect in combination with the existent three-factor model. A topic that is relevant not only for academic studies, but it might also be useful for practitioners of the subject. The goal of this paper was to look if several forms of momentum anomalies improve the three-factor model. We examined average excess returns related to size, B/M ratio, momentum, short-term reversal and long-term reversal. By extending the Fama and French three-factor model (1993) with various combinations of momentum factors we tried to find the best performing model. We pick our best performing model after looking several indicators of model performance for both our dependent (LHS) and independent (RHS) variables. Finally, we run regressions on this model to determine the existence of monthly average excess returns in the US from January 1965 to March 2017 of stocks listed on the NYSE, AMEX, or NASDAQ. In line with Fama and French (2015) we used GRS and the Adjusted R-squared statistics to determine the best performing model. We also looked at the average absolute intercept and the standard errors of the mean for our model. We construct 50 single-sorted and 24 double-sorted portfolios and investigated 74 portfolios in total. We noticed that the single-sorted portfolios mainly perform better than the double-sorted portfolios. We therefore continue to use all the single-sorted portfolios as dependent variables to run regressions on.

Our results indicate that the original three-factor model is likely to fare poorly when applied to portfolios that include strong tilts toward various combinations of momentum and reversal factors. It can be concluded that the six-factor model is better in describing the average excess returns than the three-, four- and five-factor model based on the statistics of GRS, the adjusted R-squared, average absolute intercepts and the standard error of the mean.

The six factors are excess return, size, B/M ratio, momentum, short-term reversal and long-term reversal. For the 50-decile portfolios on the 6-factor model we end up with a GRS statistic

of 2.363, an average absolute intercept of 0.072, and Adjusted R-squared value of 91.3% and a standard error of the mean of 0.062.

Neglecting a few exceptions we can safely conclude that our intercept was insignificant for almost all of the single-sorted portfolios. In line with our expectations we see that the excess market return showed a beta of around 1.0 in almost all of our portfolios. The size-factor (SMB) proved to one of the best performing factors out of our six-factor model. It showed that it was significant in almost all of the 50 single-sorted portfolios with a few exceptions in the decile of the short-term and long-term reversal portfolios. However, we see that some of the values around the momentum-related (momentum, short-term reversal and long-term reversal) portfolios show significant negative excess returns. This is obviously not in line with our expectations, because we expect them to be positive. The value-factor (HML) showed to generate significant average excess returns for most of the single-sorted portfolios. Despite a few insignificant values of the value-factor for the long-term reversal portfolios we can conclude that this factor performed well in general. The remaining factors of the six-factor model MOM, ST and LT showed less desirable results. First, the momentum-factor (MOM) showed to have only insignificant values. This is inconsistent with the findings of (1997). If there were any significant values they were found in the portfolios related to the factor. For example, the significant values for the momentum-factor were mainly found in the single-sorted portfolios of momentum. The same holds for the short-term reversal factor (ST) and the long-term reversal factor (LT). The short-term reversal factor (ST) only showed significant values in the single-sorted portfolios formed on short-term reversal. While the long-term reversal factor (LT) only showed significant values in the single-sorted portfolios formed on long-term reversal. It is notable that for both factors the portfolios showed positive excess returns in the lower deciles, while they were negative in the higher deciles.

In conclusion we can say that our six-factor model did not entirely improve the original three-factor model. Despite some significant values generated by our model, they do not show consistent significant excess returns. However, it does provide insights about various forms the three-factor model extended with momentum related factors. One of the limitations of our research is that we did not correct for periods of recessions. Throughout our investigating

period there were several periods of recessions we did not correct for. In a recession, significant deviations of economic activity spreads across the economy and can last for months to more than a year. We could have run regressions with a dummy intercept. For example, the Energy Crisis in 1980, the 9/11 recession and the Financial Crisis in 2007. Another limitation is that we could have investigated more factors that could describe the average excess returns in the United States. We solely looked at momentum-related factors which is one of many patterns we have seen throughout the years. Furthermore our research only investigated the United States. There might be totally different results in Europe or any other countries in the world. Last limitation is that we neglect transaction costs. Many papers have argued that effects on the market are the result of mispricing. In order for mispricing to persist, it must be that costs limit arbitrageurs in their efforts at keeping markets efficient (see Scholes (1972), Shiller (1984), De Long, Shleifer, Summers, and Waldmann (1990), Pontiff (1996), (2006). If Momentum occurs it might be the result of mispricing, but transaction costs may be the binding costs that limit arbitrage. This argument is in line with the findings of Lesmond et al. (2004), who show that there is cross-sectional relation between transaction costs and momentum profits. In conclusion we can say that we did not find many significant forms of momentum anomalies with our model in the US from January 1965 to March 2017.

References

- Arshanapalli, B., Fabozzi, F. J., & Nelson, W. (2006). The value, size, and momentum spread during distressed economic periods. *Finance Research Letters*, 3(4), 244-252.
- Bachelier, L., & Cootner, P. H. (1964). The random character of stock market prices. *Theorie de la speculation*, Gauthiers, MA, 17-18.
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3-18.
- Black, F., Jensen, M. C., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests. *Studies in the Theory of Capital Markets*, 81(3), 79-121.
- Black, F. (1986). Noise. *The Journal of Finance*, 41(3), 528-543.
- Bondt, W. F. de., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of Finance*, 40(3), 793-805.
- Bremer, M., & Sweeney, R. J. (1991). The reversal of large stock-price decreases. *The Journal of Finance*, 46(2), 747-754.
- Cakici, N., & Topyan, K. (2014). Short-Term Reversal. In *Risk and Return in Asian Emerging Markets* (pp. 91-103). Palgrave Macmillan US.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57-82.
- Chan, K., Hameed, A., & Tong, W. (2000). Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis*, 35(2), 153-172.
- Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: do stocks overreact?. *Journal of Financial Economics*, 31(2), 235-268.
- Chordia, T., & Shivakumar, L. (2002). Momentum, business cycle, and time-varying expected returns. *The Journal of Finance*, 57(2), 985-1019.
- Chordia, T., Roll, R., & Subrahmanyam, A. (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics*, 76(2), 271-292.
- Chui, A. C., Titman, S., & Wei, K. J. (2010). Individualism and momentum around the world. *The Journal of Finance*, 65(1), 361-392.
- Connolly, R., Stivers, C., & Sun, L. (2005). Stock market uncertainty and the stock-bond return relation. *Journal of Financial and Quantitative Analysis*, 40(1), 161-194.
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *the Journal of Finance*, 53(6), 1839-1885.

- Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. *The Journal of Finance*, 56(3), 921-965.
- De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of Finance*, 40(3), 793-805.
- De Bondt, W. F., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance*, 557-581.
- De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990a). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4), 703-738.
- Drew, M. E., Veeraraghavan, M., & Ye, M. (2007). Do momentum strategies work? Australian evidence. *Managerial Finance*, 33(10), 772-787.
- Du, D. (2008). The 52-week high and momentum investing in international stock indexes. *The Quarterly Review of Economics and Finance*, 48(1), 61-77.
- Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, 38(1), 34-105.
- Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance¹. *Journal of Financial Economics*, 49(3), 283-306.
- Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance*, 50(1), 131-155.
- Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1), 55-84.
- Fama, E. F., & French, K. R. (2005). Financing decisions: who issues stock?. *Journal of Financial Economics*, 76(3), 549-58
- Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, 63(4), 1653-1678.
- Ferson, W. E., & Harvey, C. R. (1999). Conditioning variables and the cross section of stock returns. *The Journal of Finance*, 54(4), 1325-1360.
- George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. *The Journal of Finance*, 59(5), 2145-2176.
- Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society* 57, 1121-1152.
- Griffin, J. M., Ji, X., & Martin, J. S. (2005). Global momentum strategies. *Journal of Portfolio Management*, 31(2), 23-39.

- Grinblatt, M., & Titman, S. (1989). Mutual fund performance: An analysis of quarterly portfolio holdings. *Journal of Business* 62, 393-416.
- Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *The Journal of Finance*, 43(3), 617-633.
- Grundy, B. D., & Martin, J. S. M. (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies*, 14(1), 29-78.
- Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54(6), 2143-2184.
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.
- Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, 56(2), 699-720.
- Jiang, Z. Q., Chen, W., & Zhou, W. X. (2008). Scaling in the distribution of intertrade durations of Chinese stocks. *Physica A: Statistical Mechanics and its Applications*, 387(23), 5818-5825.
- Ji, X. (2014). Parton physics from large-momentum effective field theory. *Science China Physics, Mechanics & Astronomy*, 57(7), 1407-1412
- Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49(5), 1541-1578.
- Lee, C. M., & Swaminathan, B. (2000). Price momentum and trading volume. *The Journal of Finance*, 55(5), 2017-2069.
- Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1), 1-28.
- Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. *Journal of Financial Economics*, 71(2), 349-380.
- Liu, C., & Lee, Y. (2001). Does the momentum strategy work universally? Evidence from the Japanese stock market. *Asia-Pacific Financial Markets*, 8(4), 321-339.
- Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, 20(4), 587-615.
- Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives*, 17(1), 59-82.
- Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383-417.

- Petkova, R. (2006). Do the Fama–French factors proxy for innovations in predictive variables?. *The Journal of Finance*, 61(2), 581-612.
- Pontiff, J. (1996). Costly arbitrage: Evidence from closed-end funds. *The Quarterly Journal of Economics*, 111(4), 1135-1151.
- Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, 42(1-2), 35-52.
- Poterba, J. M., & Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics*, 22(1), 27-59.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425-442.
- Shiller, R. J., Fischer, S., & Friedman, B. M. (1984). Stock prices and social dynamics. *Brookings Papers on Economic Activity*, 1984(2), 457-510.
- Stiglitz, J. E. (1989). Imperfect information in the product market. *Handbook of Industrial Organization*, 1, 769-847.
- Summers, L. H., & Summers, V. P. (1989). When financial markets work too well: A cautious case for a securities transactions tax. *Journal of Financial Services Research*, 3(2-3), 261-286.
- Vayanos, D., & Woolley, P. (2013). An institutional theory of momentum and reversal. *The Review of Financial Studies*, 26(5), 1087-1145.
- Wang, C., & Yu, M. (2004). Trading activity and price reversals in futures markets. *Journal of Banking & Finance*, 28(6), 1337-1361.

Tables

Table 1 – Construction of Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal factors

We use independent sorts to assign stocks to two *Size* groups, and three *B/M*, Momentum (*MOM*), Short-term Reversal (*ST REV*) and Long-Term Reversal (*LT REV*) groups. The value-weighted portfolios defined by the intersections of the groups are the building blocks for the factors. We label these portfolios with two or four letters. The first always describes the *Size* group, small (*S*) or big (*B*). The second describes the *B/M* group, high (*H*), neutral (*N*), or Low (*L*), or the *MOM*, *ST REV* and *LT REV* group, up (*U*) or down (*D*). The factors are *SMB* (small minus big), *HML* (high minus low *B/M*), *MOM* (up minus down), *ST REV* (down minus up) and *LT REV* (down minus up).

Sort	Breakpoints	Factors and their components
2x3 sorts on Size and B/M	<i>Size</i> : NYSE Median	$SMB = (SH+SN+SL)/3 - (BH+BN+BL)/3$
2x3 sorts on Size and B/M	<i>B/M</i> : 30th & 70th NYSE percentiles	$HML = (SH+BH)/2 - (SL+BL)/2$
2x3 sorts on Size and Mom	<i>MOM</i> : 30th & 70th NYSE percentiles	$MOM = (SU+BU)/2 - (SD+BD)/2$
2x3 sorts on Size and ST Rev	<i>ST REV</i> : 30th & 70th NYSE Percentiles	$ST REV = (SD+BD)/2 - (SU+BU)/2$
2x3 sorts on Size and LT Rev	<i>LT REV</i> : 30th & 70th NYSE Percentiles	$LT REV = (SD+BD)/2 - (SU+BU)/2$

Table 2 – Average monthly excess returns for portfolios formed on Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal; January 1965 - March 2017, 627 months

At the end of June each year, stocks are allocated to ten *Size*, *B/M*, Momentum, *ST Rev*, *LT Rev* and two *Size* groups (Small and Big) using NYSE market cap breakpoints. To construct double-sorted portfolios stocks are allocated independently to three *B/M*, *ST Rev* and *LT rev* (low to high), again using NYSE breakpoints. In the sort for June of year *t*, *B* is book equity at the end of the fiscal year ending in year *t-1* and *M* is market cap at the end of December of year *t-1*, adjusted for changes in shares outstanding between the measurement of *B* and the end of December. The *Size-Mom*, *Size-ST Rev* and *Size-LT Rev* are formed in the same way, except that the second sort variable is respectively Momentum, Short-term Reversal and Long-term Reversal.

	Lo 10	2-Dec	3-Dec	4-Dec	5-Dec	6-Dec	7-Dec	8-Dec	9-Dec	Hi 10
Panel A: Size										
	0,35	0,33	0,39	0,33	0,37	0,29	0,29	0,25	0,19	0,04
Panel B: Value										
	0,02	0,12	0,18	0,13	0,13	0,25	0,21	0,29	0,45	0,49
Panel C: Mom										
	-0,59	-0,09	0,06	0,10	0,04	0,09	0,13	0,27	0,33	0,69
Panel D: St_Rev										
	0,20	0,36	0,33	0,23	0,19	0,09	0,07	0,08	-0,05	-0,13
Panel E: Lt_Rev										
	0,51	0,31	0,31	0,24	0,23	0,22	0,20	0,17	0,05	0,05
	Low	Med	High				Low	Med	High	
Panel F: Size-B/M										
Small	0.12	0.48	0.62				Panel G: Size-Mom			
Big	0.08	0.12	0.29				Small	0.78	0.41	-0.11
							Big	0.35	0.03	-0.08
Panel H: Size-ST Rev							Panel I: Size-LT Rev			
Small	0.64	0.41	-0.03				Small	0.59	0.50	0.29
Big	0.26	0.12	-0.05				Big	0.31	0.18	0.06

Table 3 – Summary statistics for monthly factor returns; January 1965 - March 2017, 627 months

At the end of June each year, stocks are allocated to two Size groups (Small and Big) using NYSE market cap breakpoints. The LHS variables are the monthly excess returns on the 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios. Rm-Rf is the value-weight return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. At the end of each June, stocks are assigned to two Size groups using the NYSE median market cap as breakpoint. Stocks are also assigned independently to three book-to-market equity (B/M), momentum, short-term reversal and long-term reversal groups, using NYSE medians of B/M, MOM, ST REV and LT REV or the 30th and 70th percentiles.

	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Panel A: Size										
Mean	0.75	0.73	0.79	0.73	0.77	0.69	0.69	0.65	0.59	0.44
Std Dev	6.39	6.41	6.09	5.86	5.66	5.31	5.21	5.07	4.63	4.25
Panel B: B/M										
Mean	0.42	0.52	0.58	0.53	0.53	0.65	0.61	0.69	0.85	0.89
Std Dev	5.11	4.67	4.65	4.68	4.49	4.39	4.61	4.66	5.00	6.15
Panel C: Momentum										
Mean	-0.19	0.31	0.46	0.50	0.44	0.49	0.53	0.67	0.73	1.09
Std Dev	8.16	6.26	5.36	4.81	4.49	4.52	4.38	4.47	4.83	6.21
Panel D: ST Rev										
Mean	0.60	0.76	0.73	0.63	0.59	0.49	0.47	0.48	0.35	0.27
Std Dev	7.33	5.79	5.15	4.74	4.51	4.35	4.32	4.47	4.78	5.53
Panel E: LT Rev										
Mean	0.91	0.71	0.71	0.64	0.63	0.62	0.60	0.57	0.45	0.45
Std Dev	6.72	5.32	4.82	4.53	4.43	4.29	4.39	4.42	4.80	5.95
<hr/>										
	SL	SN	SH	BL	BN	BH				
Panel F: Size-B/M										
Mean	0.52	0.88	1.02	0.48	0.52	0.69				
Std Dev	6.90	5.46	5.63	4.63	4.31	4.87				
<hr/>										
	SD	SM	SU	BD	BM	BU				
Panel G: Size-MOM										
Mean	1.18	0.81	0.29	0.75	0.43	0.32				
Std Dev	6.22	5.26	7.20	4.86	4.28	5.91				
Panel H: Size ST Rev										
Mean	1.04	0.81	0.37	0.66	0.52	0.35				
Std Dev	7.11	5.46	6.02	5.56	4.26	4.61				
Panel I: Size LT Rev										
Mean	0.99	0.90	0.69	0.71	0.58	0.46				
Std Dev	6.49	5.17	5.99	4.98	4.16	4.87				
<hr/>										
	Rm-Rf	SMB	HML	MOM	ST	LT				
Panel J: Six Factors										
Mean	0.50	0.24	0.35	0.66	0.49	0.27				
Std Dev	4.47	3.12	2.85	4.28	3.15	2.52				

Table 4 (continued)

Panel K: Correlations between different deciles of the single-sorted portfolios

Size											Value									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.96	0.94	0.91	0.89	0.86	0.85	0.82	0.78	0.65	1.00	0.90	0.86	0.81	0.77	0.74	0.73	0.71	0.71	0.66
20	0.96	1.00	0.98	0.97	0.95	0.93	0.91	0.89	0.84	0.73	0.90	1.00	0.93	0.90	0.86	0.84	0.82	0.80	0.81	0.75
30	0.94	0.98	1.00	0.98	0.97	0.96	0.94	0.92	0.88	0.77	0.86	0.93	1.00	0.93	0.90	0.89	0.86	0.84	0.85	0.78
40	0.91	0.97	0.98	1.00	0.98	0.97	0.95	0.93	0.90	0.79	0.81	0.90	0.93	1.00	0.92	0.91	0.88	0.86	0.85	0.80
50	0.89	0.95	0.97	0.98	1.00	0.98	0.97	0.96	0.92	0.82	0.77	0.86	0.90	0.92	1.00	0.91	0.89	0.86	0.86	0.80
60	0.86	0.93	0.96	0.97	0.98	1.00	0.98	0.97	0.94	0.85	0.74	0.84	0.89	0.91	0.91	1.00	0.91	0.88	0.87	0.80
70	0.85	0.91	0.94	0.95	0.97	0.98	1.00	0.98	0.96	0.87	0.73	0.82	0.86	0.88	0.89	0.91	1.00	0.90	0.88	0.84
80	0.82	0.89	0.92	0.93	0.96	0.97	0.98	1.00	0.97	0.89	0.71	0.80	0.84	0.86	0.86	0.88	0.90	1.00	0.91	0.87
90	0.78	0.84	0.88	0.90	0.92	0.94	0.96	0.97	1.00	0.92	0.71	0.81	0.85	0.85	0.86	0.87	0.88	0.91	1.00	0.90
Hi 10	0.65	0.73	0.77	0.79	0.82	0.85	0.87	0.89	0.92	1.00	0.66	0.75	0.78	0.80	0.80	0.80	0.84	0.87	0.90	1.00

Momentum											ST Rev									
	Lo 10	20	30	40	50	60	70	80	90	Hi 10	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.91	0.86	0.82	0.78	0.73	0.67	0.63	0.59	0.54	1.00	0.93	0.88	0.84	0.83	0.80	0.77	0.76	0.72	0.69
20	0.91	1.00	0.93	0.90	0.86	0.81	0.74	0.69	0.64	0.55	0.93	1.00	0.92	0.89	0.88	0.86	0.81	0.79	0.75	0.69
30	0.86	0.93	1.00	0.92	0.89	0.85	0.78	0.72	0.68	0.55	0.88	0.92	1.00	0.90	0.90	0.88	0.85	0.81	0.76	0.70
40	0.82	0.90	0.92	1.00	0.91	0.89	0.84	0.80	0.75	0.61	0.84	0.89	0.90	1.00	0.92	0.91	0.88	0.86	0.82	0.75
50	0.78	0.86	0.89	0.91	1.00	0.91	0.87	0.84	0.80	0.67	0.83	0.88	0.90	0.92	1.00	0.92	0.90	0.87	0.84	0.77
60	0.73	0.81	0.85	0.89	0.91	1.00	0.91	0.88	0.86	0.73	0.80	0.86	0.88	0.91	0.92	1.00	0.91	0.89	0.85	0.78
70	0.67	0.74	0.78	0.84	0.87	0.91	1.00	0.91	0.90	0.76	0.77	0.81	0.85	0.88	0.90	0.91	1.00	0.92	0.90	0.81
80	0.63	0.69	0.72	0.80	0.84	0.88	0.91	1.00	0.93	0.84	0.76	0.79	0.81	0.86	0.87	0.89	0.92	1.00	0.91	0.84
90	0.59	0.64	0.68	0.75	0.80	0.86	0.90	0.93	1.00	0.88	0.72	0.75	0.76	0.82	0.84	0.85	0.90	0.91	1.00	0.90
Hi 10	0.54	0.55	0.55	0.61	0.67	0.73	0.76	0.84	0.88	1.00	0.69	0.69	0.70	0.75	0.77	0.78	0.81	0.84	0.90	1.00

LT Rev										
	Lo 10	20	30	40	50	60	70	80	90	Hi 10
Lo 10	1.00	0.89	0.84	0.81	0.77	0.74	0.69	0.67	0.67	0.68
20	0.89	1.00	0.90	0.87	0.84	0.83	0.79	0.76	0.77	0.74
30	0.84	0.90	1.00	0.89	0.87	0.84	0.81	0.77	0.78	0.74
40	0.81	0.87	0.89	1.00	0.90	0.88	0.86	0.82	0.82	0.77
50	0.77	0.84	0.87	0.90	1.00	0.89	0.89	0.87	0.85	0.78
60	0.74	0.83	0.84	0.88	0.89	1.00	0.90	0.89	0.87	0.80
70	0.69	0.79	0.81	0.86	0.89	0.90	1.00	0.91	0.90	0.82
80	0.67	0.76	0.77	0.82	0.87	0.89	0.91	1.00	0.92	0.86
90	0.67	0.77	0.78	0.82	0.85	0.87	0.90	0.92	1.00	0.90
Hi 10	0.68	0.74	0.74	0.77	0.78	0.80	0.82	0.86	0.90	1.00

Panel L: Correlations between double-sorted portfolios and between different factors

Size-B/M						
	SH	SM	SL	BH	BM	BL
SH	1.00	0.94	0.89	0.82	0.73	0.73
SM	0.94	1.00	0.97	0.79	0.82	0.83
SL	0.89	0.97	1.00	0.74	0.80	0.85
BH	0.82	0.79	0.74	1.00	0.86	0.78
BM	0.73	0.82	0.80	0.86	1.00	0.90
BL	0.73	0.83	0.85	0.78	0.90	1.00

Size-Momentum 2x3						
	SU	SM	SD	BU	BM	BD
SU	1.00	0.93	0.81	0.86	0.78	0.65
SM	0.93	1.00	0.91	0.79	0.84	0.78
SD	0.81	0.91	1.00	0.64	0.75	0.86
BU	0.86	0.79	0.64	1.00	0.87	0.63
BM	0.78	0.84	0.75	0.87	1.00	0.83
BD	0.65	0.78	0.86	0.63	0.83	1.00

Size-ST_REV 2x3						
	SD	SM	SU	BD	BM	BU
SD	1.00	0.95	0.90	0.87	0.80	0.74
SM	0.95	1.00	0.94	0.83	0.84	0.79
SU	0.90	0.94	1.00	0.76	0.80	0.84
BD	0.87	0.83	0.76	1.00	0.90	0.76
BM	0.80	0.84	0.80	0.90	1.00	0.89
BU	0.74	0.79	0.84	0.76	0.89	1.00

Size-LT_REV 2x3						
	SD	SM	SU	BD	BM	BU
SD	1.00	0.96	0.93	0.85	0.78	0.73
SM	0.96	1.00	0.96	0.85	0.85	0.79
SU	0.93	0.96	1.00	0.81	0.82	0.84
BD	0.85	0.85	0.81	1.00	0.88	0.79
BM	0.78	0.85	0.82	0.88	1.00	0.89
BU	0.73	0.79	0.84	0.79	0.89	1.00

Factors						
	MKT_RF	SMB	HML	MOM	ST	LT
MKT_RF	1.00	0.30	-0.26	-0.13	0.29	-0.02
SMB	0.30	1.00	-0.20	0.00	0.16	0.26
HML	-0.26	-0.20	1.00	-0.19	0.00	0.45
MOM	-0.13	0.00	-0.19	1.00	-0.29	-0.07
ST	0.29	0.16	0.00	-0.29	1.00	0.08
LT	-0.02	0.26	0.45	-0.07	0.08	1.00

Table 7 – Summary statistics for tests of four-, five- and six-factor models; January 1965 - March 2017, 627 months

The table tests the ability of four-, five- and six-factor models to explain monthly excess returns on 10 Size portfolios (Panel A), 10 B/M portfolios (Panel B), 10 Momentum portfolios (Panel C), 10 ST Rev portfolios (Panel D), 10 LT Rev portfolios (Panel E), 50 single-sorted portfolios (Panel F), 6 Size-B/M portfolios (Panel G), 6 Size-Momentum portfolios (Panel H), 6 Size-ST Rev portfolios (Panel I), 6 Size-LT Rev portfolios (Panel J) and 24 double-sorted portfolios (Panel K). For each set of 6, 10, 24 or 50 regressions, the table shows the factors that augment $R_m - R_f$, SMB and HML in the regression model, the GRS statistic testing whether the expected values of all 6, 10, 24 or 50 intercepts estimates are zero, the average absolute value of the intercepts, $A|a_i|$, the adjusted R-squared comparing the explanatory power of the models that contain different number of predictors, R_{adj}^2 and SE_μ which is the standard error of the mean.

	GRS	$A a_i $	Adj R2	SE_μ		GRS	$A a_i $	Adj R2	SE_μ
Panel A: 10-Size portfolios					Panel B: 10-B/M portfolios				
(1) MOM	2.780	0.044	0.961	0.044	(1) MOM	1.700	0.062	0.898	0.064
(2) ST	2.336	0.042	0.961	0.044	(2) ST	2.105	0.076	0.898	0.063
(3) LT	2.419	0.042	0.961	0.043	(3) LT	2.204	0.075	0.899	0.062
(4) MOM ST	2.677	0.044	0.961	0.045	(4) MOM ST	1.509	0.062	0.898	0.065
(5) MOM LT	2.770	0.044	0.961	0.044	(5) MOM LT	1.724	0.062	0.899	0.063
(6) ST LT	2.320	0.042	0.961	0.043	(6) ST LT	2.123	0.076	0.899	0.063
(7) MOM ST LT	2.673	0.044	0.961	0.045	(7) MOM ST LT	1.516	0.062	0.899	0.064
Panel C: 10-Momentum portfolios					Panel D: 10-ST Rev portfolios				
(1) MOM	3.511	0.115	0.897	0.071	(1) MOM	1.619	0.117	0.860	0.080
(2) ST	6.638	0.340	0.806	0.098	(2) ST	4.613	0.091	0.912	0.062
(3) LT	5.306	0.294	0.801	0.099	(3) LT	1.995	0.104	0.856	0.080
(4) MOM ST	3.987	0.124	0.897	0.071	(4) MOM ST	3.616	0.081	0.913	0.063
(5) MOM LT	3.501	0.114	0.898	0.070	(5) MOM LT	1.611	0.116	0.860	0.080
(6) ST LT	6.614	0.340	0.807	0.098	(6) ST LT	4.598	0.091	0.912	0.062
(7) MOM ST LT	3.998	0.124	0.898	0.071	(7) MOM ST LT	3.614	0.081	0.913	0.063
Panel E: 10-LT Rev portfolios					Panel F: 50-decile portfolios				
(1) MOM	0.691	0.051	0.857	0.078	(1) MOM	1.918	0.078	0.895	0.067
(2) ST	0.799	0.063	0.856	0.078	(2) ST	2.715	0.123	0.887	0.069
(3) LT	1.101	0.062	0.889	0.067	(3) LT	2.213	0.116	0.881	0.070
(4) MOM ST	0.589	0.048	0.857	0.079	(4) MOM ST	2.367	0.072	0.905	0.065
(5) MOM LT	0.687	0.046	0.891	0.067	(5) MOM LT	1.927	0.077	0.902	0.065
(6) ST LT	1.222	0.070	0.890	0.067	(6) ST LT	2.708	0.124	0.894	0.067
(7) MOM ST LT	0.590	0.047	0.891	0.068	(7) MOM ST LT	2.363	0.072	0.913	0.062

Table 5 – (continued) double-sorted portfolios

	<i>GRS</i>	$A a_i $	Adj <i>R</i> ²	SE_{μ}
Panel G: 6 Size-B/M portfolios				
(1) <i>MOM</i>	6.065	0.091	0.967	0.037
(2) <i>ST</i>	6.823	0.100	0.967	0.036
(3) <i>LT</i>	7.053	0.102	0.967	0.036
(4) <i>MOM ST</i>	5.605	0.085	0.967	0.037
(5) <i>MOM LT</i>	6.060	0.091	0.967	0.037
(6) <i>ST LT</i>	6.809	0.100	0.967	0.036
(7) <i>MOM ST LT</i>	5.600	0.085	0.967	0.037
Panel I: 6 Size-ST Rev portfolios				
(1) <i>MOM</i>	7.659	0.184	0.921	0.062
(2) <i>ST</i>	6.774	0.097	0.965	0.042
(3) <i>LT</i>	8.017	0.121	0.917	0.063
(4) <i>MOM ST</i>	4.821	0.096	0.967	0.042
(5) <i>MOM LT</i>	7.658	0.185	0.922	0.062
(6) <i>ST LT</i>	6.750	0.096	0.966	0.042
(7) <i>MOM ST LT</i>	4.838	0.096	0.968	0.041
Panel K: 24 (2x3) portfolios				
(1) <i>MOM</i>	5.392	0.114	0.945	0.050
(2) <i>ST</i>	6.220	0.152	0.935	0.053
(3) <i>LT</i>	6.585	0.146	0.928	0.056
(4) <i>MOM ST</i>	4.611	0.086	0.956	0.045
(5) <i>MOM LT</i>	5.398	0.114	0.952	0.047
(6) <i>ST LT</i>	6.231	0.151	0.942	0.050
(7) <i>MOM ST LT</i>	4.623	0.086	0.964	0.042

	<i>GRS</i>	$A a_i $	Adj <i>R</i> ²	SE_{μ}
Panel H: 6 Size Momentum portfolios				
(1) <i>MOM</i>	6.366	0.112	0.959	0.046
(2) <i>ST</i>	11.822	0.344	0.879	0.078
(3) <i>LT</i>	10.730	0.305	0.874	0.079
(4) <i>MOM ST</i>	5.680	0.108	0.959	0.047
(5) <i>MOM LT</i>	6.345	0.112	0.960	0.046
(6) <i>ST LT</i>	11.785	0.343	0.880	0.078
(7) <i>MOM ST LT</i>	5.675	0.108	0.960	0.046
Panel J: 6 Size-LT Rev portfolios				
(1) <i>MOM</i>	3.009	0.068	0.931	0.055
(2) <i>ST</i>	3.695	0.067	0.928	0.056
(3) <i>LT</i>	3.360	0.055	0.956	0.044
(4) <i>MOM ST</i>	2.224	0.056	0.931	0.056
(5) <i>MOM LT</i>	3.013	0.067	0.960	0.043
(6) <i>ST LT</i>	3.703	0.065	0.957	0.044
(7) <i>MOM ST LT</i>	2.236	0.056	0.960	0.043

Table 6 –Regressions for 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios; January 1965 - March 2017, 627 months

At the end of June each year, stocks are allocated to five Size groups (Small to Big) using NYSE market cap breakpoints. The LHS variables are the monthly excess returns on the 10 Size, B/M, Momentum, Short-Term Reversal and Long-Term Reversal portfolios. The RHS variables are the excess market return, RM-RF, the Size factor, SMB, the value factor, HML, the momentum factor, MOM, the short-term reversal factor, ST, and the long-term reversal factor, LT, constructed using independent 2x3 sorts on Size and each of B/M, MOM, ST and LT. The first two rows of Panel A show the six-factor models intercepts and their t-statistics. The remainder of Panel A shows the six-factor models slopes for SMB, HML, MOM, ST and LT, and their t-statistics using the factors from the 2x3 sorts.

$$R_t - R_{ft} = \alpha + \beta(R_{Mkt} - R_{ft}) + \gamma SMB_t + \delta HML_t + \varepsilon MOM_t + \zeta ST_t + \eta LT_t + e_t$$

	Lo10	20	30	40	50	60	70	80	90	Hi10
Panel A: Mkt SMB HML MOM ST LT										
	α									
Size	-0.07	-0.12	-0.01	-0.03	0.05	0.01	0.04	0.04	0.03	0.04
B/M	0.12	0.09	0.07	-0.04	-0.03	0.02	-0.06	-0.06	0.07	-0.06
Mom	-0.30	0.19	0.28	0.20	0.01	-0.01	-0.04	-0.04	-0.08	0.09
ST	-0.34	-0.08	-0.04	0.01	0.04	0.00	0.07	0.14	0.08	-0.02
LT	0.05	-0.02	0.04	0.04	0.06	0.05	0.06	0.10	-0.03	0.02
	$t(\alpha)$									
Size	-1.00	-2.66	-0.17	-0.75	1.21	0.21	0.84	0.76	0.81	1.76
B/M	2.20	1.59	1.25	-0.58	-0.41	0.29	-0.84	-0.77	1.20	-0.61
Mom	-2.46	2.25	3.50	2.88	0.17	-0.08	-0.50	-0.53	-0.08	0.88
ST	-3.32	-1.23	-0.51	0.11	0.58	-0.07	1.08	2.54	1.19	-0.30
LT	0.61	-0.29	0.63	0.65	0.82	0.66	0.90	1.45	-0.39	0.24
Panel B: Mkt SMB HML MOM ST LT										
	β									
Size	0.90	1.02	1.04	1.03	1.05	1.03	1.05	1.05	1.01	0.98
B/M	1.00	0.98	1.01	1.01	0.98	0.96	0.99	0.99	1.05	1.19
Mom	1.20	1.08	0.98	0.96	0.94	0.97	0.96	0.98	1.04	1.16
ST	1.17	1.03	0.99	0.99	0.97	0.94	0.98	1.00	1.06	1.12
LT	1.11	1.03	0.98	0.96	0.97	0.94	0.96	0.95	1.03	1.16
	$t(\beta)$									
Size	50.4	93.1	117.1	105.4	105.0	89.9	93.4	94.3	100.7	206.1
B/M	76.3	75.9	72.3	46.1	35.2	59.2	47.5	42.5	73.3	47.8
Mom	27.4	53.2	54.0	54.5	44.5	42.2	39.0	59.2	43.1	40.1
ST	32.3	60.0	55.1	43.6	53.2	70.3	73.5	67.3	64.4	40.8
LT	34.2	60.6	53.3	49.1	46.8	41.4	38.2	47.3	64.5	61.1

Panel C: Mkt SMB HML MOM ST LT

	γ									
Size	1.22	1.09	0.94	0.84	0.69	0.52	0.37	0.27	0.08	-0.28
B/M	-0.11	-0.05	-0.03	0.00	-0.05	0.00	0.00	0.17	0.20	0.41
Mom	0.42	0.13	0.00	-0.03	-0.05	-0.04	-0.09	-0.03	0.01	0.38
ST	0.38	0.12	-0.02	-0.05	-0.06	-0.05	-0.09	-0.03	0.06	0.35
LT	0.48	0.08	-0.02	0.02	-0.08	-0.08	-0.08	-0.06	-0.03	0.14
	$t(\gamma)$									
Size	46.70	67.80	71.95	58.67	47.32	31.05	22.59	16.22	5.76	-40.77
B/M	76.26	75.95	72.33	46.08	35.19	59.19	47.50	42.50	73.26	47.75
Mom	27.39	53.22	54.01	54.50	44.52	42.18	39.03	59.25	1.04	40.13
ST	10.87	5.10	-0.74	-1.63	-2.68	-2.60	-2.95	-1.31	2.32	9.33
LT	11.32	2.07	-0.63	0.60	-2.57	-2.67	-2.65	-1.76	-0.98	4.39

Panel D: Mkt SMB HML MOM ST LT

	δ									
Size	0.25	0.20	0.22	0.19	0.17	0.17	0.11	0.09	0.11	-0.07
B/M	-0.49	-0.15	0.04	0.24	0.33	0.44	0.54	0.68	0.70	0.85
Mom	-0.09	0.05	0.10	0.16	0.18	0.21	0.19	0.20	0.21	-0.08
ST	-0.07	0.05	0.04	0.09	0.08	0.07	0.12	0.03	0.04	0.00
LT	0.05	0.05	0.05	0.23	0.24	0.25	0.22	0.20	0.14	-0.19
	$t(\delta)$									
Size	8.03	10.54	14.03	11.24	9.54	8.39	5.50	4.83	6.50	-7.90
B/M	-21.29	-6.48	1.71	3.54	6.41	15.29	9.48	12.09	27.90	22.04
Mom	-1.27	1.08	1.98	2.65	3.52	3.99	3.39	3.90	0.21	-1.64
ST	-1.37	1.26	1.32	2.33	2.06	2.96	3.55	1.32	1.09	0.06
LT	0.93	1.08	1.04	4.75	4.52	4.91	4.15	3.43	2.16	-4.93

Panel E: Mkt SMB HML MOM ST LT

	ε									
Size	-0.01	0.00	-0.02	-0.01	-0.02	-0.01	0.00	-0.02	-0.01	0.00
B/M	0.00	0.00	0.00	0.00	-0.03	0.03	-0.02	-0.01	-0.04	-0.10
Mom	-0.94	-0.69	-0.53	-0.31	-0.15	-0.04	0.09	0.25	0.35	0.55
ST	-0.14	-0.03	0.04	0.01	0.02	0.01	-0.03	-0.04	-0.06	-0.04
LT	-0.16	-0.06	-0.01	-0.04	0.00	0.04	0.07	0.03	0.06	0.01
	$t(\varepsilon)$									
Size	-0.40	-0.31	-2.55	-0.60	-2.35	-0.67	0.08	-1.68	-0.68	-0.58
B/M	-0.38	-0.19	-0.27	-0.12	-0.78	2.08	-0.80	-0.67	-2.81	-2.08
Mom	-21.16	-27.16	-12.08	-10.51	-4.04	-1.05	3.02	8.08	0.35	14.11
ST	-2.70	-1.89	1.32	0.62	0.75	0.89	-1.30	-2.19	-2.48	-1.56
LT	-4.92	-2.87	-0.18	-1.60	0.12	1.21	2.02	0.93	1.83	0.25

Panel F: Mkt SMB HML MOM ST LT

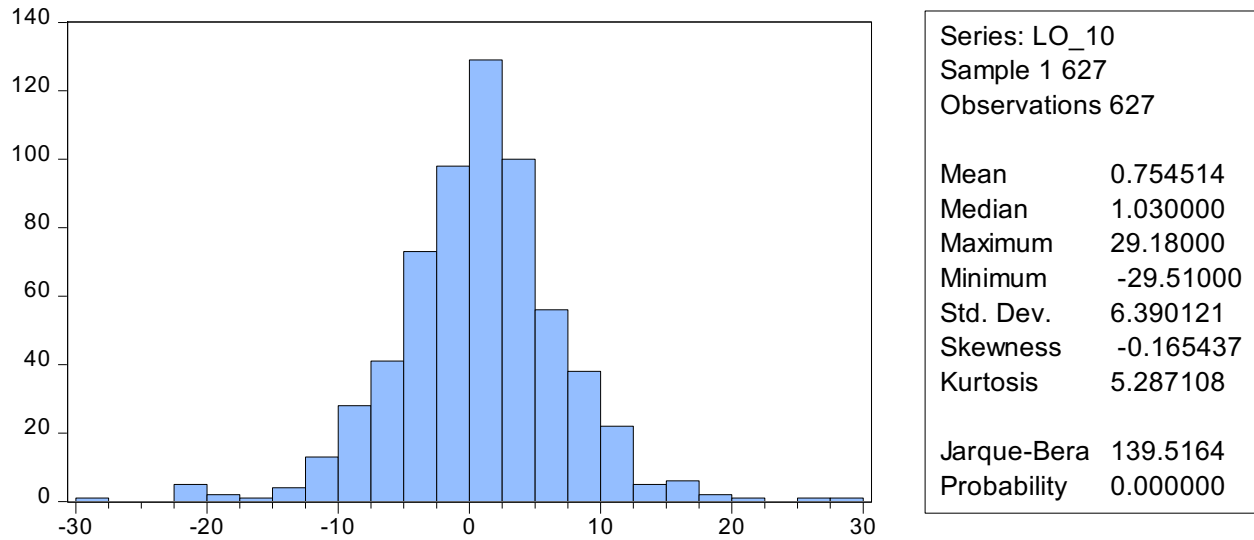
	ζ									
Size	0.00	0.00	0.01	-0.02	-0.03	0.02	0.00	0.00	0.01	0.00
B/M	0.00	0.02	-0.02	0.02	0.01	-0.03	0.03	-0.04	-0.01	-0.05
Mom	0.10	-0.01	-0.03	0.00	0.03	-0.01	0.01	0.04	0.05	-0.01
ST	0.79	0.61	0.46	0.17	0.09	0.01	-0.16	-0.29	-0.49	-0.66
LT	0.00	0.05	-0.02	-0.01	-0.02	0.01	0.00	0.02	-0.02	0.01
	$t(\zeta)$									
Size	0.19	0.31	0.95	-1.66	-2.11	1.49	-0.13	0.13	0.66	-0.34
B/M	0.19	1.04	-0.84	0.46	0.21	-1.13	1.20	-1.26	-0.66	-1.00
Mom	1.62	-0.44	-0.67	0.01	0.66	-0.15	0.23	1.25	0.05	-0.22
ST	16.85	22.66	11.10	3.61	2.47	0.55	-4.61	-7.89	-14.27	-18.71
LT	0.11	1.47	-0.46	-0.37	-0.61	0.31	0.11	0.57	-0.56	0.49

Panel G: Mkt SMB HML MOM ST LT

	η									
Size	-0.01	0.01	-0.06	-0.06	-0.03	-0.08	0.00	0.01	-0.05	0.02
B/M	-0.03	-0.02	0.00	-0.10	-0.09	-0.04	-0.07	-0.03	-0.04	0.16
Mom	0.04	-0.03	0.05	-0.09	-0.03	-0.11	-0.11	-0.13	-0.14	0.00
ST	-0.05	0.01	0.03	0.02	-0.01	-0.03	-0.04	0.00	-0.07	-0.02
LT	0.97	0.70	0.64	0.23	0.10	-0.01	-0.18	-0.34	-0.41	-0.49
	$t(\eta)$									
Size	-0.15	0.40	-3.36	-3.14	-1.50	-3.78	-0.22	0.48	-2.53	2.16
BM	-1.13	-0.62	-0.02	-1.86	-1.62	-1.30	-1.38	-0.76	-1.31	3.41
Mom	0.56	-0.68	1.22	-2.04	-0.75	-2.21	-1.77	-2.62	-0.14	0.01
ST	-1.20	0.20	1.05	0.78	-0.42	-1.22	-0.97	-0.16	-1.68	-0.48
LT	17.35	17.33	16.44	5.55	2.21	-0.16	-3.33	-7.14	-8.93	-10.96

Appendix

Example of lowest decile of Size portfolios



Example of summary statistics of Short-Term Reversal decile portfolios

	LO_10	_2	_3	_4	_5	_6	_7	_8	_9	HI_10
Mean	0.597273	0.763573	0.729426	0.625486	0.587735	0.487337	0.470542	0.478612	0.348660	0.265359
Median	0.660000	0.830000	0.980000	0.990000	0.890000	0.850000	0.730000	0.780000	0.500000	0.410000
Maximum	34.35000	26.69000	21.71000	20.11000	18.56000	13.96000	15.32000	16.47000	20.14000	23.98000
Minimum	-30.22000	-25.63000	-24.67000	-21.69000	-21.99000	-19.27000	-21.30000	-21.08000	-27.44000	-27.70000
Std. Dev.	7.334083	5.794635	5.148055	4.738951	4.511748	4.345729	4.319626	4.466994	4.778521	5.525747
Skewness	-0.249552	-0.233958	-0.296384	-0.303105	-0.362717	-0.470269	-0.363547	-0.425077	-0.469312	-0.246160
Kurtosis	5.796181	5.362518	5.402130	4.912139	4.997874	4.564039	4.693856	4.599715	5.835095	5.000055
Jarque-Bera	210.7695	151.5364	159.9269	105.1208	118.0263	87.01786	88.76789	85.73834	233.0031	110.8379
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	374.4900	478.7600	457.3500	392.1800	368.5100	305.5600	295.0300	300.0900	218.6100	166.3800
Sum Sq. Dev.	33671.77	21019.70	16590.55	14058.49	12742.78	11822.24	11680.64	12491.23	14294.25	19114.21
Observations	627	627	627	627	627	627	627	627	627	627

Example of Breusch-Pagan-Godfrey

Dependent Variable: SIZE3

Method: Least Squares

Date: 08/18/17 Time: 16:01

Sample: 1 627

Included observations: 627

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006493	0.037369	-0.173761	0.8621
MKT_RF	1.039087	0.008876	117.0711	0.0000
SMB	0.938542	0.013045	71.94888	0.0000
HML	0.218869	0.015596	14.03388	0.0000
MOM	-0.022639	0.008890	-2.546566	0.0111
ST	0.011583	0.012235	0.946633	0.3442
LT	-0.057648	0.017176	-3.356360	0.0008

R-squared	0.979086	Mean dependent var	0.792791
Adjusted R-squared	0.978884	S.D. dependent var	6.094359
S.E. of regression	0.885594	Akaike info criterion	2.605986
Sum squared resid	486.2518	Schwarz criterion	2.655566
Log likelihood	-809.9765	Hannan-Quinn criter.	2.625248
F-statistic	4837.606	Durbin-Watson stat	2.087096
Prob(F-statistic)	0.000000		

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	3.488651	Prob. F(6,620)	0.0021
Obs*R-squared	20.47691	Prob. Chi-Square(6)	0.0023
Scaled explained SS	34.01261	Prob. Chi-Square(6)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/18/17 Time: 16:06

Sample: 1 627

Included observations: 627

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.711263	0.059659	11.92204	0.0000
MKT_RF	-0.009203	0.014170	-0.649495	0.5163
SMB	0.038216	0.020825	1.835037	0.0670
HML	0.032069	0.024898	1.287998	0.1982
MOM	0.043212	0.014193	3.044640	0.0024
ST	0.021277	0.019534	1.089231	0.2765
LT	0.035347	0.027421	1.289075	0.1979

R-squared	0.032659	Mean dependent var	0.775521
Adjusted R-squared	0.023297	S.D. dependent var	1.430602
S.E. of regression	1.413840	Akaike info criterion	3.541597
Sum squared resid	1239.344	Schwarz criterion	3.591177
Log likelihood	-1103.291	Hannan-Quinn criter.	3.560859
F-statistic	3.488651	Durbin-Watson stat	1.817382
Prob(F-statistic)	0.002118		

Example of Newey-West test

Dependent Variable: BM8
 Method: Least Squares
 Date: 08/21/17 Time: 13:25
 Sample: 1 627
 Included observations: 627

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.055803	0.056364	-0.990052	0.3225
MKT_RF	0.994169	0.013387	74.26255	0.0000
SMB	0.168513	0.019675	8.564753	0.0000
HML	0.676025	0.023523	28.73884	0.0000
MOM	-0.013997	0.013409	-1.043842	0.2970
ST	-0.038216	0.018455	-2.070807	0.0388
LT	-0.025904	0.025906	-0.999924	0.3177
R-squared	0.918464	Mean dependent var		0.686427
Adjusted R-squared	0.917675	S.D. dependent var		4.655387
S.E. of regression	1.335743	Akaike info criterion		3.427954
Sum squared resid	1106.209	Schwarz criterion		3.477533
Log likelihood	-1067.663	Hannan-Quinn criter.		3.447216
F-statistic	1163.995	Durbin-Watson stat		1.997740
Prob(F-statistic)	0.000000			

Dependent Variable: BM8
 Method: Least Squares
 Date: 08/21/17 Time: 13:27
 Sample: 1 627
 Included observations: 627
 HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.055803	0.072261	-0.772246	0.4403
MKT_RF	0.994169	0.023394	42.49698	0.0000
SMB	0.168513	0.031413	5.364402	0.0000
HML	0.676025	0.055922	12.08870	0.0000
MOM	-0.013997	0.021042	-0.665193	0.5062
ST	-0.038216	0.030387	-1.257662	0.2090
LT	-0.025904	0.033985	-0.762217	0.4462
R-squared	0.918464	Mean dependent var		0.686427
Adjusted R-squared	0.917675	S.D. dependent var		4.655387
S.E. of regression	1.335743	Akaike info criterion		3.427954
Sum squared resid	1106.209	Schwarz criterion		3.477533
Log likelihood	-1067.663	Hannan-Quinn criter.		3.447216
F-statistic	1163.995	Durbin-Watson stat		1.997740
Prob(F-statistic)	0.000000	Wald F-statistic		431.3775
Prob(Wald F-statistic)	0.000000			

Example GRS Test on Stata:

```
. grstest2 Size1 Size2 Size3 Size4 Size5 Size6 Size7 Size8 Size9 Size10 BM1 BM2 BM3 BM4
BM5 BM6 BM7 BM8 BM9 BM10 MOM1 MOM2 MOM3 MOM4 MOM5 MOM6 MOM7
MOM8 MOM9 MOM10 ST1 ST2 ST3 ST4 ST5 ST6 ST7 ST8 ST9 ST10 LT1 LT2 LT3 LT4
LT5 LT6 LT7 LT8 LT9 LT10, flist(MktRF SMB HML ST LT)
```

R[2,7]

	Mean alpha	Test stati~c	P-value	Mean adj R2	Mean SE	Mean abs a~a	SR
J0	-.02701049	148.43049	1.080e-11	.89373745	.06657991	.12375495	0
J1	-.02701049	2.7082054	1.458e-08	.89373745	.06657991	.12375495	

.49969384

Example of Regression on Lowest Decile BM Portfolio after Newey-West Correction

Dependent Variable: BM1
Method: Least Squares
Date: 08/21/17 Time: 11:20
Sample: 1 627
Included observations: 627

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.121682	0.055208	2.204058	0.0279
MKT_RF	0.999929	0.013113	76.25682	0.0000
SMB	-0.108509	0.019272	-5.630524	0.0000
HML	-0.490637	0.023041	-21.29444	0.0000
MOM	-0.004938	0.013134	-0.375977	0.7071
ST	0.003511	0.018076	0.194228	0.8461
LT	-0.028684	0.025375	-1.130431	0.2587
R-squared	0.935019	Mean dependent var		0.416635
Adjusted R-squared	0.934390	S.D. dependent var		5.107869
S.E. of regression	1.308348	Akaike info criterion		3.386508
Sum squared resid	1061.299	Schwarz criterion		3.436088
Log likelihood	-1054.670	Hannan-Quinn criter.		3.405771
F-statistic	1486.883	Durbin-Watson stat		1.879064
Prob(F-statistic)	0.000000			

Dependent Variable: BM1
 Method: Least Squares
 Date: 08/21/17 Time: 11:24
 Sample: 1 627
 Included observations: 627
 HAC standard errors & covariance (Bartlett kernel, Newey-West fixed
 bandwidth = 7.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.121682	0.057047	2.133001	0.0333
MKT_RF	0.999929	0.018680	53.52953	0.0000
SMB	-0.108509	0.029007	-3.740791	0.0002
HML	-0.490637	0.036799	-13.33279	0.0000
MOM	-0.004938	0.021688	-0.227680	0.8200
ST	0.003511	0.025176	0.139456	0.8891
LT	-0.028684	0.038461	-0.745798	0.4561
R-squared	0.935019	Mean dependent var		0.416635
Adjusted R-squared	0.934390	S.D. dependent var		5.107869
S.E. of regression	1.308348	Akaike info criterion		3.386508
Sum squared resid	1061.299	Schwarz criterion		3.436088
Log likelihood	-1054.670	Hannan-Quinn criter.		3.405771
F-statistic	1486.883	Durbin-Watson stat		1.879064
Prob(F-statistic)	0.000000	Wald F-statistic		950.1408
Prob(Wald F-statistic)	0.000000			

