On Front-Running Momentum and Portfolio Optimization

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Abstract

Most of the empirical research on momentum in finance has been conducted using monthly data and horizons for the formation and holding period of winner and loser portfolio. This research paper studies momentum using a weekly approach and examines strategies that are more flexible than the crowded month-end approach. In particular, this paper is interested in analyzing the legal front-running of month-end momentum strategies by one to five weeks. Furthermore this study analyzes how momentum profits change by using different start dates within a month ("week-effect") as well as within a year ("month-effect") and finds that the second-last week of the month as well as the cluster of months September, October and November exhibit higher Sharpe ratios, more favorable levels of skewness and better protection against downside risk. In addition, this study demonstrates evidence that momentum investing using the widespread "month-end" view is rarely a strictly dominant strategy.

Keywords

Momentum, Stock Market, Week-Effect, Month-Effect, Front-Running

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This thesis is submitted by John R. Segeritz in partial fulfillment of the requirements for the degree of Master of Commerce in Finance (specialization Investment Management)

Signed by candidate

Signature removed

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Abbreviations

AMEX	American Stock Exchange
AQR	AQR Capital Management, LLC
BM	Benchmark
BPS	Basis Points
CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
EUR	Euro
FF	Fama-French
FR	Front-Running
HML	High Minus Low
JSE	Johannesburg Stock Exchange
JT	Jegadeesh-Titman
NYSE	New York Stock Exchange
P/E	Price-Earnings Ratio
PF	Portfolio
RW	Random Walk
SMB	Small Minus Big
SR	Sharpe Ratio
SXXE	Eurostoxx Index
T-Bill	Treasury Bill
USD	US-Dollar
WML	Winner Minus Loser

Schedule of Corrections

(Approved by the supervisor - see page 8)

Section “Related Literature”

Page 11: The author added that momentum was a highly researched study field during the 1990s; this is to justify the choice of numerous research papers from the 1990s.

New version: *“It is mainly due to the seminal research of Jegadeesh (1990) and JT (1993) - as well as numerous other groundbreaking studies conducted during the 1990s - that ‘momentum’ made its way from the realm of classical mechanics into the financial literature…”*

Page 15: The author added a brief explanation for the expression of “world beta”.

New version: *“World beta is the aggregate of all countries’ betas and started to increase considerably at the beginning of the 1990s.”*

Page 20: The author made a grammatical correction.

New version: *“Carhart (1997) started with the FF three-factor model and added a momentum regressor, which in turn improved the model by better predicting cross-sections of returns…”*

Page 27: The author made a grammatical correction.

New version: “*The authors’ main argument was that many people suffer from the negligence of statistical truths.*”

Section “Data”

Page 31: The author explained the decision of removing penny stocks from his study.

New version: “*Penny Stocks (…) are removed due to their low levels of liquidity - thus tradability - as well as their disadvantage of having highly volatile returns, which would* *classify them as winners in one week, as losers in the following week and then as winners thereafter etc.*"

Section "Results"

Page 53: The author adjusted Table 16 by limiting the maximum drawdown to minus 100%.

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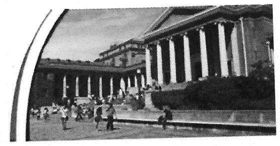

Certification of Corrections

I, the undersigned, supervisor hereby certify that

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has completed the corrections to his/her Masters dissertation to my satisfaction and as required by the Higher Degrees Committee. The schedule of corrections are attached; where any corrections were not made an explanation was given.

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1. Introduction

Momentum, in its purest form, is the tendency for an object or particle to exhibit persistence in its relative performance. In finance, momentum refers to the net zero long-short investment strategy that buys past winners and sells past losers. A successfully implemented momentum strategy for US equities over the period 1965-1989 yielded, on average, an annualized excess return of 17.5% with a Sharpe ratio of 0.86. Over the same horizon a long-only US stock portfolio returned on average 6.42% with a Sharpe ratio of 0.43 (Jegadeesh & Titman, 1990, 1993 and 2001).

There are four main tasks addressed in this research endeavor. Number one: The study looks at price momentum on the European stock market over the past 11.5 years and examines how strong the momentum effect has been for the broad and liquid EuroStoxx (SXXE) index constituents using weekly data as well as the technical approach described and implemented by Jegadeesh & Titman (1993, 2001). Number two addresses the question whether momentum profitability differs within a month, depending on what week momentum investing is launched. If there exists a difference in returns, then momentum strategies would exhibit a pattern that is referred to as "week-effect". Under number three the paper studies a potential "month-effect" and examines whether there are months within a year that are more lucrative than others for momentum investors. Lastly, number four develops a strategy that legally front-runs commonly applied month-end momentum by a couple of weeks, and eventually tests whether front-running is a dominant strategy that generates competitive advantage.

The effect of front-running momentum strategies, described under number four, is tested for one, two, three, four and five weeks. Other studies found enhanced excess returns and lower levels of risk by front-running crowded end-of-month momentum strategies (see literature review); the calculation and comparison of Sharpe ratios as well as other statistical and financial metrics like maximum drawdown, skewness or portfolio beta help to see where and how the use of front-running can optimize investors' portfolios.

The structure of this research work is organized as follows:

Section two looks at previous momentum studies and their findings, the rise of momentum in the financial literature as well as the role of momentum within the concepts of random walk and market efficiency. Then follows section three with the sources, description and treatment of data. In section four methodological approaches necessary to answer the four above-mentioned goals are described; of particular interest are questions like “How to construct winner and loser portfolios (PF)?”, “What is the benchmark (BM) to compare momentum returns with?” or “What regression model is used for estimating portfolio betas?”. This section of the research also explains and compares strategies how to front-run momentum practically. Section five presents the results as well as the analysis thereof; the analysis mainly consists of verifying to what extent findings, calculations and regressions have statistical power. Section six contains a conclusion and looks at the findings of the research from a portfolio management point of view, and tries to extract where to add tangible value by optimizing momentum strategies. Besides the study’s most startling and important findings, this section also comprises an objective critique as well as a motivation for future studies. In section seven and eight the reader can refer to the bibliography as well as the appendix, which contains the code and algorithms designed with Matlab.

2. Related Literature

2. 1 The Momentum Evidence

The earliest mention of momentum in a financial context goes back to 1838 when a British newspaper editor, James Grant, noted the following:

> When a member possessed a stock, and prices are rising, he ought not to sell until prices had reached their highest'.

Even though the notion of momentum in the financial context is relatively new, a lot of the below-described evidence suggests that momentum, in one form or another, has been part of the (financial) markets for a very long time.
In 1985, DeBondt & Thaler examined long-term contrarian strategies that consisted of buying past underperforming stocks and selling past outperforming stocks: depending on the timeframe over which past returns have been measured, they found that holding such a contrarian portfolio over one to five years yielded significantly positive returns.

It is mainly due to the seminal research of Jegadeesh (1990) and Jegadeesh & Titman (JT) (1993) - as well as numerous other groundbreaking studies conducted during the 1990s - that 'momentum' made its way from the realm of classical mechanics into the financial literature and is nowadays a popular investment strategy. At the beginning of each month, by looking at the previous' 2-to-12-month return history, JT ranked US stocks in ascending order of cumulative return before creating "winner" and "loser" portfolios that corresponded to the highest and lowest return decile. Once ranking of past stock returns has been done, JT waited one week before practically entering the positions in order to avoid some of the negative effects generated by short-term price reversals and bid-ask spreads associated with microstructure effects (Lehman, 1990 as well as Jegadeesh, 1990). The momentum strategy consisted of creating equally weighted portfolios that bought the "winner" and sold the "loser" stocks simultaneously. In theory this would be equivalent to a zero net investment where the short positions finance the long positions; JT documented that holding such a portfolio for a horizon of 3-12 months yielded approximately 1% of excess return per month (± 12% p.a.) during the time period of 1965 until 1989. The most successful momentum strategy meant taking a formation period of 12 months and holding it for 3 months: more specifically, this strategy yielded a monthly excess return of 1.31% (without lag between formation and holding period) with a t-stat of 3.74; the monthly excess return including a lag between formation and holding period was 1.96% with a t-stat of 4.73. The main contributor to the excess performance, as the authors noted, was not the short side, but the long side of the momentum strategy. Furthermore JT found that momentum strategies were lucrative for small-, mid-, and large-capitalization stocks on the US stock market.

2.1.1 Evidence across Geographical Markets

By replicating Jegadeesh & Titman's (1993) approach, Rouwenhorst (1998) tested the momentum strategy for both European-only equities and a portfolio consisting of well-diversified global equities and found similar positive excess returns. The main difference between these two studies is that Rouwenhorst, in addition to JT's 12-month window for the formation period, also made use of shorter formation and holding periods of 3, 6 and 9 months. The author found higher t-statistics for Europe, meaning that the volatility of momentum strategies was lower in Europe than in the United States, or that the mean of the former momentum returns was higher.

Since the European and US market share various commonalities, a separate study has been conducted to examine the momentum effect on the Asian market. Chui, Titman & Wei (2000) came to the conclusion that, on the aggregate Asian equities level, momentum was also observable, but to a less pronounced extent than in the US. For Japan they found that momentum was not working at all, which might partially be due to the fact that during the time of consideration value-strategies performed exceptionally well, and momentum and value were negatively correlated (-0.64) during the period 1981-2003. For the non-performance of momentum strategies on the Japanese stock market Daniel, Hirshleifer & Subrahmanyam (1998) argued that this could also be due to the "low levels of biased self attribution". Asness & Frazzini (2013) as well as Asness, Frazzini, Israel & Moskowitz (2014) confirmed the positive and statistically significant momentum effect on the aggregate European stock market: their study focused on highly liquid assets and combined the momentum strategy with a value-investing component because the combination of both strategies yielded a higher explanation of cross-sectional returns than one of those strategies applied in isolation.

For the African market, Griffin, Ji & Martin (2003, 2005) found a positive momentum effect that was even stronger than the monthly returns of JT. In fact, Greece and South Africa were among those countries experiencing the biggest momentum profits between late 1980s and the end of 1999. A research examining the South African stock market context has been conducted by Van Rensburg (2001) who looked at momentum profits using data from 1983 until 1999. He used share prices of industrial sector companies and looked at what formation period was best for generating superior momentum returns: by comparing formation periods of 3-, 6- and 12-month history, Van Rensburg concluded that the latter was the most profitable approach. Page, Britten & Auret (2013) verified how JSE price momentum strategies fared between 1995 and 2010. For the first sub-sample they found positive evidence for momentum, but surprisingly, not so for the second sub-sample. The authors concluded that the global financial crisis might have been an explanation for this. They underwent another interesting approach by looking at momentum effects in low-, medium- and high-liquidity South African stocks and found that medium- and high-liquidity stocks contributed largely to momentum profits whereas low-liquidity stocks decreased momentum returns.

2.1.2 Evidence Across Different Formation / Observation Techniques

Gutierrez & Kelley (2008) departed from the traditional month-to-month horizon for categorizing, evaluating and analyzing portfolios and used weekly data instead. How was momentum measured? They applied the calendar-time method (Fama, 1998 as well as Mitchell & Stafford, 2000) for measuring the performance of the WML portfolio. This method accounts for the positive serial correlation in returns that stems from the fact that weekly returns are overlapping. They found that holding portfolios longer than 12 weeks - in contrast to holding periods smaller than 12 weeks - yielded statistically significant returns; in fact the returns within the first 12 weeks were negative. Furthermore, they introduced a 'news' versus 'no-news' scenario in their study: concerning that, the authors remarked the following: "We find that the markets' reactions to explicit news (price movements associated with public news) and to implicit news (price movements without public news) are not categorically different. […] Return momentum following explicit news is stronger than return momentum following implicit news." Gutierrez and Kelley's weekly approach is particularly interesting and serves as example for this paper, because the main questions of this study rely on higher-frequency data (weekly data) in order to make in-depth analysis of intra-month momentum setups.

Hong, Lim & Stein (2000) focused not on the aggregate of stock market but on subsamples and found that momentum on the US stock market appeared to be stronger for small firms than for large firms and Sagi & Seascholes (2007) reported that firms with large revenue growth volatility had higher momentum returns than firms with low revenue growth volatility.

2.1.3 Evidence Across Time

Should there not be a decrease or even disappearance of those excess returns generated by momentum strategies given its rise in popularity across the globe? Like arbitrage, given the fact that exploiting a strategy in a vast and continuous fashion could lead someone to making the assumption that returns should erode over time.

JT (2001) reran their study from the early nineties and checked whether the profitability eroded since the "discovery of financial momentum". Surprisingly it did not: by performing out-of-sample tests they found that the monthly returns were still significant and amounted to approximately 1.39% per month; in their initial study from 1993 monthly returns were approximately the same. Griffin, Ji & Martin (2003) confirmed the robustness of momentum strategies across time and found that during the nineties international momentum strategies were indeed lucrative. In their 2001 study, the JT duo also found that momentum returns, on average, were less in January than during the rest of the year; in other words, momentum returns in Januaries dragged down the year-all momentum returns and, in some cases, could even render the year-to-year momentum returns negative if profitability between February and December was low.

2.1.4 Evidence Across Asset Classes

Asness, Moskowitz & Pedersen (2013) verified if momentum is visible beyond the equities spectrum and found statistically significant momentum effects for cross-country government bonds, currency, commodity futures and other future contracts. In the same study they also found that value and momentum strategies were negatively correlated, both within and across asset classes, and that this correlation became more negative over time. This may explain why in Japan, where the value component was historically high, there was no evidence for momentum profitability. For their study they used data with starting point 1972 for equities, 1979 for currencies and 1982 for bonds, all up until 2011.

Besides the existence of momentum in asset classes like bonds or currency, Chan, Hameed & Tong (2000) also found a positive momentum effect for international stock market indices. Between 1980 and 1995 they observed stock index returns of 23 sample countries, both within emerging- and non-emerging-markets, where the momentum strategy consisted of going long “winner countries” and short “loser countries”; in order to eliminate the bias of country-specific risk levels, they introduced a world beta risk. World beta is the aggregate of all countries’ betas and started to increase considerably at the beginning of the 1990s. Another interesting finding of their study was that momentum profits tended to be higher after an increase in last period’s trading volume.

2.2 Potential Sources of Momentum

The reasons for explaining momentum are plentiful and depending of the field of expertise, different researchers look at it from different angles. Up to the writing of this research paper researchers still have not found a consensus explanation. In general it is possible to put the findings into five categories: behavioral finance, conventional risk-based models, transaction costs, sector- and firm-specific approaches as well as luck.

2.2.1 Behavioral Finance

The most appealing and intuitive answers to momentum are found in behavioral finance. Thaler (2005) suggests that stock prices exhibit the tendency to underreact to new information, e.g. earnings announcements; put differently, the price adjustments due to new information are not instantaneous. This argument had its supporters from the very beginning and was also addressed by Jegadeesh & Titman (1993). Hvidkjaer (2006) and Grinblatt & Han (2005) also supported the behavioral approach to explaining momentum. In Hvidkjaer's research paper the author found that especially small and infrequent traders are contributors to the existence of momentum who act "sluggishly on past returns"; however this effect was not observable for large investors. This then means that it is mainly small investors and households who create the momentum effect. Does this mean that, seeing no momentum effect in Japan, average Japanese investors and households are quicker in processing information and more efficient in trading on it? As Asness et al. (2013) note, behavioral theories "will have difficulties explaining the global co-movement structure (in momentum and value)."

Looking at the following study, it is important to state that the theory about the aggregate of "average" momentum investors, often influenced by so-called "financial experts" and financial news columns, has its validity. Hong, Lim & Stein (2000) examined stock analysts' buy and sell recommendations and concluded that for scarcely covered securities, momentum was stronger than for stocks with high coverage. In fact for highly covered securities the momentum effect was weak. Furthermore, the authors found that the effect of analyst coverage was bigger for past loser stocks than for stocks that were past winners.

Grinblatt & Han (2005) based their argument on the well-known disposition effect (Shefrin & Statman, 1985), which is the tendency for investors to sell winning assets too early and get rid of losing assets too late, and found that "a variable proxying for aggregate unrealized capital gains appears to be the key variable that generates the profitability of a momentum strategy".

Hong & Stein (1999) emphasized that momentum is not only driven by under-reaction to news but also by over-reaction to news. Under-reaction happens because information diffuses only slowly across the investor population. Jegadeesh & Titman (2001) confirmed this standpoint by analyzing post-formation periods. Over-reaction occurs because once investors see share prices picking up, they tend to become more overconfident and aggressive on their winner portfolio, which in turn drives prices above their fundamental values. In the long-run prices that are currently trading above their fundamentals will then start to reverse. In addition to their over-reaction explanation, Hong and Stein distinguished between two kinds of market participants who only differ in their information-processing capabilities: momentum traders and news watchers. Unlike news watchers, momentum traders do condition on the past and if they make a decision on t_0 given information of t_{-1-k} up to t_{-1}, the dynamics of moving into one direction, e.g. going up, will continue unless there is a directional change in past fundamental data. Momentum traders will only learn whether last period's (t_{-1}) stock price peak was actually a peak during t_{+1}, because it is in t_{+1} where the decision maker can check whether $Pt_{-1} > Pt_0$ (price peak reached in t_{-1}) or whether $Pt_{-1} < Pt_0$ (no price peak yet in t_{-1}; upward trend likely to continue). Daniel, Hirshleifer & Subrahmanyam (1998), taking a similar approach, based their study on investors' overconfidence where differences in confidence levels were attributed to biased self-attribution. An overconfident investor is defined as somebody who "overestimates the precision of his private information signal, but not of information signals publicly received by all". By analyzing the dynamic price path by a group "with attribution bias" and another one "without attribution bias" they found that the group "with attribution bias" overestimated average price levels, both in the short- and long-run.

Another behavioral finance theory, called "herd behavior", was described by Banerjee (1992). Each decision maker bases his or her investment decision on what the majority of agents has recently done. By doing so, decision makers do not base their choice on fundamentals (own signals), but on other people's behavior (foreign signals). While the theory seems compelling in terms of explaining over-reactions, there are various shortcomings, e.g. the unrealistic assumption that decision makers recall the history of other decision makers' moves - in a game theoretical sense - up to time t_0. What would be the effect on stock price levels? Even though this has not been tackled directly by Banerjee, the author noted that "the equilibrium pattern of choices may be inefficient […]" and that "the equilibrium pattern of choices will be very volatile across several plays of the same game". From this it is possible to conclude that - within a stock market context - herd behavior a) drives stock prices away from their intrinsic face value, and b) herd behavior results in higher-perceived risk (volatility). Bikhchandani, Hirshleifer & Welch (1992) took the same line of thinking and used the term "informational cascades" where the actions by early investors influenced the decision of later investors who did not base their decision on fundamentals but on the flow and direction of early movers: The authors remarked the following: "The arrival of a little information or the mere possibility of a value change can shatter an informational cascade." Scharfstein & Stein (1990) examined the roots of herd behavior and found that herding is one of the main drivers of volatility. The authors' main point is not the emphasis on free-riding but on the fact that an investor's contrarian strategy might result in a loss of reputation to him or her. However, the two authors also pointed out that their specific model, which relies on symmetry arguments and further simplifications, is not necessarily representative for the analysis of stock markets.

The last behavioral set of explanations for momentum comes from Barberis, Shleifer & Vishny (1998). Their starting point was forming a parsimonious investor expectations model that consisted of different finite states, which - by observing real-world outcomes and conditioning in a Bayesian fashion - increased or decreased future expectations. The model can account both for under- and overreaction and is consistent with conservatism (Edwards, 1968) and the representativeness heuristics (Griffin & Tversky, 1992). The representativeness heuristics means that news with more weight - in a sense of news getting more attention - should generate bigger reactions than news with less weight: the aftermath of the 1987 market crash is an example of where high- and low-weight news caused investor overreaction.

2.2.2 Conventional Risk-based Models

In Johnson's (2002) research paper he argued that momentum in general does not necessarily imply some of the behavioral anomalies like those presented in the previous sub-section, e.g. investor irrationality, expectational cascades or underreaction: "If growth rate risk has a positive price, then higher growth rates must entail higher expected returns. And momentum effects then follow because positive cumulative returns typically imply ex-post that recent growth rate shocks have been positive."

If the serial covariance of factor returns is positive, this could be an explanation for momentum. To test that, Jegadeesh & Titman (2001) used the approach of an equally weighted portfolio but came to the conclusion that the serial covariance of six-month returns was negative (-0.0028).

The main rationale behind risk-based models is Markowitz' (1952) simple yet - at that time - groundbreaking idea that higher expected returns are associated with the willingness to assume higher risk. The challenge is to understand how stock returns are exposed to a given set of risk factors; it is at that stage where asset-pricing models come into play: Can risk explain cross-sectional differences in momentum returns?

Fama & French (1996) make use of their three-factor model (Fama & French, 1992): the expected return on a portfolio in excess of the risk-free rate (r_{PF} - r_f) is explained by the sensitivity to three factors: a) r_m-r_f, which is the excess market return, b) SMB, which is the difference in return between a portfolio of small versus large stocks and c) HML, which is the difference in return between a high book-to-market stock and a low book-to-market stock. This results in the following model where b_{PF}, s_{PF} and h_{PF} denote factor sensitivities.

$$r_{PF} - r_f = \alpha + b_{PF}\,(r_m - r_f) + s_{PF}\,(SMB) + h_{PF}\,(HML) \tag{1}$$

According to the authors, the market betas (b_{PF}) are roughly the same regardless of whether the portfolio belongs to the winner or loser group. But the factor sensitivities for SMB (s_{PF}) and HML (h_{PF}) tend to be significantly higher for loser portfolios than for winner portfolios; this means that loser portfolios are in general riskier than winner portfolios due to the high sensitivities of the FF risk factors. Evidence for this has been provided by Jegadeesh & Titman (2001) who compare CAPM alphas with FF alphas and find that the latter are indeed larger. Furthermore, it turns out that the CAPM alpha of the winner minus loser portfolio is more or less the same than the raw return between winner and loser portfolio since the betas for loser and winner portfolios are approximately the same. The Fama-French alpha is larger than its corresponding raw return difference. What does this entail about the momentum story? As Thaler (2005) noted: "The cross-sectional differences in average expected returns under CAPM or the Fama-French three-factor model cannot account for the momentum profits."

Grundy & Martin (2001) confirmed that both single and multi-factor models cannot properly explain the profitability of momentum, neither are industry-specific arguments able to. Their study reveals that factor models can explain "approximately 95% of the variability of returns on portfolios of the top and bottom 10% of the prior winners and losers, but not their mean returns." By hedging out the strategy's dynamic exposure to market factors and size (provided by the Fama-French three-factor model), Grundy and Martin argue that this would lead to a decrease in monthly returns variability of 78.6% and a simultaneous increase in monthly excess returns.

Carhart (1997) started with the FF three-factor model and added a momentum regressor, which in turn improved the model by better predicting cross-sections of returns; this is commonly known as the Carhart four-factor model. Asness (2014, 2016), former PhD student of Eugene Fama and cofounder of AQR Capital, a privately held investment management firm overseeing 135 billion USD, uses a comparable but more sophisticated approach in modeling and practical trading.

Thaler (2005) remarked that the "difference between winner and loser portfolio returns could simply be compensation for risk, and if the premiums for bearing certain types of risk vary across time in a serially correlated fashion, momentum strategies will be profitable. […] In other words, past winners may be riskier than past losers, and the difference between winner and loser portfolio returns could simply be compensation for risk".

Lo & MacKinlay (1990) and Jegadeesh & Titman (1995) made use of a delayed-reactions model which looked at the following return-generating process (from Thaler, 2005):

$$r_{it} = \mu_i + \beta_{0,i}f_t + \beta_{1,i}f_{t-1} + e_{it} \tag{2}$$

where $\beta_{0,i}$ and $\beta_{1,i}$ represent factor sensitivities to contemporaneous (t) and lagged (t-1) realizations (f_t), r_{it} is the idiosyncratic return, μ_i the market return and e_{it} a time-varying idiosyncratic error term. Higher betas for stocks indicate that they have higher returns in the subsequent period, which is due to delayed reaction. "When lead-lag effects are generated in this way, large factor realizations will be followed by large delayed reactions, and hence profit in any period will depend on the magnitude of factor realizations in the previous period." The authors' conclusion is that momentum profits are lower when followed by large realization in factors.

According to DeLong, Shleifer, Summers & Waldmann's (1990) study, asset price risk does not come from fundamental risk but rather from the fact that noise traders' random, sometimes irrational and unpredictable moves generate inconsistencies that are hard to interpret or bet against. As the authors described, the risk is that "noise traders' belief will not revert to a mean for a long time and might in the meantime become more extreme." Noise traders often have the tendency to go even more bearish once their bearish standpoint manifests; on the other side, noise traders might push up prices even higher if they believe that a given price increase is just the beginning of a bull phase. "Arbitrage cannot eliminate those effects because noise itself creates additional risk. […] Noise traders can earn higher expected returns from their own destabilizing influence, not because they perform the useful social function of bearing fundamental risk."

Chordia & Shivakumar (2002) found that momentum strategies are generally strong in economic expansion cycles and non-existent during recessions. This result is puzzling, because expansionary phases usually imply a low risk premium and recessionary phases a higher risk premium. Due to the procyclical behavior of expected momentum returns with economic cycles, risk-based models have a very hard time explaining the prevalent momentum effects.

2.2.3 Transaction Costs

It is evident that the existence of direct and indirect transaction costs, brokerage and commission fees impacts investment returns negatively. Korajczyk & Sadka (2004) investigated whether, in the presence of transaction costs and market friction, momentum strategies could be exploited. Value-weighted strategies suffer less from transaction costs than equal-weighted portfolio strategies because the former is more invested in highly liquid and large positions. Especially when considering the liquidity component, Korajczyk and Sadka found that momentum profits did not vanish due to transaction costs. One big disadvantage of their study is that they only considered the long side of the momentum strategy and ignored the short side, which is often more illiquid than the long side. In fact, they derived a model where abnormal momentum returns shrank and eventually became insignificant at a portfolio size of USD 2 billion or more. Fund sizes larger than USD 5 billion encounter transaction costs for momentum strategies that would render such strategies unprofitable.

Both Hong et al. (2000) and Jegadeesh & Titman (1993) checked the transaction cost impact and could not find an impediment to momentum strategy returns. Given the fact that both trading and transaction costs declined sharply over the past decade - with the advance in technology progress and the rise of cost-efficient brokerage firms that have contributed significantly, it seems unconvincing trying to explain momentum with aid of transaction costs. Even though this approach is mentioned in many financial studies and textbooks the transaction cost approach is flawed, because it actually cannot not explain the true sources of momentum.

2.2.4 Sector- and Company-Specific Approaches

This approach starts with the idea that momentum returns are generated by a compensation for sector-specific risk because, as Moskowitz & Grinblatt (1999) remarked, often times, winner and loser portfolios find themselves concentrated within the same or similar industry. By forming value-weighted industry portfolios with a 6-month formation period, the authors found that high-momentum industries outperformed low-momentum industries. To check whether momentum returns could be attributed to specific industries, Moskowitz and Grinblatt replaced the best (winner) and least performing stocks (loser) of an industry momentum strategy by stocks of other industries that had approximately the same returns in the previous time period as the ones that were removed from the original context. Surprisingly the momentum returns of those "random industry" portfolios gained no excess return at all.

Taking a similar approach, Grundy & Martin (2001) found a statistically significant return for industry momentum strategies of 0.78% per month and 0% for the "random industry" strategy. They based their findings on a 6-month formation and 6-month holding period. A startling outcome of their study occurred when they added the one-month lag between formation and holding period: sector momentum returns vanished. Recall that the inclusion of the discontiguous state (1-week or 1-month lag) is needed in order to mitigate biases generated by bid-ask bounces and short-term return reversals. "Therefore, industry momentum seems to benefit from positive first-order serial correlation in industry returns while individual stock momentum is hurt by short-horizon return reversals." (Thaler, 2005)

O'Neal (2000) and Lewellen (2002) studied industry momentum extensively and found that instead of taking equally-weighted portfolios, using value-weighted portfolios could improve intra-industry momentum returns. Lewellen's conclusion was that industry momentum - in general - is driven "primarily by a lead-lag effect within industry."
Asness, Moskowitz & Pedersen (2003) found that part of momentum could be attributed to liquidity risk. Industries that exhibit high liquidity risk are more likely to generate positive momentum returns; the occurrence and seasonality of liquidity risk is not

discussed at this point. One practical problem arising with Asness et al.'s idea is that stocks characterized or threatened by liquidity risk are hard to trade, sometimes even making investors unable to borrow that stock in order to go short. At some stage trade can even be halted by the exchange if liquidity for a specific security runs dry.

Alternative explanations for momentum returns take a more microscopic view and look at company-specific characteristics. Eisdorfer (2008) studied firms being at the brink of bankruptcy and found that integrating those firms into momentum strategies sees overall momentum profits soaring. Others investigated the effect of company credit ratings on momentum profits (Avramov, Chordia, Jostova & Philipov, 2007 as well as Pastor & Stambaugh, 2003) and found that firms with low credit rating exhibited larger momentum returns than firms with medium to high credit rating. Sagi & Seascholes (2007) examined revenue growth volatility and came to the conclusion that firms with high revenue growth volatility exhibited larger momentum than companies with low revenue growth. Berk, Green & Naik (1999) pointed out that momentum effects might result from the "variation of exposures over the life-cycle of firms` endogenously chosen projects."

2.2.5 The Role of Luck and Other Approaches

Unless the true source of evidence is proved, luck might always play a role. Given the fact that momentum returns persisted for quite a long time and with 25 years out-of-sample evidence in the US and across the globe, the probability of attributing momentum excess returns to luck approaches zero very quickly. Still, one of the biggest supporters of this theory is Eugene Fama, advocate of EMH and Nobel Prize laureate in 2013, who hopes that some day momentum will disperse. Fama & French (2009) studied mutual fund performances in order to see which part of excess returns could be attributed to luck, and which to skill. If a portfolio manager thinks that momentum strategies are part of his alpha, then it is possible to say that repeatedly achieving excess returns is not due to luck alone.

2.3 Who trades on Momentum?

Institutional investors belong to one of the main groups who trade on momentum. In fact, as Grinblatt, Titman & Wermers (1995) calculated, 77% of 155 examined mutual funds engaged in momentum trading, but the component of buying past winners was always stronger than selling past losers; this phenomenon is called "positive-feedback" strategy. For their study, the authors collected quarterly portfolio holdings of US mutual funds over the period 1974 until 1984 and found that mutual funds employing momentum strategies had significantly higher performances than those employing contrarian strategies. If at some point in the future momentum effects start to decrease, this will have a large negative effect on the overall (mutual) funds industry, given the fact that momentum plays such a large role among those players. By looking at the disclosing of fund holdings and how it evolved over time, Grinblatt and his team were able to back up their findings in a statistically stable way.

Other investors trading on momentum are those who take analysts' advice and buy-sell-recommendations to heart and implement it for their portfolios. Stock analysts generally recommend high-momentum stocks more frequently than low-momentum stocks (Jegadeesh, Kim, Krische & Lee 2004). This fact itself can reinforce momentum and lead to a self-fulfilling prophecy. People, often households with no-to-mediocre financial knowledge, become momentum traders - without knowing - if they rely and implement analysts' advice blindly. At this stage it is interesting to answer the question why analysts recommend momentum stocks more often than non-momentum stocks? Do they really see "momentum" potential in fundamentals? Do they sense the growth opportunity of stocks on the long side of a momentum strategy? Or are they recommending the stock because they know that people will bet on their advice and the self-fulfilling prophecy could manifest anytime soon? A simple yet logical explanation therefore is that analysts try - primarily - not to be wrong in their stock picking advice because the opposite would increase the risk of deteriorating their reputation, job quality, the bank's competitive advantage, client relationships and prospective bonus payments.

The problem for average investors is the implementation of the short side of momentum.

What is the legislation of short-selling for particular investors that are located in different countries? Is borrowing of particular securities feasible? What are the associated borrowing costs? The author's conclusion is that average investors tend to play the momentum game as well, but notably on the long-side by buying stocks that are deemed "momentum stocks" by analysts and market gurus.

Asness, Frazzini, Israel and Moskowitz (2014) explained that not all market participants are interested in momentum trading. In fact, many research firms and hedge funds use momentum simply for "screening" purposes.

2.4 Momentum versus Statistics

As seen above, empirical evidence for momentum is plentiful and robust, but it is interesting to see which laws and statistical conventions momentum violates. In statistics, "regression toward the mean" is an irrefutable phenomenon described by the English statistician Sir Francis Galton in the 19^{th} century, which states that the succession of two or more extreme data points or outcomes is very unlikely. Given the expected average return of an investment, if a given strategy yields above-average returns this year one should expect returns that are closer to the mean in the following year. Engaging in momentum strategies is to believe that for a certain time "regression toward the mean" will not occur.

It is very important to keep in mind that good news, followed by high valuations, can lead to securities getting overpriced. Securities that are overpriced will at some stage in the future revert to their mean because of market forces, broader market corrections, earnings corrections or arbitrageurs. The case for the above-mentioned statistical phenomenon, applied in the context of stock markets, has been studied thoroughly by De Bondt & Thaler (1985).

A strong statistical evidence of "regression toward the mean" in the stock price context was also found by Fluck, Malkiel & Quandt (1997). By restricting their research to large company stocks and accounting for transaction costs, they found that contrarian strategies are indeed profitable in the long run. How are contrarian strategies measured? For the horizon 1980 until early 1990, they created hypothetical portfolios based on stocks' past three-to-five years aggregate returns and found that shares with very low past returns had higher returns in the following period than stocks that previously exhibited high returns. Yet, concerning the occurrence of contrarian strategy returns they noted: "Superior performance of contrarian strategies cannot adequately be explained by the superior performance of stocks with low expected growth." Even though the authors provided proof for the phenomenon of mean reversion, they also noted that basing a financial strategy solely on the contrarian approach would not necessarily result in a statistically significant alpha.

Having the relevance of statistical phenomena in mind is crucial when building momentum portfolios and managing its risk. Griffin & Tversky (1992) addressed this issue, by using Bayesian reasoning, where they tried to evaluate evidence and assess confidence while individuals were in the process of decision-making. The authors' main argument was that many people suffer from the negligence of statistical truths.

2.5 Efficient Market Hypothesis, Random Walks and the Role of Momentum

The ample evidence of momentum above presents a stark challenge to both the efficient market hypothesis (EMH) and the theory of random walk (RW). The concept of RW in the context of financial markets goes back to Fama (1965) and Cootner (1962, 1964). The theory states that tomorrow's chance for a stock going up is 50% and the chance of going down is also 50%. In other words, there is no correlation between present and future returns. In their famous book "A Non-Random Walk Down Wall-Street" which came as a response to the Malkiel's (1973) book called "A Random Walk Down Wall-Street", Lo & MacKinlay (1999) contested the random walk hypothesis and were able to depict much evidence against it.

The theory of randomness, which has been taken for granted for a long time, was refuted by LeRoy (1973) and Lucas (1978). Both researchers "constructed explicit examples of informationally efficient markets in which the efficient market hypothesis holds but where prices did not follow random walks." (from Lo & MacKinlay, 1999) Other researchers also support the idea of turning away from random walk due to its simplistic and unrealistic features, e.g. Larson (1960), Osborne (1962), Steiger (1964), Niederhoffer & Osborne (1966) and Schwartz & Whitcomb (1977). Grossman (1976) as well as Grossman & Stiglitz (1980) went one step further. They argued that "perfectly informationally efficient markets are an impossibility, for if markets are perfectly efficient, the return to gathering information is nil, in which case there would be little reason to trade and markets would eventually collapse."

The random walk hypothesis suggests that markets are efficient, i.e. all relevant information is incorporated fully in today's price. It is impossible to predict future changes in returns based on historical or present data and it is impossible to make profits from arbitrage, because stock prices are trading at their intrinsically fair values.

Samuelson (1965) takes a mathematical approach and demonstrates that if markets are efficient, price changes must be "unforcastable if they fully incorporate the expectations and information of all market participants". For further details about the degrees of EMH including weak, semi-strong and strong form, the reader may refer to Fama (1965, 1969).

Where does momentum fit into these concepts? Momentum strategies count on past price data, which means that momentum supporters believe that markets do not fluctuate randomly and are, to a certain extent, forecastable. Momentum strategies together with any of the three levels of efficient markets cannot coexist simultaneously.

Are markets efficient? The author of this research article does not believe so because empirical evidence is too strong, here are other examples - besides momentum - that support that markets are not efficient: day-of-the-week effect where on average stock markets decline on Mondays and soar on Thursdays and Fridays before heading into the weekend; earnings announcements and their positive or negative impact depending on the expectations and outcomes; merger arbitrage and the underlying *ex ante* price behavior of target versus takeover firm. Shiller's (2003) argument against EMH is a macroscopic critique and looks at P/E ratios and dividends over many decades: "How is it possible that prices rationally vary so much given the relative stability of dividends?"

2.6 Momentum Crashes

A momentum crash occurs when the strategy based on momentum experiences significant, sustained and unexpected losses. Daniel & Moskowitz (2013) in their seminal paper "Momentum Crashes" examined momentum crashes and discovered that momentum strategies tend to perform worst during market recoveries following severe market crashes, e.g. in the second half of 2008 after the global financial crisis that culminated in the bankruptcy of Lehman Brothers. When in 1930, one year after the Wall-Street Market Crash of 1929, price levels hit rock bottom and recovery was about to start, momentum returns plummeted sharply (Yan, 2013). For both Yan and Daniel & Moskowitz "the conditionally high premium attached to the option-like payoffs of the past-loser portfolio gives rise to momentum crashes." During a stock market crash usually all stocks, regardless of whether they did well in the past or not, become losers. So does momentum investing in general: under the assumption that all companies survive and continue operating after a crash, buying past winners (low betas) and selling past losers (high betas) would become a devastating strategy if we believe that markets start rebounding. Why? This is because the short side of the momentum strategy (loser stocks) will eventually see higher positive aggregate returns (due to their higher market betas) than the long side with low-beta stocks, and this in turn becomes a counterproductive strategy when using the WML framework; following a crash being bullish empirically tends to be a winning strategy, e.g. invest 100% into longs and avoid shorting because everything is moving up.

Asness (2016) also documented the existence of momentum crashes and warns at the same time that it might be possible to see those crashes not only after recovery phases once market levels hit rock bottom, but also at other stages, e.g. market corrections or market distress. Risk, for Asness and AQR, is not only the chance of losing money, it is about "when you lose, and losing after the worst is over and during the rebound […] ".

2.7 Front-Running Momentum

Henker, Martens & Huynh (2006) use an interesting concept of front-running momentum where, given the original formation periods that usually close at month-end, the investor shortens the formation period by several days and starts the holding period a few days earlier than the usual momentum traders. The authors found that front-running end-of-the-month momentum strategies could generate excess returns for small-capitalization stocks. For large-sized stocks, front-running end-of-the-month momentum strategies yielded the same return as the common strategy, but at a lower level of risk measured by the standard deviation. Having this in mind, front-running momentum has not only the potential of outperforming, but it can provide portfolio managers with a tool for lowering portfolio risk levels. To check this concept for the European context is one of the main goals of this research study hereafter. Since arbitrageurs cannot eliminate momentum profits over time, front-running common momentum strategies should yield a tangible result, which is either an increase in returns or a risk-reduction characteristic, or the combination of both.

Another remark concerning Henker et al.'s (2006) study: they used US stock prices listed on the AMEX, Nasdaq and NYSE covering the period 1993 up to 2004. Given the fact that legal momentum front-running on the US market is a significant return-enhancing as well as risk-reduction technique, and the fact that the US stock market on average is "more efficient" than other markets in a technical sense, e.g. emerging markets, the author expects a similar outcome for the European context.

3. Data

This research study is interested in weekly stock price momentum on the European stock market for the period beginning 2005 until mid 2016: that is enough data in order to achieve statistically meaningful results. Daily stock price data of the EuroStoxx members, cleaned up from noise, corporate action etc. has been provided by SalientQuants, a South Africa-based quantitative investment management firm. Weekly returns are calculated by averaging all daily returns within a week.

Returns, instead of price levels, are used because they enable normalization of data and throughout this research thesis the arithmetic technique is applied. Why? It is because log-returns assume prices that are normally distributed, which is a very inadequate and simplistic setting. The source of other data, e.g. index levels (SXXE) and the 3-month (EUR) Euribor, a proxy for the risk-free rate of return, is Bloomberg.

Penny Stocks (stocks worth less than 0.5 EUR) are removed due to their low levels of liquidity - thus tradability - as well as their disadvantage of having highly volatile returns, which would classify them as winners in one week, as losers in the following week and then as winners thereafter etc.

In case of delisting, the given stock is removed before the subsequent formation period, and its momentum return will not be measured anymore, even though the holding period would dictate holding it "a bit longer". In case of listing, the new stock in question gets added to the pool of eligible assets-to-be-chosen-from before the subsequent formation date so that it becomes a candidate for the momentum portfolio.

Bank holidays are considered, e.g. if a bank holiday falls on a Friday, the algorithms are designed in a way that they recognize Thursday as the last trading day of that week. *

* Due to Matlab's unavailability of built-in European bank holidays, this study uses US bank holidays, which are mostly overlapping with the European ones.

4. Methodology

4.1 Ranking and Classification

In order to rank stocks according to their relative performance, this research study looks at the cumulative return over the period dictated by the formation period, on a rolling basis week after week. At the end of each week all securities are ranked in descending order (vector n x 1 format), based on their past 52-week aggregate returns. Those stocks within the top 10% belong to the winner portfolio (denoted as "W"), the bottom 10% are part of the loser portfolio (denoted as "L"). This approach is in accord with Jegadeesh & Titman's (1993) decile ranking. A decile ranking is chosen for this study because there are enough stocks assigned to both the winner and loser group, and this is thanks to the large amount of stocks in the original data set (after clean-up approx. 300 in total). Winner and loser portfolios are equally weighted, regardless of their market capitalization.

4.2 Portfolio Formation and Holding Period

The following table shows the overview and framework of how the momentum strategies are set up. If not stated explicitly, the formation period of 52 weeks is applied throughout this paper and labeled "base strategy" or "vanilla strategy".

Formation Period	**Holding Period**
52 weeks	4, 12 and 24 weeks

Table 1: Setup of Base Momentum Strategy

For every week (either Friday or last business day of any week) momentum portfolios are built and their profitability is measured over the upcoming 4, 12 and 24 weeks.

The choice for the formation and different holding periods is made in such a way that it tries to cover a multitude of scenarios where - *à priori* - other studies have found significant momentum returns, e.g. the optimal 12-month formation period in Van Rensburg's (2001) research, which corresponds to the 52-week formation period in this paper. It is well known that there is a price reversal to be expected in the very long-term and very short-term, so the 4-week holding period will measure short-term momentum, the 12-week holding will measure intermediary momentum and the 24-week holding will measure mid-to-long-term momentum. Momentum strategies in general are known to best perform for the intermediary holding strategies due to the price return continuation that is prevalent for that horizon.

In order to reduce the effect of bid-ask bounces, short-term price reversals and nonsynchronous trading, the algorithms are designed in a way that they always include a one-week gap between the formation and holding period. This approach is in accord with JT's (1993) as well as Lehman's (1990) work: since they make use of monthly data, their gap consists of one month, whereas in this paper a gap of one week is chosen, given the use of weekly data.

The framework for the front-running (FR) strategies is presented in table 2; note that each row within the table represents a distinct strategy that is tested independently from the others.

Front-Running by	**Formation Period**	**Holding Period**
1 week	51 weeks	4, 12 and 24 weeks
2 weeks	50 weeks	4, 12 and 24 weeks
3 weeks	49 weeks	4, 12 and 24 weeks
4 weeks	48 weeks	4, 12 and 24 weeks
5 weeks	47 weeks	4, 12 and 24 weeks

Table 2: Front-Running Momentum

The formation period is shortened in such a way that it cuts off weeks at the end of the formation period. This enables the investor to start the holding period earlier than investors who apply the crowded month-end strategy. This research article is interested in examining how the momentum profitability changes once investors deviate from that common view. Hereafter comes a table overview that visualizes how the front-running is set up: the first row is the base (vanilla) momentum strategy whose formation period is 52 weeks. The second row makes a 1-week front-run and only has 51 weeks of formation, and that one week has been cut off on the right-hand side (Δ1w).

The same rationale is valid for the other front-running strategies, too.

Base	.	.	.	.	.	.	.	.	52w
FR1week	.	.	.	.	.	.	.	51w	Δ1w
FR2weeks	.	.	.	.	.	.	50w	Δ1w	Δ1w
FR3weeks	.	.	.	.	.	49w	Δ1w	Δ1w	Δ1w
FR4weeks	.	.	.	.	48w	Δ1w	Δ1w	Δ1w	Δ1w
FR5weeks	.	.	.	47w	Δ1w	Δ1w	Δ1w	Δ1w	Δ1w

Table 3: Setup of Front-Running Month-End Momentum: Formation Period shrinks, Holding stays the same

It is important to stress that front-running, in a methodological context, does not mean that the algorithms exclude the one-week gap between formation and holding period because the models must not suffer from bid-ask bounces or short-term reversals.

What front-running in this paper's context simply means is that the investor goes long (and short) before all other momentum traders do, in order to gain competitive advantage. The results of front-running are then compared to the vanilla strategies for each month-end. Since there are five front-running scenarios, there will be five t-tests that compare front-running means to the month-end means. Beside the t-tests there is also the Kruskal-Wallis test that tries to detect whether there are differences in mean among groups; the details about KW are discussed in sub-section 4.6 below.

In addition to this, there will also be a comparison of standard deviations, skewness as well as other metrics like maximum drawdown and Sharpe ratio. The Sharpe ratio is a useful tool used in finance and especially popular in the evaluation of (portfolio) performance: it measures expected return per unit of risk for a given net-zero investment strategy and is calculated in the following way:

$$\text{SR} = \frac{R_{PF} - r_f}{\sigma_{PF}} \tag{3}$$

where R_{PF} is the strategy's portfolio return, r_f denotes risk-free rate of return and σ_{PF} captures the portfolio standard deviation.

4.3 Measuring Profitability

The profitability of momentum is measured by the difference between winner and loser portfolio (WML = "winner minus loser") and is technically a zero-cost investment, whereas the proceeds of selling the loser shares finance the "longs" of the winner portfolio. The combination of jointly "being short the loser PF" and "being long the winner PF" is held for the length of the holding period and the profitability is calculated in the following way:

$$\text{Profitability}_{\mathbf{t}} = 0.5 \text{ x LoserPF}_{\mathbf{t}} \text{ x } (-1) + 0.5 \text{ x WinnerPF}_{\mathbf{t}} \quad (4)$$

where (-1) indicates that the loser portfolio gets shorted and (0.5) indicates that both the winner and loser portfolios are equally weighted. The strategies that use formula 4 to measure profitability are also referred to as "static" momentum strategies throughout this research thesis.

For the dynamic momentum strategy (also labeled "time series momentum" occasionally), profitability is calculated under more logical and dynamic rules: if the aggregate return of the loser portfolio is negative and the aggregate return of the winner portfolio positive, i.e. $\sum_{t=-52}^{-1} LoserPF_t < 0 \cap \sum_{t=-52}^{-1} WinnerPF_t > 0$, formula 4 is used.

For the case where the aggregate return (past 52 weeks) of both the loser portfolio and winner portfolio is positive, i.e. $\sum_{t=-52}^{-1} LoserPF_t > 0 \cap \sum_{t=-52}^{-1} WinnerPF_t > 0$, the following concentrated strategy is executed: in this case the investor ignores the loser portfolio and invests 100% in the winner portfolio:

$$\text{Profitability}_{\mathbf{t}} = \text{WinnerPF}_{\mathbf{t}} \text{ x } (1) \quad (5)$$

For the case where both the aggregate loser and winner portfolio is negative, i.e. $\sum_{t=-52}^{-1} LoserPF_t < 0 \cap \sum_{t=-52}^{-1} WinnerPF_t < 0$, the algorithms goes short 100% the loser portfolio in order to enhance relative returns:

$$\text{Profitability}_t = \text{LoserPF}_t \times (-1) \quad (6)$$

At this stage it is important to note that, for the sake of simplicity, portfolio rebalancing costs are ignored: the rebalancing of weekly momentum portfolios is more expensive than the rebalancing of monthly strategies. In general, rebalancing costs increase with the frequency of rebalancing. In practice there would be a point where the benefit of momentum investing is equal to the costs of rebalancing, and eventually be less than the total costs, which in turn would render momentum into a non-profitable strategy.

4.4 "Week-effect"

The idea of "week-effect" divides each month into date containers of one week (or 5-6 days to be precise) and tries to extract information about which week is most optimal to launch momentum investing. For examining this, the formation and holding period are as described in the first table of the methodology section (vanilla strategy). Since this research is dealing with weekly data, examining "week-effects" is an interesting and more flexible approach than for example settings that rely on monthly data. The motivation for studying "week-effects" is that so far, momentum has been widely used as a monthly / month-end strategy where investors did not have any other option than ending the formation period at month-end and start holding the momentum portfolio at month-end (in theory one month later, if one-month gap is taken into account).

4.5 "Month-effect"

Is there a particular month within the year where the start of momentum investing is more profitable than in other months? Are there months where momentum investing should be avoided? In order to examine the momentum returns among different months, twelve date containers are designed with which, eventually, the author of this paper is able to test whether the differences in mean are significantly different from one another. Instead of conducting pairwise t-tests (for 12 groups this would amount to 66 t-tests when applying the combination rule) or the one-way ANOVA, this paper makes use of the Kruskal-Wallis test where it is deemed appropriate.

4.6 One-Way ANOVA versus Kruskal-Wallis Test

One-way ANOVA is a non-parametric technique that tests whether a set of group means are the same or not. The ANOVA equations are as follows:

$$\text{SS (Within)} = \sum_{j=1}^{p} \sum_{i=1}^{n_j} (x_{ij} - \overline{x_J})(x_{ij} - \overline{x_J}) \tag{7}$$

$$\text{SS (Between)} = \sum_{j=1}^{p} n_j (\overline{x_J} - \bar{x})(\overline{x_J} - \bar{x}) \tag{8}$$

$$\text{SS (Total)} = \sum_{j=1}^{p} \sum_{i=1}^{n_j} (x_{ij} - \bar{x})(x_{ij} - \bar{x}) \tag{9}$$

where x_{ij} represent realisations for *i* and *j*, n_j denotes number of in-group variables of *j* and $\bar{x}$ represents averages. This research thesis is interested in studying inter-group means in the context of “week-effect”, “month-effect” as well as comparing means of month-end base momentum with its front-running strategy scenarios. If the null hypothesis cannot be rejected, this means that the means of all groups are the same. If the null hypothesis is rejected, this means that not all group means are the same. One of the big disadvantages of ANOVA is that it does not report which group means are different. The other drawback is that ANOVA assumes in-group homoscedasticity as well as a normal distribution of returns, which is not congruent with the findings of this study: as reported in the results section, with one or two exceptions only, all momentum distributions exhibit negative skewness.

A more realistic and useful test is the Kruskal-Wallis (KW) test (Kruskal & Wallis, 1952). This non-parametric method is rank-based and does not make the assumption of normally distributed returns. The formula for the Kruskal-Wallis test is the following:

$$\mathrm{KW} = \frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} - 3(N+1) \tag{10}$$

where R_j is the sum of ranks of sample j, n_j the size of sample j and N is defined as $N = \sum_{j=1}^{k} n_j$. The non-rejection of the null hypothesis means that group distributions resemble each other strongly, which in turn can be interpreted as group means (and modal values) being located at identical locations and thus no difference in momentum returns. The KW tests are then executed at pre-defined significance levels. There are four assumptions that need to be passed before using this test: firstly, the dependent variable must be of either continuous or ordinal nature. Since stock prices are continuous and returns are based on that, this assumption is fulfilled. Secondly, the independent variable must consist of two or more categorical, independent groups. This assumption is fulfilled partially in a sense that there are more than two groups (for the "month-effect" 12 in total). Thirdly, there is the assumption that observations within and across groups have to be "independent". This is a stark assumption that cannot be fulfilled fully because data points in this research study are indeed overlapping, e.g. through the moving sum calculations and same stock returns that make it into successive momentum portfolios. And lastly, when the underlying distributions have a similar shape, e.g. all group distributions are negatively skewed, interpretations and comparisons of the KW-test on the rank can be made using the medians. In case of different shapes among group distributions, Kruskal-Wallis suggests using mean ranks as comparison. At any point within this research paper where KW is applied, a skewness or histogram analysis is made in order to comprehend the shape of the distributions first.

4.7 Portfolio Betas and their Measurement

Beta is a measure of systemic risk and tells the investor how volatile a strategy is, compared to the market as a whole. The betas presented in this paper are the outcome of the following linear regression model where the dependent variable is defined as “PF return minus rf” and the independent variable as “Market return minus rf”.

$$[RPF_t - rf_t] = \alpha_i + \beta_i [RM_t - rf_t] + \varepsilon_{it} \qquad (11)$$

where rf denotes risk-free rate of return, RPF portfolio return and RM market return. Alpha (α_i) is the intercept, beta (β_i) the slope of the regression function and epsilon (ε_{it}) represents the error term.

5. Results

5.1 Results of Static Momentum Strategy

Over the entire period, from 2005 until mid-2016, the different momentum strategies performed the following way (see table 4). The formation period of 52 weeks is the same for all momentum strategies under investigation and the static strategies differ only in their holding periods of 4, 12 and 24 weeks. Percentage returns and standard deviations are expressed in an annualized form in order to allow straightforward comparisons.

	MomHold4Weeks	MomHold12Weeks	MomHold24Weeks
Annualized Mean	8.45%	6.71%	5.12%
Annualized Std. Dev.	13.97%	13.74%	13.78%

Table 4: Mean and Standard Deviation of Momentum Strategies 2005 - 2016 (annualized)

Over the same period, the market index (SXXE) returned 2.19% annually at a standard deviation of 21.85%. Since the market return seems rather low, a closer look at how the market performed before, during and after the financial crisis of 2008 is appropriate. Note that pre-crisis is defined as the time period between January 2005 and end of July 2008, inter-crisis as interval August 2008 until December 2009 and post-crisis as time period between January 2010 and mid-2016.

	Pre-Crisis	Crisis	Post-Crisis
Annualized Mean	-0.330%	-2.755%	4.254%
Annualized Std. Dev.	15.984%	36.463%	19.549%

Table 5: Breakdown Pre-, Inter- and Post-Crisis for Market Return (SXXE) and Std. Dev.
All values are expressed in annualized form and cover the time period 2005 – 2016

From the two tables above the reader shall note that all of the three momentum strategies outperformed the index market return, and exhibited lower risk.

Usually when a stock market is not finding itself in a financial depression, market volatility hovers around 14-20%, depending on the market under consideration, and according to table 5 it was especially during the crisis where the perceived risk in terms of volatility was almost double as before and after the crisis.

Mean and standard deviations are important metrics in finance, but can be misleading if investors base their decisions solely on that; this is the reason why the following sub-

sections below look at other metrics and graphs that visualize the findings. Anscombe (1972) underlined this point and showed how a multitude of data sets with nearly the same descriptive statistics can look very differently when graphed.
The following table takes a look at the shape of the return distribution of the momentum strategies and the according graph is plotted on the following page (figure 1).

	MomHold4Weeks	MomHold12Weeks	MomHold24Weeks
Skewness	-1.421	-1.529	-2.038
Kurtosis	9.224	10.207	10.379

Table 6: Skewness and Kurtosis for 52-Week Formation and different Holding Periods

Skewness, also called the third central moment, is very important in financial decision analysis because it enables a closer look at the asymmetry of a given distribution. Positive skewness is defined as a distribution with an asymmetric tail reaching toward positive values; on the other hand, negative skewness is defined as a distribution with an asymmetric tail reaching toward negative values. All of the three momentum strategies exhibit negative skewness, which in turn leads to the conclusion that the normal distribution is not a good proxy for those strategies.
In figure 1 below it is interesting to see that the most extreme outliers on the negative side belong either to the 4-week or 12-week momentum strategy and the negative skewness is observable clearly for all strategies. Investment strategies with strict mandates, e.g. maximum drawdown levels, might have an incentive to use a longer momentum holding in order to limit their downside risk. In contrast the 4-week momentum strategy seems to have tremendous downside risk.
Even though skewness becomes more negative with the holding period (table 6), this cannot be distinguished precisely by solely looking at the histogram.

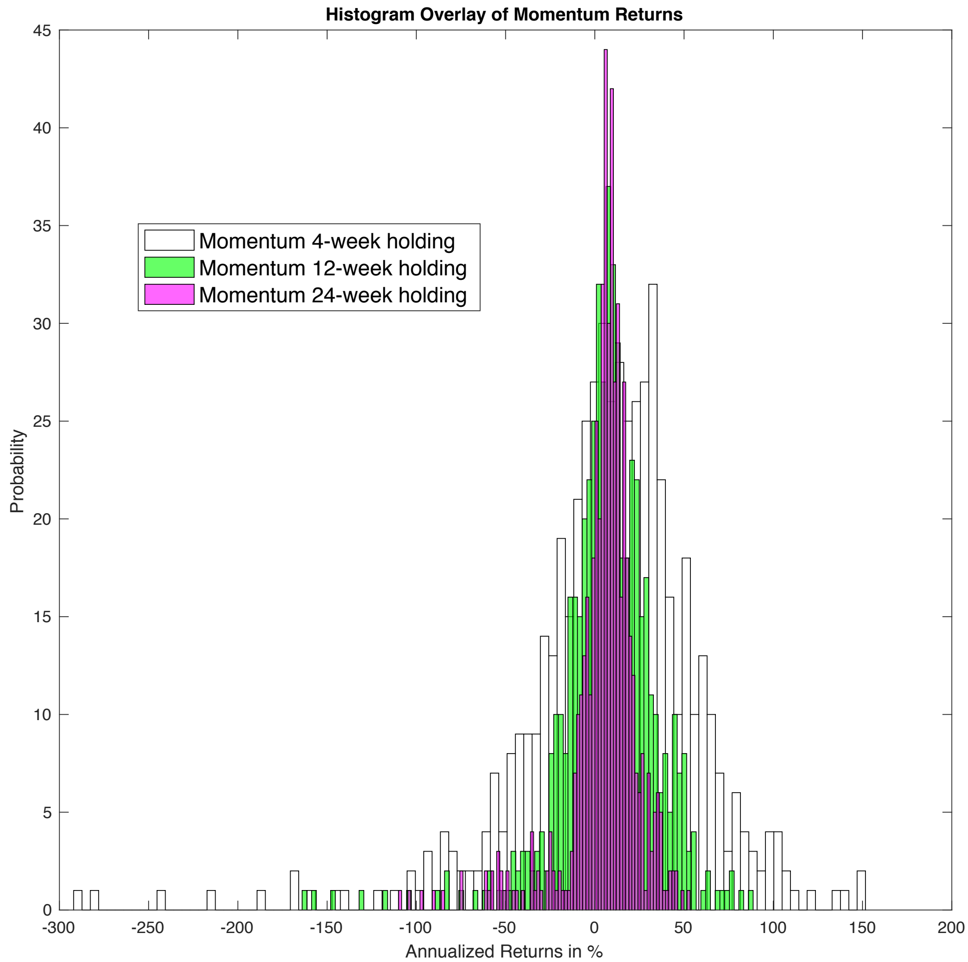

Figure 1: Histogram Overlay Momentum 4, 12 and 24 Weeks. Returns are annualized in order to allow straightforward comparison

Kurtosis is the fourth central moment of a distribution and indirectly measures the sharpness of the distribution peak. In general terms, positive kurtosis (or $k > 3$, to be precise) means that the peak is sharper than the normal distribution peak; negative kurtosis (or $k < 3$, to be precise) means that the peak is flatter than the normal distribution peak. In the context of momentum returns in this study, the findings above (table 6) show that all strategies exhibit a leptokurtic shape where most returns appear to be centrally located within the probability density space. An interesting finding is that the kurtosis increases with the holding length of the portfolio: the longer the holding period, the more concentrated the momentum returns seem to become. This is clearly observable in figure 1 when comparing the 24-week distribution (pink) with the 4-week distribution (white).

The following constitutes bar charts that try to give a good explanation for why the negative skewness is prevalent: most of the negative returns, expressed in annualized rolling momentum returns, are almost as double in magnitude as the largest positive returns.

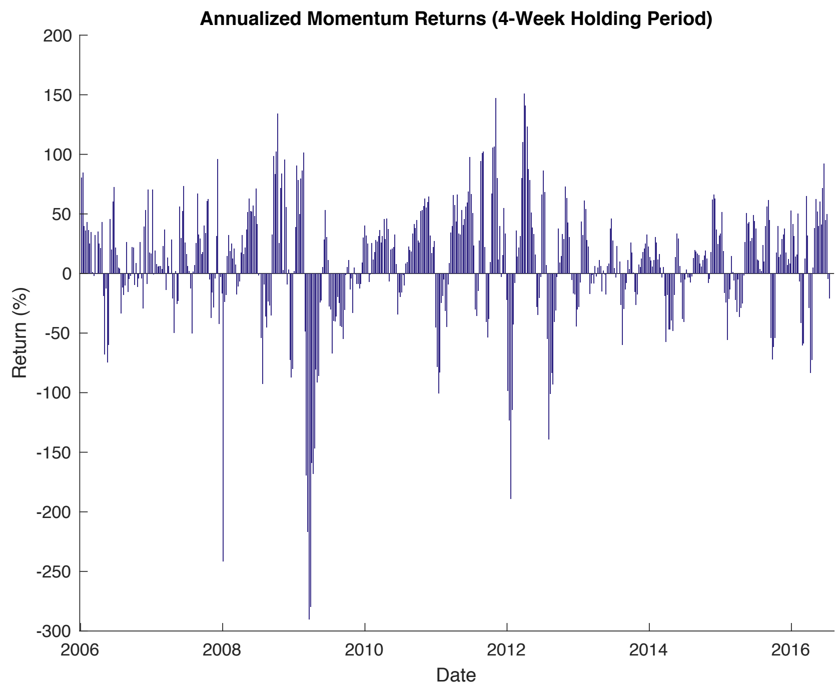

Figure 2 : Bar Chart with Worst Return -290% and Best Return +150%

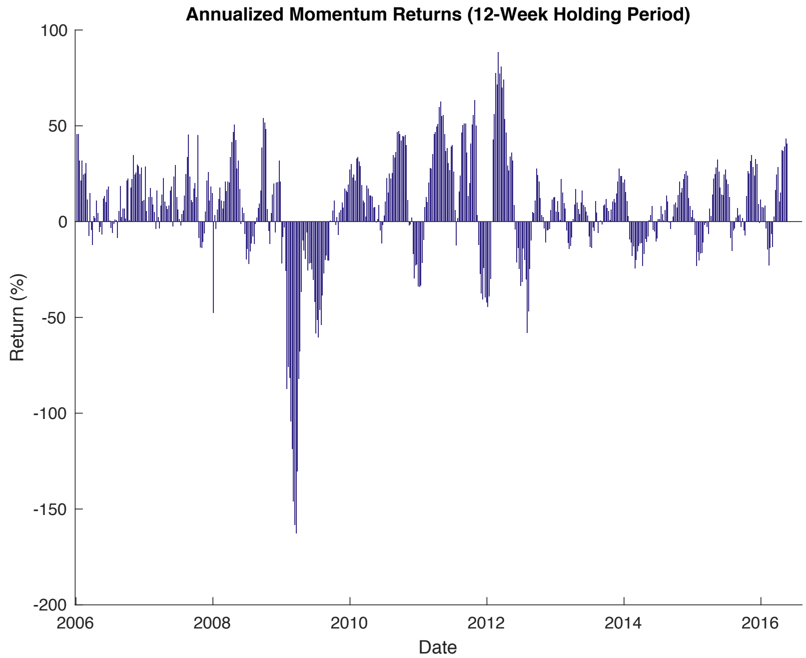

Figure 3: Bar Chart with Worst Return -160% and Best Return +85%

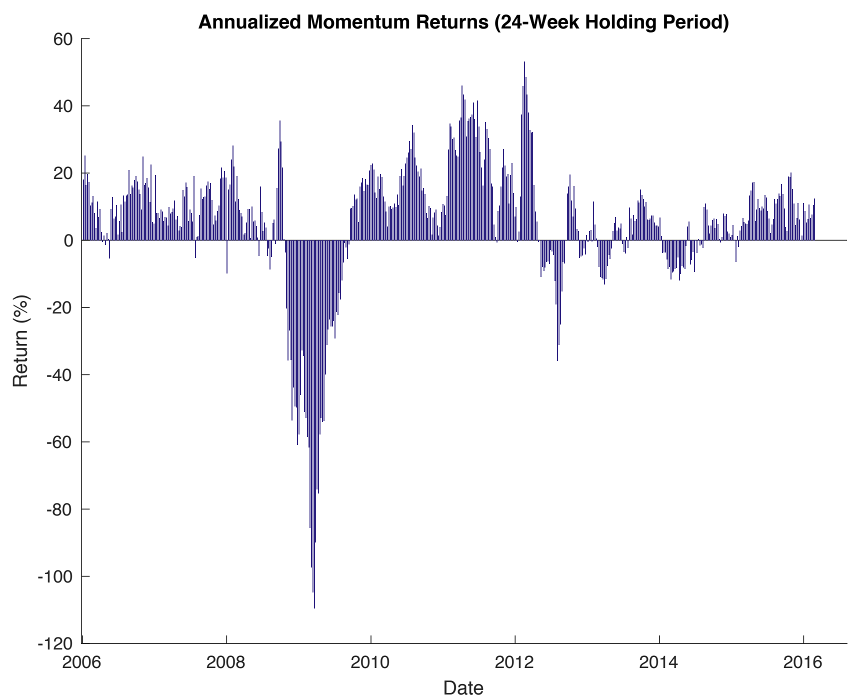

Figure 4: Bar Chart with Worst Return -110% and Best Return +55%

For the sake of interest, these three bar charts are now overlapped in order to make direct comparisons about the momentum strategies. The 4-week momentum strategy oscillates most whereas the 12- and 24-week strategy display significantly lower oscillation.

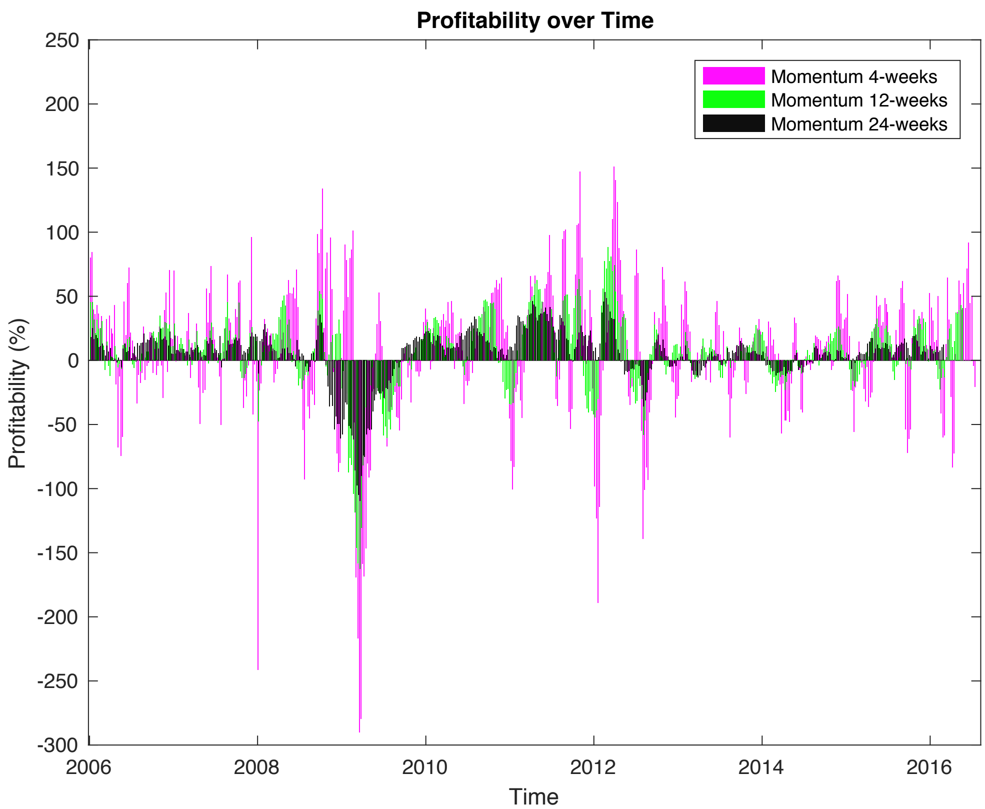

Figure 5: Bar Chart Overlay

The 24-week strategy seems to have no negative returns during the pre-crisis time, nor between 2010 and 2012 or after mid-2014.

Another graphical representation of the three momentum strategies is shown hereafter. From this representation the principal aspect to keep in mind is the fact that the upside potential is more or less the same for all of the three strategies; it seems to be bounded at 100-130%, but the downside drops deeper and deeper during times of distress, the shorter the momentum holding period.

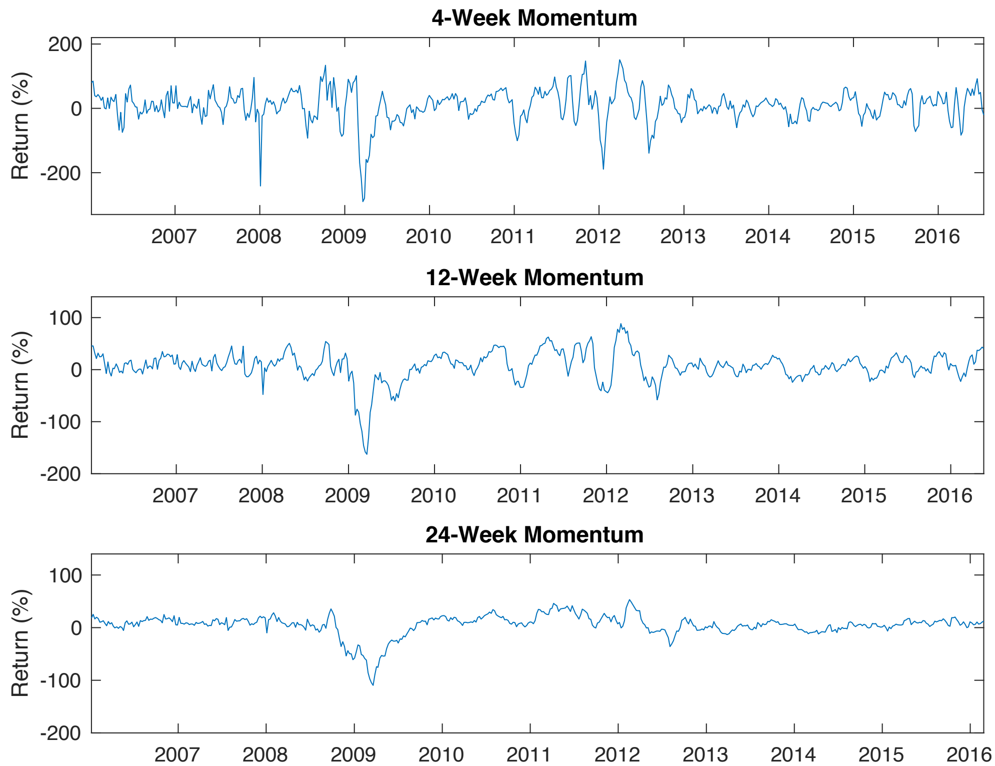

Figure 6: Momentum Strategies over Time (Subplot of 4-week, 12-week and 24-week Bar Chart) Returns are in annualized form

In the methodology section the technicalities for the loser and winner portfolio have been explained. The following figures 7, 8 and 9 constitute time series charts, which plot cumulative returns of both the winner and loser portfolio separately over time. There are a few results that are worth mentioning: firstly, the spread between winner and loser portfolio widens over time. Secondly, during times of financial distress, the spread tightens, e.g. between 2008 and 2010: it looks like the distinction between winners and losers gets blurred due to the fact that the entire market is crashing. Thirdly, the spread over the entire period - measured at the end of the data recording - is largest for the 24-week momentum strategy (+/- 2500 bps), followed by the 12-week strategy (+/- 1600 bps) and eventually the 4-week strategy (+/- 700 bps). Another astonishing point to mention is that, contrary to the author's initial belief, the cumulative return of the loser portfolio over the entire time period is positive; this is true for all three scenarios. This finding then led to the idea of rethinking the static momentum strategy, which consists of simply "going long the winner portfolio" and "going short the loser portfolio", and eventually resulted in the launch of the dynamic momentum strategy.

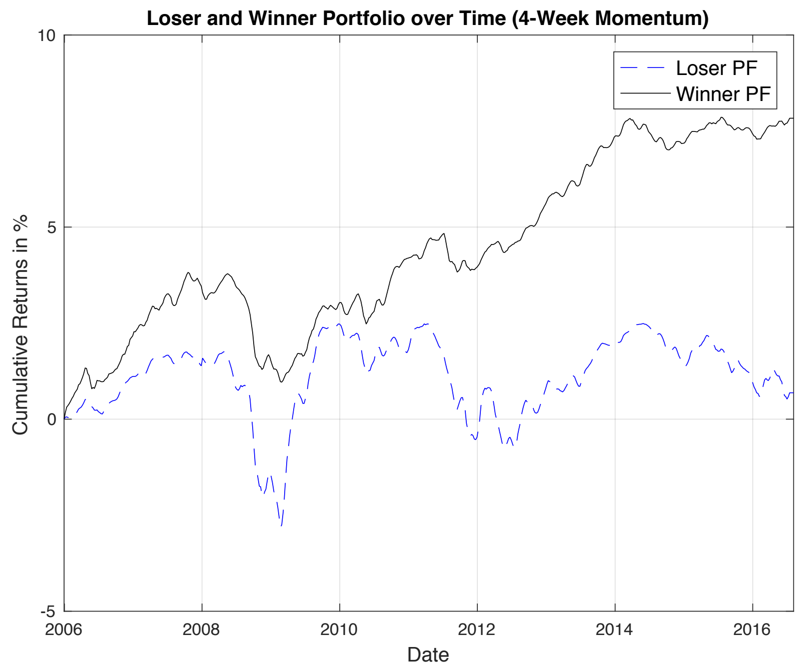

Figure 7: Winner vs. Loser Portfolio over Time (4-Week Holding Period)

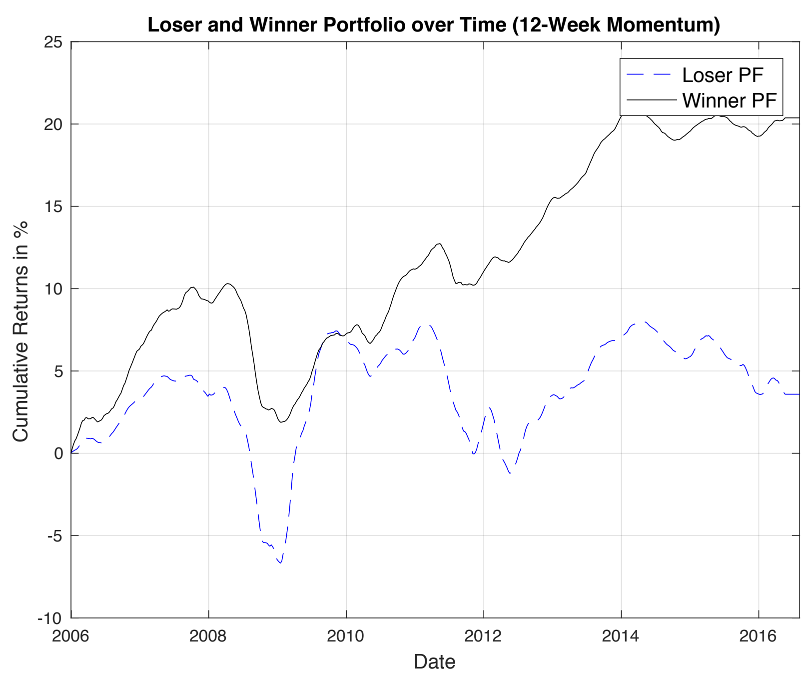

Figure 8: Winner vs. Loser Portfolio over Time (12-Week Holding Period)

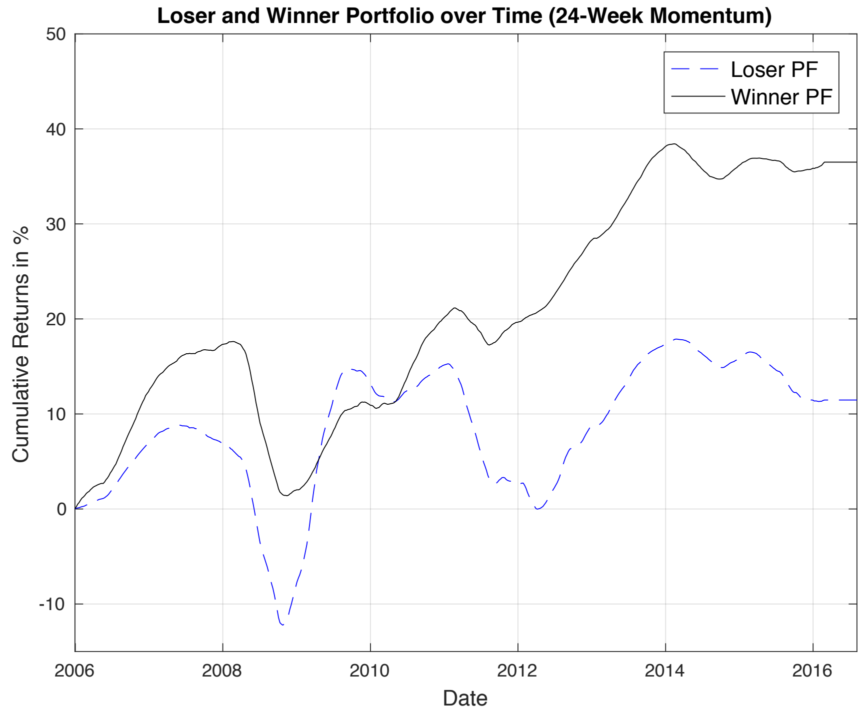

Figure 9: Winner vs. Loser Portfolio over Time (24-Week Holding Period)

The idea of the dynamic momentum strategy, whose details have been explained in the methodology section above, is to test whether the returns differ from the static momentum strategy. In order to test this, the author runs two-sided t-tests on the differences in mean between static and dynamic strategies. The result for all of the three momentum scenarios (4-week, 12-week and 24-week) is that the null hypothesis (means are the same) gets rejected at the 1% significance level, which in turn means that the dynamic strategy clearly performs better. The details are reported hereafter:

	4-Week Momentum	12-Week Momentum	24-Week Momentum
P Value	0	0	0
T Statistics	19.834	21.401	22.078
Outcome Hyp. Test	1	1	1

Table 7: Two-Sided t-test Results Static Vs. Dynamic Momentum

The avid reader may have noticed that in figure 7, 8 and 9 during the financial crisis the loser portfolio dropped by more than the winner portfolio. The following dynamic beta analysis of winner and loser portfolio is able to explain this phenomenon, and the approach is consistent with Daniel and Moskowitz' (2014) research. Beta, a systemic risk measure, explains how volatile a strategy is compared to the market as a whole. Trend-following strategies, like momentum, are expected to have positive betas.

A zero-beta portfolio is a portfolio that has no market exposure at all. Positive betas greater than 1 can be interpreted in the following way: if the market moves up, profitability of the portfolio goes up proportionally higher than the market; however if the market tanks, momentum strategies plummet by even more than the market.

In general, over the entire period 2005 - 2016 and for all of the three momentum scenarios (table 8), both the winner and loser portfolio exhibited significantly different values for beta: in all cases the loser PF had a higher beta value than the winner PF. This can explain the bigger drawdown of the loser PF - compared to the winner PF - in the time series charts above. The adjusted R^2 values in the table refer to the outcome of the regression analysis as explained in the methodology section (equation 11). Note that the adjusted R^2 values increase with the holding period.

		4-Week Mom.	12-Week Mom.	24-Week Mom.
Loser PF	Beta	1.342	1.623	1.755
	Adjusted R^2	0.542	0.654	0.710
Winner PF	Beta	0.841	1.041	1.199
	Adjusted R^2	0.515	0.619	0.691

Table 8: Beta Values for Loser and Winner Portfolio over entire period 2005 – 2016.

Besides the startling findings in table 8, where loser PF betas were significantly greater than the winner PF betas, the following table constitutes a refinement by additionally taking into account pre-crisis, crisis and post-crisis periods. This is done in order to understand why and how momentum strategies crashed during the crisis as well as during the rebound following the crisis.

		4-Week Momentum	12-Week Momentum	24-Week Momentum
Pre-Crisis	Loser PF	0.713	0.993	1.567
	Winner PF	0.936	1.093	1.655
Crisis	Loser PF	1.886	2.242	2.315
	Winner PF	0.917	1.308	1.235
Post-Crisis	Loser PF	1.175	1.459	1.530
	Winner PF	0.760	0.816	0.948

Table 9: Beta Values for Loser and Winner Portfolio (Pre-Crisis, Crisis and Post-Crisis)

During the pre-crisis phase, the winner PF contained stocks with higher betas than the loser PF, in other words during the pre-crisis period where markets were in good mood, momentum profitability was mainly driven by the long side of the portfolio. During the crisis this relationship changed, meaning that all of a sudden it was the loser portfolio that contained the highest beta values: in fact the beta values for the loser portfolio more than doubled during the crisis period compared to the pre-crisis period, except for the 24-week momentum strategy where the beta-increase was roughly 50%. The post-crisis period still saw beta values for the loser portfolio being much higher than the betas of the winner portfolio; this is an explanation for why momentum crashes are *persistent* and *pervasive*, even though the actual crisis is already over: the loser PF has the highest beta stocks during the crisis; within the WML framework, once markets are about to recover relative returns of the loser portfolio (high betas) are greater than the ones of the winner portfolio (low betas) so the calculation "winner minus losers" becomes a negatively yielding strategy because 'L' is greater than 'W'. As Daniel & Moskowitz (2014) noted: "Crashes tend to occur in times of market stress, when the market has fallen and ex-ante measures of volatility are high, coupled with an abrupt rise in contemporaneous market returns". Evidence for the elevated volatility in times of distress has been depicted in table 5.

Another interesting aspect to mention is that even though the post-crisis period (6 years) in this paper - in absolute terms - is designed in a way that it is much longer than the pre-crisis (3.5 years) or crisis period (1.5 years), the beta domination of the loser portfolio over the winner portfolio seems to be prolonged and it looks like it takes some time until the pre-crisis world order, where the winner PF had a higher beta than the loser PF, is reached again.

The annualized ex-post Sharpe ratios for the momentum strategies are reported in the following table. Note that from a risk-return tradeoff, the best strategy is holding the momentum portfolio for 12 weeks. If an investor chooses a longer holding period, e.g. 24 weeks, there is not much of a difference when judging by the Sharpe ratios.

	4-Week Mom.	12-Week Mom.	24-Week Mom.
Sharpe Ratios	0.138	0.183	0.181

Table 10: Annualized Sharpe Ratios

5.2 Results of "Week-Effect"

The mean momentum returns for the "week-effect" are shown hereafter; the reader may take notice that the numbers are expressed in annualized form, which enables to compare different momentum strategies with different holding horizons at once. As described above, the different date containers represent different starting points for momentum investing, leaving formation and holding period in "vanilla" form. The cells within the tables highlighted in grey represent the best-possible scenarios in terms of investment decision or optimal timing. The second-last week of any month, i.e. 21st until 25th, had the highest momentum returns over the period 2005 - 2016.

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	8.16%	6.57%	10.54%	5.14%	12.38%	8.01%
12-Week Mom.	9.62%	5.33%	6.28%	6.49%	9.21%	3.71%
24-Week Mom.	6.42%	3.83%	4.50%	5.16%	7.31%	3.69%

Table 11: Annualized Means of Different Momentum Strategies for Different Time Containers

Hereafter the results for the annualized standard deviations; again, the second-last week of the month seems to have the most favorable numbers (here in terms of risk).

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	15.12%	13.58%	12.89%	16.15%	11.38%	14.37%
12-Week Mom.	12.60%	15.37%	13.52%	15.02%	10.91%	14.55%
24-Week Mom.	13.66%	15.41%	13.46%	14.62%	10.90%	14.33%

Table 12: Annualized Std. Dev. of Different Momentum Strategies for Different Time Containers

Finally, hereafter the paper reports the annualized ex-post Sharpe ratios for the different time periods within the month. Financial theory suggests that if there are several investment strategies to choose from, opting for the one with the highest Sharpe ratio is strictly dominating all other options.

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	0.4410	0.3766	0.7073	0.2266	0.9603	0.4567
12-Week Mom.	0.6457	0.2523	0.3576	0.3364	0.7104	0.1554
24-Week Mom.	0.3631	0.1563	0.2268	0.2553	0.5378	0.1620

Table 13: Annualized Sharpe Ratios (Week-Effect)

Again, the week preceding the last, from the 21st until 25th, exhibits the best pre-requirements for launching momentum investing since it has the highest Sharpe ratios. In fact, month-end strategies are *strictly dominated* by all other strategies with starting points other than month-end (exception 4-week momentum where 6^{th}-10^{th} and 16^{th}-20^{th} have a lower SR than at month-end).

Conclusively, the following Kruskal-Wallis test is there to see whether there are any statistically significant differences in mean.

	WeekEffect (4-Week Mom.)	WeekEffect (12-Week Mom.)	WeekEffect (24-Week Mom.)
Chi-squared	0.68	1.76	1.71
p value	0.984	0.881	0.888
Reject Ho	No	No	No

Table 14: Kruskal-Wallis Test on Differences in Means (Week-Effect)

The outcomes indicate that the KW tests cannot reject the null hypothesis (mean returns among the different date containers same) at any significance level.

The following skewness values shed light on the different intra-month distribution shapes. With the exception of the 12-week momentum strategy that is positively skewed for the date container "21^{st} until 25^{th}", all distributions exhibit negative skewness. It is again the second-last week of the month that is best, because it has the least negative skewness (or even slightly positive) among all other date containers; this is a finding worth mentioning, because investor portfolios can be optimized in such a way that momentum should be launched during this time period, resulting in a limitation of the downside risk measured by the skewness.

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	-1.23	-1.02	-1.42	-1.88	-0.32	-1.58
12-Week Mom.	-0.50	-1.41	-2.37	-2.01	0.39	-1.61
24-Week Mom.	-1.49	-1.86	-2.49	-2.39	-0.72	-2.25

Table 15: Skewness "Week-Effect"

The following metric is linked to the skewness outcome and quantifies the left-tail distribution (worst-period returns): among all other weeks within the month, date container "21^{st} until 25^{th}" exhibits a minmax characteristic in a sense that among all worst-possible returns of the data set, that week seems to minimize the extent of momentum return losses. This is true for the 4-week, 12-week and 24-week momentum scenario.

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	-100.00%	-100.00%	-100.00%	-100.00%	-93.08%	-100.00%
12-Week Mom.	-82.03%	-100.00%	-100.00%	-100.00%	-46.06%	-100.00%
24-Week Mom.	-74.21%	-97.33%	-100.00%	-100.00%	-52.85%	-89.87%

**Table 16: Worst-Case Drawdowns for Momentum Strategies (2005 – 2016).
All values are annualized**

For the metrics "profitable periods" (table 17), which is calculated as the ratio between positive momentum returns and the sum of positive and negative momentum returns, as well as "best-period returns" (table 18), there is not a particular pattern that allows straightforward investor guidance on when to invest. It is however interesting to see that the probability for a profitable momentum strategy never drops below 60% (table 17): on average, momentum is a winning strategy. In other words, momentum investing is more successful than repeatedly flipping a coin whose payoff depends on the outcome of either "head" or "tail".

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	61.11%	62.92%	64.13%	60.87%	63.64%	63.64%
12-Week Mom.	70.45%	66.67%	69.23%	65.93%	68.97%	65.31%
24-Week Mom.	75.58%	74.12%	71.59%	80.90%	74.12%	73.20%

Table 17: Profitable Periods for Momentum Strategies (2005 – 2016)

	From_1st_5th	From_6th_10th	From_11th_15th	From_16th_20th	From_21st_25th	From_26th_31st
4-Week Mom.	147.29%	133.90%	123.24%	101.40%	110.11%	150.93%
12-Week Mom.	88.44%	77.26%	55.60%	80.95%	71.50%	74.19%
24-Week Mom.	43.33%	46.11%	43.36%	53.24%	48.64%	37.48%

**Table 18: Best-Case Period Returns for Momentum Strategies (2005 – 2016).
All values are annualized**

5.3 Results of "Month-Effect"

The idea about "month-effect" is to examine what months of the year are best for launching momentum strategies. The exact details have been described in the methodology section above. The following table reports the findings, whereas the highlighted cells in grey indicate best-possible scenarios:

	January	February	March	April	May	June
4-Week Momentum	-3.36%	12.45%	-7.79%	1.65%	11.38%	30.79%
12-Week Momentum	-1.38%	2.79%	-0.42%	14.97%	14.33%	1.92%
24-Week Momentum	2.83%	7.42%	-0.90%	1.90%	1.69%	5.81%
	July	August	September	October	November	December
4-Week Momentum	-3.56%	-6.06%	9.42%	25.61%	24.29%	8.48%
12-Week Momentum	-6.38%	4.50%	15.02%	17.86%	10.38%	7.12%
24-Week Momentum	4.55%	6.42%	11.38%	10.64%	5.75%	4.12%

Table 19: Annualized Means over the period 2005 - 2016

Apart from the outlier return of 30.79% for the 4-week momentum in June, the most profitable months for the launch of momentum investing are in September and October, regardless of whether the momentum portfolio was held for a short- (4 weeks) mid- (12 weeks) or long- (24 weeks) horizon. On the other hand, January and March are the months where the launch of momentum investing was not successful at all: regardless of the length of the momentum holding period, an investor lost money - on average - if he invested in March solely and did not engage in any sort of rebalancing or other momentum investing throughout the year.

The following table shows annualized standard deviations for the different months of the year:

	January	February	March	April	May	June
4-Week Momentum	18.78%	9.94%	22.29%	17.59%	11.34%	9.59%
12-Week Momentum	12.18%	18.67%	25.37%	14.07%	9.70%	9.37%
24-Week Momentum	12.83%	18.58%	23.74%	17.81%	13.19%	10.89%
	July	August	September	October	November	December
4-Week Momentum	9.61%	12.86%	11.15%	11.65%	10.29%	10.58%
12-Week Momentum	10.94%	11.00%	9.01%	9.92%	7.71%	10.68%
24-Week Momentum	10.54%	10.61%	5.83%	5.45%	11.02%	13.00%

Table 20: Annualized Standard Deviations over the period 2005 - 2016

For the 4-week momentum it is least risky if the start is happening in June or July, for the longer-term momentum strategies the best returns are located between September and November. When reasoning via the exclusion principle, which seems to be easier in this regard, one should exclude January, February, March and April because of the high risk in those months.

The next table depicts the annualized Sharpe ratios for the different “month containers”:

	January	February	March	April	May	June
4-Week Momentum	-0.252	1.116	-0.419	0.015	0.887	3.085
12-Week Momentum	-0.219	0.077	-0.071	0.975	1.339	0.024
24-Week Momentum	0.124	0.329	-0.101	0.026	0.019	0.389
	July	August	September	October	November	December
4-Week Momentum	-0.526	-0.609	0.701	2.085	2.236	0.673
12-Week Momentum	-0.735	0.258	1.501	1.667	1.170	0.546
24-Week Momentum	0.290	0.459	1.707	1.718	0.400	0.218

Table 21: Sharpe Ratios (Annualized)

If the outlier Sharpe ratio of 3.085 for the 4-week momentum strategy starting in June (table 21) is ignored for now, it looks like the highest Sharpe ratios are all concentrated in the months of September, October and November. Furthermore, all of the lowest Sharpe ratios are concentrated in the months at the beginning of the year (Q1).

Are the means between the twelve different months statistically significant from one another? There exist several tests and techniques how to check that (see methodology section), however at this stage only the one-way ANOVA and Kruskal-Wallis test are executed. The null hypothesis is that all twelve group means are the same; the rejection of the null hypothesis then leads to the conclusion that the means are not similar and that there is indeed something like a "month-effect" within momentum investing. The outcome of the one-way ANOVA is reported in the following table.

	4-Week Momentum	12-Week Momentum	24-Week Momentum
F-statistics	3.153	3.409	1.234
p value	0.000	0.000	0.261
Reject Ho ?	Yes	Yes	No

Table 22: ANOVA Results

An important result from the ANOVA findings is that there is a significant difference in momentum returns among months, but only for the 4-week and 12-week strategy. For the 24-week holding period the difference in means seems to vanish statistically, thus the non-rejection of the null hypothesis. A logical explanation for the latter is that there are too many different months involved in the 24-holding period and as seen above, often the good and bad months are clustered together. When a long-term holding period dictates holding it for 24 weeks, then necessarily not only the good months but also the bad months enter into the calculation. But for the short- to mid-term momentum strategies, the "month-effect" is statistically prevalent.

Since ANOVA does not tell which means outperform the others, the following boxplots will guide the reader into the right direction. The crosses (+) in figure 10, 11 and 12 indicate outliers, the lines in the middle of the blue boxes represent medians, the upper and lower boundary of the blue boxes represent inter-quartile ranges and the vertical dashed lines, which are above and below every blue box, mark the 25th (bottom) and 75% percentile (top).

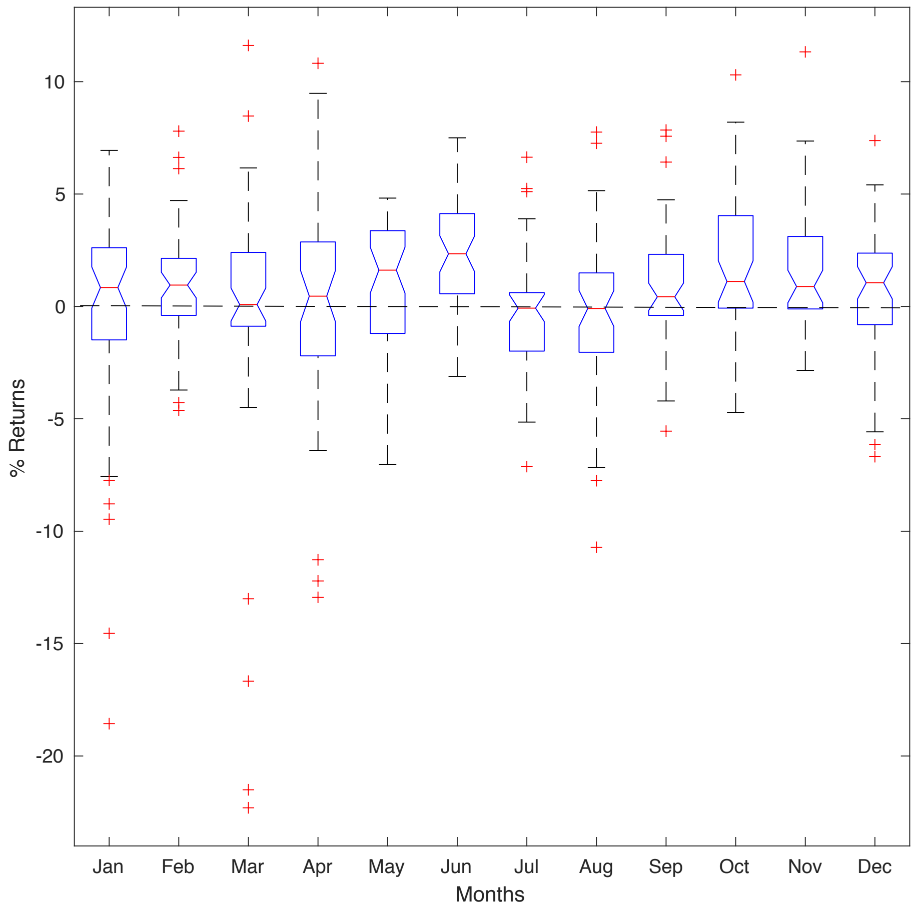

Figure 10: Boxplot 4-Week Momentum

The boxplot for the 4-week momentum strategy reveals clearly the multitude of negative outliers in the concentrated "region" between January and April. If investors were to make a decision about the timing of momentum, the best months would be June, September, October and November. A remarkable observation for the boxplot above is that during Q3 and Q4 the downside observations are very rare and limited, compared to the high concentration of negative returns during Q1 and beginning of Q2.

The boxplot hereafter displays the 12-week momentum scenario. Again, it is interesting

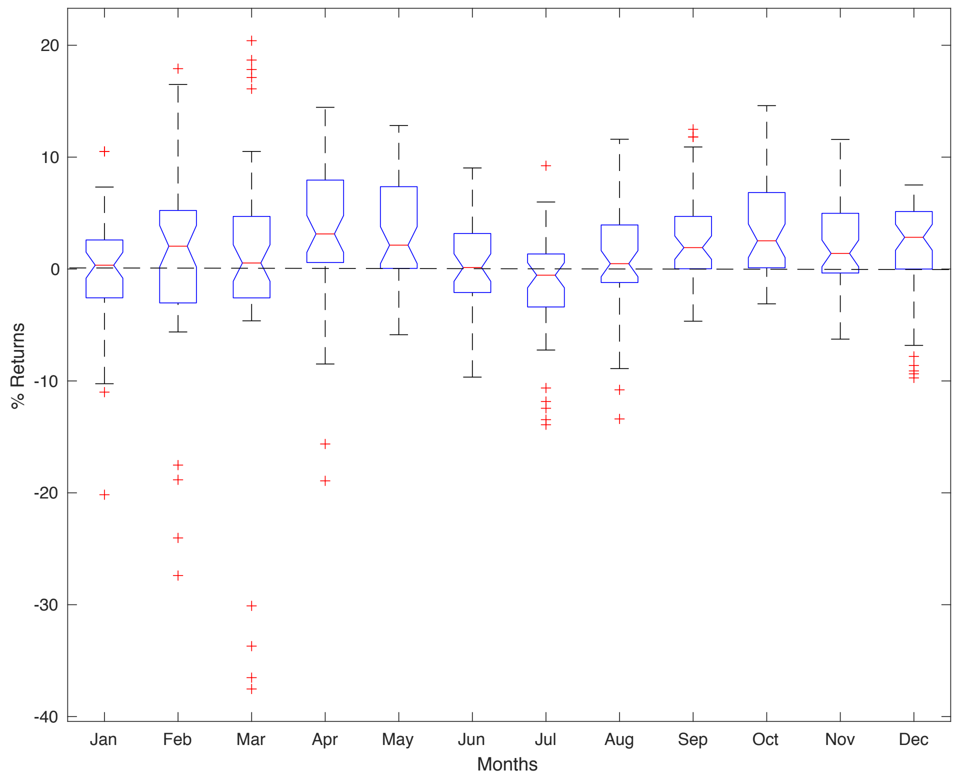

Figure 11: Boxplot 12-Week Momentum

to see that Q1 and Q2 seem to have a concentration or "cluster" of negative outliers, which in turn makes those months utterly unattractive for starting momentum investing. It is - again - the months of September and October that seem to have the best overall performance.

The last boxplot displays the 24-week strategy. As with the findings above it is striking to see how concentrated negative outliers are during Q1 and Q2. A big difference to the boxplots above is that with the 24-week holding period there are no more positive outliers for the second half of the year (Q3 and Q4), whereas with the other strategies

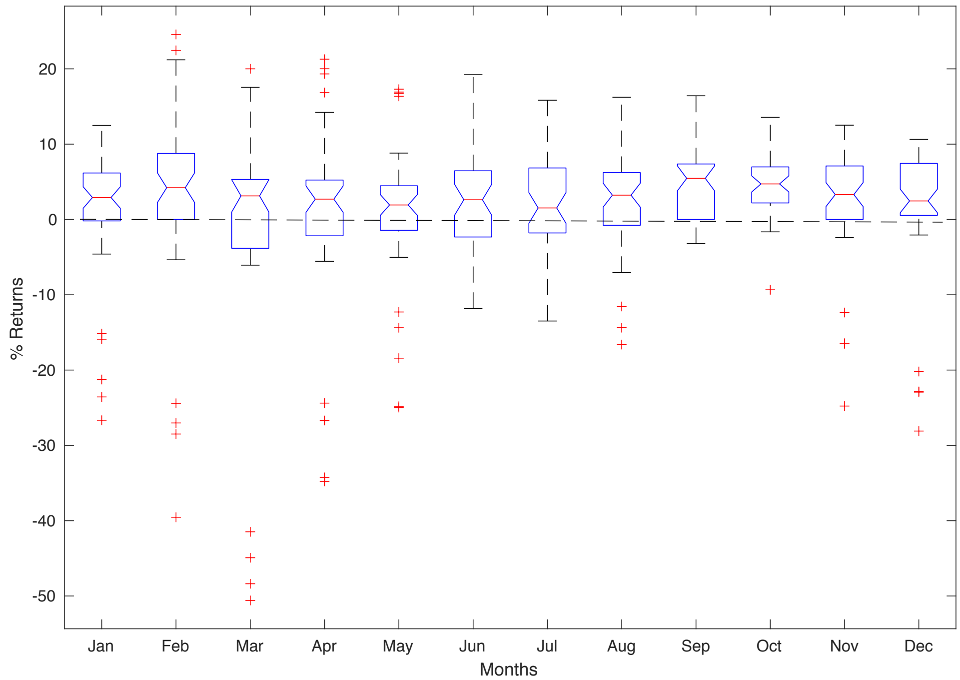

Figure 12: Boxplot 24-Week Momentum

there was at least some sort of upside potential. This small yet important characteristic may be an explanation for the non-rejection of the null hypothesis.

For the Kruskal-Wallis test, the rejection of the null hypothesis means that not all data samples under question come from the same distribution, measured at a pre-defined significance level. The results are reported hereafter:

	4-Week Momentum	12-Week Momentum	24-Week Momentum
Chi-squared	36.270	43.079	16.802
p value	0.000	0.000	0.114
Reject Ho ?	Yes	Yes	No

Table 23: Kruskal-Wallis Results at the 1% significance level

With Kruskal-Wallis both the 4-week and 12-week momentum strategies seem to exhibit a "month-effect", since the underlying distributions for every month are not congruent. But for the 24-week holding period, there does not seem to be a statistically significant "month-effect". The outcomes of ANOVA and KW, measured by the outcome of the null hypothesis, are matching.

The analysis of the shape of distribution yields another support for September, October and November being the months with the most favorable momentum pre-requirements (table 24): strategies with positive skewness are strictly dominating those with negative skewness.

	January	February	March	April	May	June
4-Week Mom.	-1.533	0.058	-2.012	-0.655	-0.865	-0.420
12-Week Mom.	-0.837	-1.194	-1.574	-1.070	0.149	-0.114
24-Week Mom.	-1.699	-1.493	-2.005	-1.346	-0.936	0.101
	July	August	September	October	November	December
4-Week Mom.	0.174	-0.346	0.134	0.470	0.893	-0.495
12-Week Mom.	-0.665	-0.375	0.577	0.518	0.082	-1.066
24-Week Mom.	0.047	-0.533	0.577	-1.035	-1.977	-2.105

Table 24: Skewness "Month-Effect"

5.4 Results of Front-Running Month-End Momentum

Is there a benefit when moving away from the common idea of month-end horizons for momentum investing by engaging in legal front-running? The idea, explained in detail in the methodology section, is to shorten the formation period by 1, 2, 3, 4 and 5 weeks and start the holding period 1, 2, 3, 4 and 5 weeks earlier than the widespread month-end strategy. If the answer to the question above is yes, then there should exist a first-mover advantage in terms of enhanced profitability and / or lower risk.

The following tables looks at the annualized momentum returns:

	Month-End	FR by 1 Week	FR by 2 Weeks	FR by 3 Weeks	FR by 4 Weeks	FR by 5 Weeks
4-Week Mom.	6.47%	5.04%	4.74%	4.79%	3.76%	5.53%
12-Week Mom.	4.34%	4.13%	3.80%	3.69%	3.09%	3.37%
24-Week Mom.	4.80%	4.74%	4.58%	4.66%	4.17%	4.43%

Table 25: Annualized Means Month-End vs. Front-Running

Judging by the values in the returns table, there is no advantage gained by front-running. However, a quick look at the following table, it is obvious to see that engaging in front-running decreases portfolio risk, which is a good sign. It seems that the 5-week front-running strategy strictly dominates all other strategies in terms of risk. When running a 4-week momentum strategy, the annual risk in terms of standard deviation can be effectively decreased by 4.7% (or 66 bps) when opting for a FR-5-week strategy, instead of crowded month-end.

	MonthEnd	FR_1Week	FR_2Weeks	FR_3Weeks	FR_4Weeks	FR_5Weeks
4-Week Mom.	14.03%	13.96%	13.88%	13.76%	13.62%	13.37%
12-Week Mom.	13.93%	13.68%	13.53%	13.40%	13.62%	13.36%
24-Week Mom.	13.82%	13.48%	13.40%	13.46%	13.55%	13.18%

Table 26: Annualized Std. Dev. Month-End vs. Front-Running

The following table displays skewness for the month-end scenario as well as for the front-running strategies.

	MonthEnd	FR_1Week	FR_2Weeks	FR_3Weeks	FR_4Weeks	FR_5Weeks
4-Week Mom.	-1.479	-1.314	-1.517	-1.382	-1.309	-1.405
12-Week Mom.	-1.587	-1.555	-1.690	-1.550	-1.608	-1.658
24-Week Mom.	-2.236	-2.367	-2.473	-2.397	-2.391	-2.452

Table 27: Skewness Overview Month-End vs. Front-Running

For both the 4-week and 12-week momentum strategy front-running by 1 week yields an improvement in skewness; but the extent by which it improves is very low. For the 24-week strategy, deviating from month-end does not bring a skewness benefit at all.

In order to test whether there is a significant difference in means (table 25) between month-end and front-running outcomes, two-sample t-tests are the preferred choice of testing; the null hypothesis tests whether the means of two groups have the same mean. A rejection of the null hypothesis indicates that momentum returns differ between month-end and the front-running scenarios. The results are shown hereafter:

		FR_1Week	FR_2Weeks	FR_3Weeks	FR_4Weeks	FR_5Weeks
4-Week Mom.	P Value	0.831	0.795	0.800	0.681	0.886
	T Stat	-0.214	-0.260	-0.254	-0.412	-0.143
	Reject Ho ?	0	0	0	0	0
12-Week Mom.	P Value	0.955	0.886	0.863	0.743	0.797
	T Stat	-0.056	-0.144	-0.172	-0.329	-0.258
	Reject Ho ?	0	0	0	0	0
24-Week Mom.	P Value	0.981	0.933	0.958	0.815	0.889
	T Stat	-0.024	-0.084	-0.052	-0.234	-0.140
	Reject Ho ?	0	0	0	0	0

Table 28: T-stat Results Month-End vs. Front-Running (at 5% Significance level)

At the 5% significance level, none of the fifteen null hypothesis can be rejected, which in turn means that there is not necessarily an incentive to deviate from month-end, if an investor's goal is to achieve additional returns. The negative values for the t-stat indicate that month-end slightly dominates the front-running strategies, in terms of mean returns; but this effect is statistically insignificant. One disadvantage of the t-test for the differences in mean is that it assumes a standard normal distribution.

The following table looks at the outcome of the Sharpe ratio calculation:

	MonthEnd	FR_1week	FR_2weeks	FR_3weeks	FR_4weeks	FR_5weeks
4-Week Mom.	0.354	0.253	0.233	0.238	0.165	0.301
12-Week Mom.	0.205	0.193	0.170	0.164	0.117	0.141
24-Week Mom.	0.245	0.246	0.235	0.241	0.203	0.228

Table 29: Annualized Sharpe Ratios (2005 - 2016)

With the exception of the 1-week front-running scenario for the 24-week momentum, it looks like front-running is not a return-enhancing strategy. Judging by table 29, deviating from month-end by shortening the formation period by a couple of weeks would not be optimal.

The last thing to test is the Kruskal-Wallis test on the differences in means, because it does not assume normality. The KW findings are presented in the following table:

	FR Strategies with 4-Week Momentum	FR Strategies with 12-Week Momentum	FR Strategies with 24-Week Momentum
Chi-squared	0.17	0.18	0.59
p value	0.999	0.999	0.988
Reject Ho	No	No	No

Table 30: Kruskal-Wallis Test on FR Scenarios (1% significance level)

The outcome is a non-rejection of the null hypothesis at the 1% significance level. Therefore, there is no statistical significance on the front-running means when compared to their month-end peers.

5.5 The Crowdedness of Trades at Month-End

The following table gives a summary of the SXXE trading volumes at different weeks (or date containers) within a month. Trading volume can be defined as the total number of securities changing hands.

	1st_5th	6th_10th	11th_15th	16th_20th	21st_25th	26th_31st
Average Trading Volume	5,355,129	5,059,690	5,222,960	5,069,453	5,436,181	5,461,253

Table 31: Crowdedness of Trades (SXXE members)

It is interesting to see that month-end indeed has the highest absolute trading volume, on average, over the period 2005 - 2016. In fact, when comparing the date container "6th

until 10th“ with that of “26th until 31st“, there is 8% more trading volume at month-end. Another way how to analyze this is taking daily data and generate daily average volume figures. At this stage the author retains that month-end is indeed characterized by a certain crowdedness of trade, but the difference is not massive. An extension to this analysis, not covered in this paper, would be to examine trading volume among those stocks only that qualified as momentum stocks (winner and loser portfolio constituents) within the past as well as a data refinement that eliminates elevated trading volume caused by corporate action, M&A, share buybacks and other noise.

6. Conclusion

It has been shown that momentum investing, if transaction costs, commissions and rebalancing costs are ignored, has been a market-beating strategy between 2005 and mid-2016, and this is true for the 4-week, 12-week and 24-week holding period. The highest annualized Sharpe ratio among those three scenarios was reached by the 12-week strategy, followed by the 24-week and finally the 4-week strategy.

Furthermore it has been shown that the static momentum strategy statistically and significantly underperforms the dynamic one (time series momentum), which shorts the loser portfolio - and goes long the winner portfolio - only once a multitude of if-conditions have been met.

For the “week-effect” that examines data of different date containers within any given month it has been shown that the Kruskal-Wallis test could not reject the null hypothesis that the different group means are equal. However, if the difference in means is statistically negligible other metrics such as standard deviation, skewness and Sharpe ratio give insightful findings for the timing of momentum strategies: investing in the second-last week of any month, instead of beginning or end of the month for example, is beneficial: it is in that week (21^{st} until 25^{th}) where the risk is lowest, the skewness most positive and the Sharpe ratios highest. In fact, for all of the three investigated momentum strategies, and especially the 12-week and 24-week strategy, the Sharpe ratios dictate that almost any week of the month is performing better than month-end, because in *almost no cases* does month-end exhibit favorable conditions for momentum investing. For a momentum investors who used the month-end approach up to now, there are incentives to deviate and shift it - leaving formation period and holding period the same - to within-month where the Sharpe ratio as well as other portfolio metrics such as skewness, minmax values as well as risk metrics are better. By doing so, the investor can optimize his portfolio and eventually move closer to the efficient frontier.

The "month-effect" has found something statistically significant, which is that the momentum returns of at least one month differ significantly from the other ones. Since both January and March are among the losers in terms of momentum returns, risk as well as Sharpe ratio, a fair rule-of-thumb would be to say that momentum investing in Q1 should be fully avoided. This finding is supported by JT's (2001) second seminal research paper in which the authors found that momentum returns are less in January than during the rest of the year.

Besides the stark finding of "Q1-avoidance", July also belongs to the months with the least preferable performance metrics.

Another interesting observation is that the highest Sharpe ratios are all concentrated and clustered in the months of September, October and November. It is in those months where momentum investing should be started. It is also those months that exhibit the most-positive skewness in their return distribution, compared to the other months.

The rationale behind front-running is to gain competitive advantage by shortening the formation period and starting the holding period earlier than the common momentum investors. From a statistical standpoint the Kruskal-Wallis test did not return a significant result for the differences in group means (month-end vs. FR1, FR2, FR3, FR4 and FR5). According to the outcome of Kruskal-Wallis, both the month-end and all front-running scenarios share the same distribution of returns. Yet, front-running month-end momentum by one week decreases skewness slightly but trying to front-run longer does not seem to improve the skewness further.

Another important take-away conclusion is that risk decreases gradually with the length of front-running: front-running should not be done in order to enhance momentum returns, but it coulud be done because of the decrease in portfolio risk: a front-running investor can decrease the portfolio's annualized volatility by 66 bps, 57 bps and 64 bps for the 4-week, 12-week and 24-week strategy if he decides to front-run by 5 weeks.

One reason for why month-end exhibits such unfavorable metrics (minmax, skewness, return, variance) - not for the front-running section but for the "week-effect" - is the relative crowdedness of trades during month-end. Even though the difference is not massive, this research article found an 8% difference in trading volume between month-end and the week of the “6th until 10th”.

To check which part of this crowdedness is attributable to momentum investors is a topic that has to be addressed in the future. What this study has demonstrated, however, is the fact the common “month-end” perspective is almost never a strictly dominant strategy, it even produces the lowest annualized Sharpe ratios (see table 14).

Another puzzle that has been solved concerned the return drops with different magnitudes of the winner and loser portfolio during the crisis (loser PF dropped by more than the winner PF in the time series charts). Evidence has been brought forward that the beta dynamics of the winner and loser portfolio vary over time, depending on the health of the overall economy: in times of economic prosperity and absence of financial distress, winner portfolios have a higher beta than the loser portfolios; in times of crisis the opposite is the case: loser portfolios have a substantially greater beta than the winner portfolios. Furthermore it has been shown that even after the financial crisis, once the market was recovering, the loser portfolios kept on having highly elevated betas, which is able to partially explain why momentum crashes have a persistent and sustained character trait.

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8. Appendix

8.1 The MATLAB Code and Algorithms

```
% Part A - BUILDING MOMENTUM PORTFOLIOS AND ANALYZING THEIR
PROFITABILITY
% --------------------------------------------------------------------


% Load data in 'column vector' form
load('Daily Price Data with Tickers.xlsx');

% Date Conversion
t = datetime(Date, 'ConvertFrom', 'Excel', 'format', 'd-MMM-y');

% Create table out of 3 column vectors
TS = table(t,Ticker,Price);

% Transforming daily into weekly data:
% Find the last business day in each week, by first finding the end of
% the week and then stepping back
hol = holidays(datetime(2005,1,1),datetime(2016,10,31));
EndOfWeekDate = dateshift(TS.t,'end','week');
TS.BusDate = busdate(EndOfWeekDate,'previous',hol);
TS.BusDate.Format = ['eee ' TS.BusDate.Format];

% Apply mean to the prices, grouping by ticker and week
T_weekly = varfun(@mean,TS,'GroupingVariables',{'Ticker' 'BusDate'},...
    'InputVariables','Price');

% T_weekly has been saved at this stage in order to calculate returns
% in Excel: (Rt-Rt-1)/(Rt-1). The result is saved as "WeeklyData.xlsx".
% Next, I only import columns 1,2 and 4 and exclude row 1 because
% 'NaN'. Also, I make sure to rename columns as following: 'Ticker',
% 'Date, 'Return'. Load in 'table' form (either via load function or
% manually)
load('WeeklyData.xlsx');

% Pivoting of table "WeeklyData"
T = unstack(WeeklyData, 'Return', 'Ticker', 'GroupingVariables',
'Date', 'AggregationFunction', @sum);

% Overwrite time that was previously in "array form" into readable
% Matlab time
T.Date = [datetime(T.Date, 'InputFormat', 'eee dd-MMM-yyyy')];

% Sort table by descending date (first column): latest date first,
oldest
% at bottom.
T = sortrows(T,1,'Descend');

% Dynamic trailing sum calculations (similar to "moving average"
```

```
% principle):
% For every date and ticker, we calculate the aggregate return of the
% past 52 weeks. Window Size for 52-week trailing sum calculations is
% defined as the technical range [0 51].
T1 = movsum(T{:,2:275}, [0 51], 'Endpoints', 'fill');

% Front-run original momentum strategy by 1 week: i.e. shorten
% formation period by 1 week to 51 weeks, not at the beginning, but at
% the end (52-1), in order to make things comparable. Consequence:
% holding period starts earlier
T1WeekFrontRun = movsum(T{:,2:275}, [0 51], 'Endpoints', 'fill') - ...
    T{:,2:275};

% Front-run by 2 weeks, i.e. formation period 50 weeks
T2WeeksFrontRun = movsum(T{:,2:275}, [0 51], 'Endpoints', 'fill') - ...
    movsum(T{:,2:275}, [0,1], 'Endpoints', 'fill');

% Front-run by 3 weeks, i.e. formation period 49 weeks
T3WeeksFrontRun = movsum(T{:,2:275}, [0 51], 'Endpoints', 'fill') - ...
    movsum(T{:,2:275}, [0,2], 'Endpoints', 'fill');

% Front-run by 4 weeks, i.e. formation period 47 weeks
T4WeeksFrontRun = movsum(T{:,2:275}, [0 51], 'Endpoints', 'fill') - ...
    movsum(T{:,2:275}, [0,3], 'Endpoints', 'fill');

% Front-run by 5 weeks, i.e. formation period 45 weeks
T5WeeksFrontRun = movsum(T{:,2:275}, [0 51], 'Endpoints', 'fill') - ...
    movsum(T{:,2:275}, [0,4], 'Endpoints', 'fill');

% Export T1, T1WeekFrontRun, T2WeeksFrontRun and T3WeeksFrontRun into
% Excel and save as "MovSumTable.xlsx". When loading data into Matlab
% again, exclude columns where NaN's everywhere (7 columns in
% total: SNH_GY, RACE_IM, ABN_NA, x1COVGY, PST_IM, AKE_FP and ZALGY).
% New table will have dimension 606 x 268.
% Important: load file in 'table' form and not column vectors
load('MovSumTable.xlsx');
load('MovSumTableFrontRun1Week.xlsx');
load('MovSumTableFrontRun2Weeks.xlsx');
load('MovSumTableFrontRun3Weeks.xlsx');
load('MovSumTableFrontRun4Weeks.xlsx');
load('MovSumTableFrontRun5Weeks.xlsx');

% Reproduce latter tables and rename moving sum tables as following
X = MovSumTable;
XFR1 = MovSumTableFrontRun1Week;
XFR2 = MovSumTableFrontRun2Weeks;
XFR3 = MovSumTableFrontRun3Weeks;
XFR4 = MovSumTableFrontRun4Weeks;
XFR5 = MovSumTableFrontRun5Weeks;

% For-loop that generates 2 variables per date point: "U" and "L".
% "U" contains all stocks that correspond to the winner portfolio
% (top 10%), "L" contains all stocks that correspond to the loser
% portfolio (bottom 10%), by looking back at the past 52 weeks
% aggregate return.
L = cell(size(X,1),1);
U = cell(size(X,1),1);
```

```
for row=1:size(X,1)
    row_values = X{row,:};
% Remove date column temporarily
    row_values = row_values(2:end);
    non_nan_indices = find(~isnan(row_values));
    if not(isempty(non_nan_indices))
       [row_values,sorted_indices] = sort(row_values(non_nan_indices));
% The +1 hereafter is necessary because date column has been removed
% above
       L_ind = non_nan_indices(sorted_indices(1:round(0.1*length...
           (row_values))))+1;
       U_ind = non_nan_indices(sorted_indices(round(0.9*length...
           (row_values)):end))+1;
       L{row} = X.Properties.VariableNames(L_ind);
       U{row} = X.Properties.VariableNames(U_ind);
    else
       L{row} = nan;
       U{row} = nan;
    end
end;

% Same rationale for Front-Running by 1 week:
L_FR1 = cell(size(XFR1,1),1);
U_FR1 = cell(size(XFR1,1),1);
for row_FR1=1:size(XFR1,1)
    row_values_FR1 = XFR1{row_FR1,:};
    row_values_FR1 = row_values_FR1(2:end);
    non_nan_indices_FR1 = find(~isnan(row_values_FR1));
    if not(isempty(non_nan_indices_FR1))
       [row_values_FR1,sorted_indices_FR1] = sort(row_values_FR1( ...
           non_nan_indices_FR1));
       L_ind_FR1 = non_nan_indices_FR1(sorted_indices_FR1(1:round( ...
           0.1*length(row_values_FR1))))+1;
       U_ind_FR1 = non_nan_indices_FR1(sorted_indices_FR1(round( ...
           0.9*length(row_values_FR1)):end))+1;
       L_FR1{row_FR1} = XFR1.Properties.VariableNames(L_ind_FR1);
       U_FR1{row_FR1} = XFR1.Properties.VariableNames(U_ind_FR1);
    else
       L_FR1{row_FR1} = nan;
       U_FR1{row_FR1} = nan;
    end
end;

% Same rationale for Front-Running by 2 weeks:
L_FR2 = cell(size(XFR2,1),1);
U_FR2 = cell(size(XFR2,1),1);
for row_FR2=1:size(XFR2,1)
    row_values_FR2 = XFR2{row_FR2,:};
    row_values_FR2 = row_values_FR2(2:end);
    non_nan_indices_FR2 = find(~isnan(row_values_FR2));
    if not(isempty(non_nan_indices_FR2))
       [row_values_FR2,sorted_indices_FR2] = sort(row_values_FR2( ...
           non_nan_indices_FR2));
       L_ind_FR2 = non_nan_indices_FR2(sorted_indices_FR2(1:round( ...
           0.1*length(row_values_FR2))))+1;
       U_ind_FR2 = non_nan_indices_FR2(sorted_indices_FR2(round( ...
           0.9*length(row_values_FR2)):end))+1;
       L_FR2{row_FR2} = XFR2.Properties.VariableNames(L_ind_FR2);
```

```
        U_FR2{row_FR2} = XFR2.Properties.VariableNames(U_ind_FR2);
    else
        L_FR2{row_FR2} = nan;
        U_FR2{row_FR2} = nan;
    end
end;

% Same rationale for Front-Running by 3 weeks:
L_FR3 = cell(size(XFR3,1),1);
U_FR3 = cell(size(XFR3,1),1);
for row_FR3=1:size(XFR3,1)
    row_values_FR3 = XFR3{row_FR3,:};
    row_values_FR3 = row_values_FR3(2:end);
    non_nan_indices_FR3 = find(~isnan(row_values_FR3));
    if not(isempty(non_nan_indices_FR3))
        [row_values_FR3,sorted_indices_FR3] = sort(row_values_FR3( ...
            non_nan_indices_FR3));
        L_ind_FR3 = non_nan_indices_FR3(sorted_indices_FR3(1:round( ...
            0.1*length(row_values_FR3))))+1;
        U_ind_FR3 = non_nan_indices_FR3(sorted_indices_FR3(round( ...
            0.9*length(row_values_FR3)):end))+1;
        L_FR3{row_FR3} = XFR3.Properties.VariableNames(L_ind_FR3);
        U_FR3{row_FR3} = XFR3.Properties.VariableNames(U_ind_FR3);
    else
        L_FR3{row_FR3} = nan;
        U_FR3{row_FR3} = nan;
    end
end;

% Same rationale for Front-Running by 4 weeks:
L_FR4 = cell(size(XFR4,1),1);
U_FR4 = cell(size(XFR4,1),1);
for row_FR4 = 1:size(XFR4,1)
    row_values_FR4 = XFR4{row_FR4,:};
    row_values_FR4 = row_values_FR4(2:end);
    non_nan_indices_FR4 = find(~isnan(row_values_FR4));
    if not(isempty(non_nan_indices_FR4))
        [row_values_FR4,sorted_indices_FR4] = sort(row_values_FR4( ...
            non_nan_indices_FR4));
        L_ind_FR4 = non_nan_indices_FR4(sorted_indices_FR4(1:round( ...
            0.1*length(row_values_FR4))))+1;
        U_ind_FR4 = non_nan_indices_FR4(sorted_indices_FR4(round( ...
            0.9*length(row_values_FR4)):end))+1;
        L_FR4{row_FR4} = XFR4.Properties.VariableNames(L_ind_FR4);
        U_FR4{row_FR4} = XFR4.Properties.VariableNames(U_ind_FR4);
    else
        L_FR4{row_FR4} = nan;
        U_FR4{row_FR4} = nan;
    end
end;

% Same rationale for Front-Running by 5 weeks:
L_FR5 = cell(size(XFR5,1),1);
U_FR5 = cell(size(XFR5,1),1);
for row_FR5 = 1:size(XFR5,1)
    row_values_FR5 = XFR5{row_FR5,:};
    row_values_FR5 = row_values_FR5(2:end);
    non_nan_indices_FR5 = find(~isnan(row_values_FR5));
```

```
    if not(isempty(non_nan_indices_FR5))
       [row_values_FR5,sorted_indices_FR5] = sort(row_values_FR5( ...
           non_nan_indices_FR5));
       L_ind_FR5 = non_nan_indices_FR5(sorted_indices_FR5(1:round( ...
           0.1*length(row_values_FR5))))+1;
       U_ind_FR5 = non_nan_indices_FR5(sorted_indices_FR5(round( ...
           0.9*length(row_values_FR5)):end))+1;
       L_FR5{row_FR5} = XFR5.Properties.VariableNames(L_ind_FR5);
       U_FR5{row_FR5} = XFR5.Properties.VariableNames(U_ind_FR5);
    else
       L_FR5{row_FR5} = nan;
       U_FR5{row_FR5} = nan;
    end
end;

% Creating a new table that depicts winners and losers,
% for any given date
Y = table(X.Date, L, U, 'VariableNames', {'Date', 'L', 'U'});
Y_FR1 = table(XFR1.Date, L_FR1, U_FR1, 'VariableNames', {'Date', ...
    'L_FR1', 'U_FR1'});
Y_FR2 = table(XFR2.Date, L_FR2, U_FR2, 'VariableNames', {'Date', ...
    'L_FR2', 'U_FR2'});
Y_FR3 = table(XFR3.Date, L_FR3, U_FR3, 'VariableNames', {'Date', ...
    'L_FR3', 'U_FR3'});
Y_FR4 = table(XFR4.Date, L_FR4, U_FR4, 'VariableNames', {'Date', ...
    'L_FR4', 'U_FR4'});
Y_FR5 = table(XFR5.Date, L_FR5, U_FR5, 'VariableNames', {'Date', ...
    'L_FR5', 'U_FR5'});

% N.b.
% The above algorithms looked backwards (t0 - X) and grouped stocks
% into winners and losers, for any given date and stock where
% data of >= 52 time steps (backwards) was available.
% For fhe following steps we look ahead (t0 + X) in order to
% analyze portfolio holdings formed at t0

% Rearranging columns and deleting rows where no momentum portfolio
% can (technically) exist
Z = [T(:,1:1) Y(:,2:3) T(:,1+1:end)];
Z([555:end],:) = [];

% Same rationale for Font-Running strategies
Z_FR1 = [T(:,1:1) Y_FR1(:,2:3) T(:,1+1:end)];
Z_FR1([555:end],:) = [];
Z_FR2 = [T(:,1:1) Y_FR2(:,2:3) T(:,1+1:end)];
Z_FR2([555:end],:) = [];
Z_FR3 = [T(:,1:1) Y_FR3(:,2:3) T(:,1+1:end)];
Z_FR3([555:end],:) = [];
Z_FR4 = [T(:,1:1) Y_FR4(:,2:3) T(:,1+1:end)];
Z_FR4([555:end],:) = [];
Z_FR5 = [T(:,1:1) Y_FR5(:,2:3) T(:,1+1:end)];
Z_FR5([555:end],:) = [];

% The new matrix dimensions are now 554 x 277

% Kernel for trailing sums (= holding period):
% 4 time steps corresponds to 4-week holding period
```

```matlab
% 12 time steps corresponds to 12-week holding period
% 24 times steps corresponds 24-week holding period
[rows, columns] = size(Z);

% This kernel computes a rolling 4-point sum
kernel4t = [0;0;0;1;1;1;1;];
onesVector = ones(rows, 1);
trailingSum4t = zeros(rows, columns);
for col = 4 : columns
    thisColumn = Z{:, col}; % Extract all rows from this column
    cellSum4t = conv(onesVector, kernel4t, 'same');
    valuesSum4t = conv(thisColumn, kernel4t, 'same');
    trailingSum4t(:, col) = valuesSum4t;
end

% This kernel computes a rolling 12-point sum
kernel12t = [0;0;0;0;0;0;0;0;0;0;0;1;1;1;1;1;1;1;1;1;1;1;1];
trailingSum12t = zeros(rows, columns);
for col = 4 : columns
    thisColumn = Z{:, col};
    cellSum12t = conv(onesVector, kernel12t, 'same');
    valuesSum12t = conv(thisColumn, kernel12t, 'same');
    trailingSum12t(:, col) = valuesSum12t;
end

% Kernel that computes trailing 24-point sum
kernel24t = [0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;1;1;1;1;...
    1;1;1;1;1;1;1;1;...
    1;1;1;1;1;1;1;1;1;1;1;1];
onesVector = ones(rows, 1);
trailingSum24t = zeros(rows, columns);
for col = 4 : columns
    thisColumn = Z{:, col};
    cellSum24t = conv(onesVector, kernel24t, 'same');
    valuesSum24t = conv(thisColumn, kernel24t, 'same');
    trailingSum24t(:, col) = valuesSum24t;
end

% Set first (1, n-1) rows to NaN due to unsufficient data for n-point
% trailing sum calculations
trailingSum4t(1:3,:) = nan;
trailingSum12t(1:11,:) = nan;
trailingSum24t(1:23,:) = nan;

% Export the three table matrices and save under the following .xlsx
names
writetable(trailingSum4t, 'PFR4weeks.xlsx');
writetable(trailingSum12t, 'PFR12weeks.xlsx');
writetable(trailingSum24t, 'PFR24weeks.xlsx');

% Import data
PFR4weeks = readtable('PFR4weeks.xlsx');
PFR12weeks = readtable('PFR12weeks.xlsx');
PFR24weeks = readtable('PFR24weeks.xlsx');
PFR4weeks(:,[1:1]) = [];
PFR12weeks(:,[1:1]) = [];
PFR24weeks(:,[1:1]) = [];
```

```
% Following code only necessary if PFR24weeks returns NaN in string
% format: Import PFR24weeks.xlsx manually and transform string arrays
% into number format so that 'NaN' becomes NaN
colNames = PFR24weeks.Properties.VariableNames;

for k = 1:numel(colNames)
  if iscell(Z_24TimeSteps.(colNames{k}))
    PFR24weeks.(colNames{k})(strcmp(PFR24weeks.(colNames{k}),'NaN'))...
     = {nan};
  else
     PFR24weeks.(colNames{k})(strcmp(PFR24weeks.(colNames{k}),nan))...
     = nan;
  end
end

% Align matrix dimensions in order to allow concatenation hereafter
Y([555:end],:) = [];
Y_FR1([555:end],:) = [];
Y_FR2([555:end],:) = [];
Y_FR3([555:end],:) = [];
Y_FR4([555:end],:) = [];
Y_FR5([555:end],:) = [];

% Concatenate 'Date', 'L' and 'U' of table Y with table values of our
% trailing sum outcomes
Z_4TimeSteps = [Y PFR4weeks];
Z_12TimeSteps = [Y PFR12weeks];
Z_24TimeSteps = [Y PFR24weeks];

% Same for Front-Running Cases
Z_4TimeSteps_FR1 = [Y_FR1 PFR4weeks];
Z_4TimeSteps_FR2 = [Y_FR2 PFR4weeks];
Z_4TimeSteps_FR3 = [Y_FR3 PFR4weeks];
Z_4TimeSteps_FR4 = [Y_FR4 PFR4weeks];
Z_4TimeSteps_FR5 = [Y_FR5 PFR4weeks];
Z_12TimeSteps_FR1 = [Y_FR1 PFR12weeks];
Z_12TimeSteps_FR2 = [Y_FR2 PFR12weeks];
Z_12TimeSteps_FR3 = [Y_FR3 PFR12weeks];
Z_12TimeSteps_FR4 = [Y_FR4 PFR12weeks];
Z_12TimeSteps_FR5 = [Y_FR5 PFR12weeks];
Z_24TimeSteps_FR1 = [Y_FR1 PFR24weeks];
Z_24TimeSteps_FR2 = [Y_FR2 PFR24weeks];
Z_24TimeSteps_FR3 = [Y_FR3 PFR24weeks];
Z_24TimeSteps_FR4 = [Y_FR4 PFR24weeks];
Z_24TimeSteps_FR5 = [Y_FR5 PFR24weeks];

% Algorithm for analyzing loser portfolio (4-week holding period):
% At this stage I also introduce a gap of 1 week between formation
% period and holding period in order to minimize reversal effects. This
% is what the {k+1} in the for-loop is there for.
L_sum4t = zeros(height(Z_4TimeSteps),1);

% Replicate header names (1*277 cell array)
col_names4tL = Z_4TimeSteps.Properties.VariableNames;
for k = 1:height(Z_4TimeSteps)-1
    % the following 'cellfun' compares each column to the values in
```

```
    % Z_4TimeSteps.L{k+1},and returns a cell array of the result for
    % each of them
    col_to_sum4tL = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tL,x),Z_4TimeSteps.L{k+1}, ...
        'UniformOutput', false).'),1);
    % then we use a logical indexing to define the columns for
    % summation
    L_sum4t(k) = nansum(Z_4TimeSteps{k,col_to_sum4tL})/ ...
        numel(Z_4TimeSteps.L{k});
end

% Same token for front-running strategies (4-week holding period)
L_sum4t_FR1 = zeros(height(Z_4TimeSteps_FR1),1);
col_names4tL_FR1 = Z_4TimeSteps_FR1.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR1)-1
col_to_sum4tL_FR1 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tL_FR1,x),Z_4TimeSteps_FR1.L_FR1{
        ... k+1}, 'UniformOutput', false).'),1);
L_sum4t_FR1(k) = nansum(Z_4TimeSteps_FR1{k,col_to_sum4tL_FR1})/ ...
    numel(Z_4TimeSteps_FR1.L_FR1{k});
end

L_sum4t_FR2 = zeros(height(Z_4TimeSteps_FR2),1);
col_names4tL_FR2 = Z_4TimeSteps_FR2.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR2)-1
col_to_sum4tL_FR2 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tL_FR2,x),Z_4TimeSteps_FR2.L_FR2{
        ... k+1}, 'UniformOutput', false).'),1);
L_sum4t_FR2(k) = nansum(Z_4TimeSteps_FR2{k,col_to_sum4tL_FR2})/ ...
    numel(Z_4TimeSteps_FR2.L_FR2{k});
end

L_sum4t_FR3 = zeros(height(Z_4TimeSteps_FR3),1);
col_names4tL_FR3 = Z_4TimeSteps_FR3.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR3)-1
col_to_sum4tL_FR3 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tL_FR3,x),Z_4TimeSteps_FR3.L_FR3{
        ... k+1}, 'UniformOutput', false).'),1);
L_sum4t_FR3(k) = nansum(Z_4TimeSteps_FR3{k,col_to_sum4tL_FR3})/ ...
    numel(Z_4TimeSteps_FR3.L_FR3{k});
end

L_sum4t_FR4 = zeros(height(Z_4TimeSteps_FR4),1);
col_names4tL_FR4 = Z_4TimeSteps_FR4.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR4)-1
col_to_sum4tL_FR4 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tL_FR4,x),Z_4TimeSteps_FR4.L_FR4{
        ... k+1}, 'UniformOutput', false).'),1);
L_sum4t_FR4(k) = nansum(Z_4TimeSteps_FR4{k,col_to_sum4tL_FR4})/ ...
    numel(Z_4TimeSteps_FR4.L_FR4{k});
end
```

```
L_sum4t_FR5 = zeros(height(Z_4TimeSteps_FR5),1);
col_names4tL_FR5 = Z_4TimeSteps_FR5.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR5)-1
col_to_sum4tL_FR5 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names4tL_FR5,x),Z_4TimeSteps_FR5.L_FR5{
        ... k+1}, 'UniformOutput', false).'),1);
L_sum4t_FR5(k) = nansum(Z_4TimeSteps_FR5{k,col_to_sum4tL_FR5})/ ...
    numel(Z_4TimeSteps_FR5.L_FR5{k});
end

% Internal check for finding empty cell content
find(cellfun(@(r) ~iscell(r), Z_4TimeSteps.L))

% Algorithm for analyzing winner portfolio (4-week holding period)
U_sum4t = zeros(height(Z_4TimeSteps),1);

% Replicating column names
col_names4tU = Z_4TimeSteps.Properties.VariableNames; % Column names

for k = 1:height(Z_4TimeSteps)-1
    % the following 'cellfun' compares each column to the values in
    % Z_4TimeSteps.U{k+1},
    % and returns a cell array of the result for each of them
    col_to_sum4tU = any(cell2mat(...
        cellfun(@(x) strcmp(col_names4tU,x),Z_4TimeSteps.U{k+1},...
        'UniformOutput', false).'),1);
    % logical indexing for defining eligible columns for summation
    U_sum4t(k) = nansum(Z_4TimeSteps{k,col_to_sum4tU})/ ...
        numel(Z_4TimeSteps.U{k});
end

% Same token for front-running strategies
U_sum4t_FR1 = zeros(height(Z_4TimeSteps_FR1),1);
col_names4tU_FR1 = Z_4TimeSteps_FR1.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR1)-1
    col_to_sum4tU_FR1 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tU_FR1,x), ...
        Z_4TimeSteps_FR1.U_FR1{k+1}, 'UniformOutput', false).'),1);
U_sum4t_FR1(k) = nansum(Z_4TimeSteps_FR1{k,col_to_sum4tU_FR1})/ ...
    numel(Z_4TimeSteps_FR1.U_FR1{k});
end

U_sum4t_FR2 = zeros(height(Z_4TimeSteps_FR2),1);
col_names4tU_FR2 = Z_4TimeSteps_FR2.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR2)-1
    col_to_sum4tU_FR2 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tU_FR2,x), ...
        Z_4TimeSteps_FR2.U_FR2{k+1}, 'UniformOutput', false).'),1);
U_sum4t_FR2(k) = nansum(Z_4TimeSteps_FR2{k,col_to_sum4tU_FR2})/ ...
    numel(Z_4TimeSteps_FR2.U_FR2{k});
end

U_sum4t_FR3 = zeros(height(Z_4TimeSteps_FR3),1);
```

```
col_names4tU_FR3 = Z_4TimeSteps_FR3.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR3)-1
    col_to_sum4tU_FR3 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tU_FR3,x), ...
        Z_4TimeSteps_FR3.U_FR3{k+1}, 'UniformOutput', false).'),1);
U_sum4t_FR3(k) = nansum(Z_4TimeSteps_FR3{k,col_to_sum4tU_FR3})/ ...
    numel(Z_4TimeSteps_FR3.U_FR3{k});
end

U_sum4t_FR4 = zeros(height(Z_4TimeSteps_FR4),1);
col_names4tU_FR4 = Z_4TimeSteps_FR4.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR4)-1
    col_to_sum4tU_FR4 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names4tU_FR4,x), ...
        Z_4TimeSteps_FR4.U_FR4{k+1}, 'UniformOutput', false).'),1);
U_sum4t_FR4(k) = nansum(Z_4TimeSteps_FR4{k,col_to_sum4tU_FR4})/ ...
    numel(Z_4TimeSteps_FR4.U_FR4{k});
end

U_sum4t_FR5 = zeros(height(Z_4TimeSteps_FR5),1);
col_names4tU_FR5 = Z_4TimeSteps_FR5.Properties.VariableNames;

for k = 1:height(Z_4TimeSteps_FR5)-1
    col_to_sum4tU_FR5 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names4tU_FR5,x), ...
        Z_4TimeSteps_FR5.U_FR5{k+1}, 'UniformOutput', false).'),1);
U_sum4t_FR5(k) = nansum(Z_4TimeSteps_FR5{k,col_to_sum4tU_FR5})/ ...
    numel(Z_4TimeSteps_FR5.U_FR5{k});
end

% Algorithm for analyzing loser portfolio (12-week holding period)
L_sum12t = zeros(height(Z_12TimeSteps),1);
col_names12tL = Z_12TimeSteps.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps)-1
    % the following 'cellfun' compares each column to the values in
    % Z_12TimeSteps.L{k+1},
    % and returns a cell array of the result for ach of them
    col_to_sum12tL = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names12tL,x),Z_12TimeSteps.L{k+1},...
        'UniformOutput', false).'),1);
    % then use a logical indexing to define the columns for summation
    L_sum12t(k) = nansum(Z_12TimeSteps{k,col_to_sum12tL})/ ...
        numel(Z_12TimeSteps.L{k});
end

% Same token for front-running strategies
L_sum12t_FR1 = zeros(height(Z_12TimeSteps_FR1),1);
col_names12tL_FR1 = Z_12TimeSteps_FR1.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR1)-1
col_to_sum12tL_FR1 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names12tL_FR1,x), ...
        Z_12TimeSteps_FR1.L_FR1{k+1}, 'UniformOutput', false).'),1);
```

```
    L_sum12t_FR1(k) = nansum(Z_12TimeSteps_FR1{k,col_to_sum12tL_FR1})/
    ... numel(Z_12TimeSteps_FR1.L_FR1{k});
end

L_sum12t_FR2 = zeros(height(Z_12TimeSteps_FR2),1);
col_names12tL_FR2 = Z_12TimeSteps_FR2.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR2)-1
col_to_sum12tL_FR2 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tL_FR2,x), ...
        Z_12TimeSteps_FR2.L_FR2{k+1}, 'UniformOutput', false).'),1);
    L_sum12t_FR2(k) = nansum(Z_12TimeSteps_FR2{k,col_to_sum12tL_FR2})/
    ... numel(Z_12TimeSteps_FR2.L_FR2{k});
end

L_sum12t_FR3 = zeros(height(Z_12TimeSteps_FR3),1);
col_names12tL_FR3 = Z_12TimeSteps_FR3.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR3)-1
col_to_sum12tL_FR3 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tL_FR3,x), ...
        Z_12TimeSteps_FR3.L_FR3{k+1}, 'UniformOutput', false).'),1);
    L_sum12t_FR3(k) = nansum(Z_12TimeSteps_FR3{k,col_to_sum12tL_FR3})/
    ... numel(Z_12TimeSteps_FR3.L_FR3{k});
end

L_sum12t_FR4 = zeros(height(Z_12TimeSteps_FR4),1);
col_names12tL_FR4 = Z_12TimeSteps_FR4.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR4)-1
col_to_sum12tL_FR4 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tL_FR4,x), ...
        Z_12TimeSteps_FR4.L_FR4{k+1}, 'UniformOutput', false).'),1);
    L_sum12t_FR4(k) = nansum(Z_12TimeSteps_FR4{k,col_to_sum12tL_FR4})/
    ... numel(Z_12TimeSteps_FR4.L_FR4{k});
end

L_sum12t_FR5 = zeros(height(Z_12TimeSteps_FR5),1);
col_names12tL_FR5 = Z_12TimeSteps_FR5.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR5)-1
col_to_sum12tL_FR5 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tL_FR5,x), ...
        Z_12TimeSteps_FR5.L_FR5{k+1}, 'UniformOutput', false).'),1);
    L_sum12t_FR5(k) = nansum(Z_12TimeSteps_FR5{k,col_to_sum12tL_FR5})/
    ... numel(Z_12TimeSteps_FR5.L_FR5{k});
end

% Algorithm for analyzing winner portfolio (12-week holding period)
U_sum12t = zeros(height(Z_12TimeSteps),1);
col_names12tU = Z_12TimeSteps.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps)-1
    % the following 'cellfun' compares each column to the values in
    % Z_12TimeSteps.U{k+1},
    % and returns a cell array of the result for each of them
```

```
    col_to_sum12tU = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tU,x),Z_12TimeSteps.U{k+1},...
        'UniformOutput', false).'),1);
    % logical indexing for define eligible columns for summation
    U_sum12t(k) = nansum(Z_12TimeSteps{k,col_to_sum12tU})/ ...
        numel(Z_12TimeSteps.U{k});
end

% Same token for front-running strategies
U_sum12t_FR1 = zeros(height(Z_12TimeSteps_FR1),1);
col_names12tU_FR1 = Z_12TimeSteps_FR1.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR1)-1
col_to_sum12tU_FR1 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tU_FR1,x), ...
        Z_12TimeSteps_FR1.U_FR1{k+1}, 'UniformOutput', false).'),1);
  U_sum12t_FR1(k) = nansum(Z_12TimeSteps_FR1{k,col_to_sum12tU_FR1})/
  ... numel(Z_12TimeSteps_FR1.U_FR1{k});
end

U_sum12t_FR2 = zeros(height(Z_12TimeSteps_FR2),1);
col_names12tU_FR2 = Z_12TimeSteps_FR2.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR2)-1
col_to_sum12tU_FR2 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tU_FR2,x), ...
        Z_12TimeSteps_FR2.U_FR2{k+1}, 'UniformOutput', false).'),1);
  U_sum12t_FR2(k) = nansum(Z_12TimeSteps_FR2{k,col_to_sum12tU_FR2})/
  ... numel(Z_12TimeSteps_FR2.U_FR2{k});
end

U_sum12t_FR3 = zeros(height(Z_12TimeSteps_FR3),1);
col_names12tU_FR3 = Z_12TimeSteps_FR3.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR3)-1
col_to_sum12tU_FR3 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tU_FR3,x), ...
        Z_12TimeSteps_FR3.U_FR3{k+1}, 'UniformOutput', false).'),1);
  U_sum12t_FR3(k) = nansum(Z_12TimeSteps_FR3{k,col_to_sum12tU_FR3})/
  ... numel(Z_12TimeSteps_FR3.U_FR3{k});
end

U_sum12t_FR4 = zeros(height(Z_12TimeSteps_FR4),1);
col_names12tU_FR4 = Z_12TimeSteps_FR4.Properties.VariableNames;

for k = 1:height(Z_12TimeSteps_FR4)-1
col_to_sum12tU_FR4 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tU_FR4,x), ...
        Z_12TimeSteps_FR4.U_FR4{k+1}, 'UniformOutput', false).'),1);
  U_sum12t_FR4(k) = nansum(Z_12TimeSteps_FR4{k,col_to_sum12tU_FR4})/
  ... numel(Z_12TimeSteps_FR4.U_FR4{k});
end

U_sum12t_FR5 = zeros(height(Z_12TimeSteps_FR5),1);
col_names12tU_FR5 = Z_12TimeSteps_FR5.Properties.VariableNames;
```

```
for k = 1:height(Z_12TimeSteps_FR5)-1
col_to_sum12tU_FR5 = any(cell2mat(...
        cellfun(@(x) strcmp(col_names12tU_FR5,x), ...
        Z_12TimeSteps_FR5.U_FR5{k+1}, 'UniformOutput', false).'),1);
  U_sum12t_FR5(k) = nansum(Z_12TimeSteps_FR5{k,col_to_sum12tU_FR5})/
  ... numel(Z_12TimeSteps_FR5.U_FR5{k});
end

% Algorithm for analyzing loser portfolio (24-week holding period)
L_sum24t = zeros(height(Z_24TimeSteps),1);
col_names24tL = Z_24TimeSteps.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps)-1
    % the following 'cellfun' compares each column to the values in
    % Z_24TimeSteps.L{k+1},
    % and returns a cell array of the result for ach of them
    col_to_sum24tL = any(cell2mat(...
        cellfun(@(x) strcmp(col_names24tL,x),Z_24TimeSteps.L{k+1}, ...
        'UniformOutput', false).'),1);
    % then use a logical indexing to define the columns for summation
    L_sum24t(k) = nansum(Z_24TimeSteps{k,col_to_sum24tL})/ ...
        numel(Z_24TimeSteps.L{k});
end

% Same token for front-running strategies
L_sum24t_FR1 = zeros(height(Z_24TimeSteps_FR1),1);
col_names24tL_FR1 = Z_24TimeSteps_FR1.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR1)-1
    col_to_sum24tL_FR1 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tL_FR1,x), ...
        Z_24TimeSteps_FR1.L_FR1{k+1}, 'UniformOutput', false).'),1);
L_sum24t_FR1(k) = nansum(Z_24TimeSteps_FR1{k,col_to_sum24tL_FR1})/ ...
    numel(Z_24TimeSteps_FR1.L_FR1{k});
end

L_sum24t_FR2 = zeros(height(Z_24TimeSteps_FR2),1);
col_names24tL_FR2 = Z_24TimeSteps_FR2.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR2)-1
    col_to_sum24tL_FR2 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tL_FR2,x), ...
        Z_24TimeSteps_FR2.L_FR2{k+1}, 'UniformOutput', false).'),1);
L_sum24t_FR2(k) = nansum(Z_24TimeSteps_FR2{k,col_to_sum24tL_FR2})/ ...
    numel(Z_24TimeSteps_FR2.L_FR2{k});
end

L_sum24t_FR3 = zeros(height(Z_24TimeSteps_FR3),1);
col_names24tL_FR3 = Z_24TimeSteps_FR3.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR3)-1
    col_to_sum24tL_FR3 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tL_FR3,x), ...
        Z_24TimeSteps_FR3.L_FR3{k+1}, 'UniformOutput', false).'),1);
L_sum24t_FR3(k) = nansum(Z_24TimeSteps_FR3{k,col_to_sum24tL_FR3})/ ...
    numel(Z_24TimeSteps_FR3.L_FR3{k});
end
```

```
L_sum24t_FR4 = zeros(height(Z_24TimeSteps_FR4),1);
col_names24tL_FR4 = Z_24TimeSteps_FR4.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR4)-1
    col_to_sum24tL_FR4 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tL_FR4,x), ...
        Z_24TimeSteps_FR4.L_FR4{k+1}, 'UniformOutput', false).'),1);
L_sum24t_FR4(k) = nansum(Z_24TimeSteps_FR4{k,col_to_sum24tL_FR4})/ ...
    numel(Z_24TimeSteps_FR4.L_FR4{k});
end

L_sum24t_FR5 = zeros(height(Z_24TimeSteps_FR5),1);
col_names24tL_FR5 = Z_24TimeSteps_FR5.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR5)-1
    col_to_sum24tL_FR5 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tL_FR5,x), ...
        Z_24TimeSteps_FR5.L_FR5{k+1}, 'UniformOutput', false).'),1);
L_sum24t_FR5(k) = nansum(Z_24TimeSteps_FR5{k,col_to_sum24tL_FR5})/ ...
    numel(Z_24TimeSteps_FR5.L_FR5{k});
end

% Algorithm for analyzing winner portfolio (24-week holding period)
U_sum24t = zeros(height(Z_24TimeSteps),1);
col_names24tU = Z_24TimeSteps.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps)-1
    % the following 'cellfun' compares each column to the values in
    % Z_24TimeSteps.U{k+1},
    % and returns a cell array of the result for each of them
    col_to_sum24tU = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tU,x),Z_24TimeSteps.U{k+1}, ...
        'UniformOutput', false).'),1);
    % then we use a logical indexing to define the columns for
summation
    U_sum24t(k) = nansum(Z_24TimeSteps{k,col_to_sum24tU})/ ...
        numel(Z_24TimeSteps.U{k});
end

% Same token for front-running strategies
U_sum24t_FR1 = zeros(height(Z_24TimeSteps_FR1),1);
col_names24tU_FR1 = Z_24TimeSteps_FR1.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR1)-1
col_to_sum24tU_FR1 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tU_FR1,x), ...
        Z_24TimeSteps_FR1.U_FR1{k+1}, 'UniformOutput', false).'),1);
U_sum24t_FR1(k) = nansum(Z_24TimeSteps_FR1{k,col_to_sum24tU_FR1})/ ...
    numel(Z_24TimeSteps_FR1.U_FR1{k});
end

U_sum24t_FR2 = zeros(height(Z_24TimeSteps_FR2),1);
col_names24tU_FR2 = Z_24TimeSteps_FR2.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR2)-1
```

```
col_to_sum24tU_FR2 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tU_FR2,x), ...
        Z_24TimeSteps_FR2.U_FR2{k+1}, 'UniformOutput', false).'),1);
U_sum24t_FR2(k) = nansum(Z_24TimeSteps_FR2{k,col_to_sum24tU_FR2})/ ...
    numel(Z_24TimeSteps_FR2.U_FR2{k});
end

U_sum24t_FR3 = zeros(height(Z_24TimeSteps_FR3),1);
col_names24tU_FR3 = Z_24TimeSteps_FR3.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR3)-1
col_to_sum24tU_FR3 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tU_FR3,x), ...
        Z_24TimeSteps_FR3.U_FR3{k+1}, 'UniformOutput', false).'),1);
U_sum24t_FR3(k) = nansum(Z_24TimeSteps_FR3{k,col_to_sum24tU_FR3})/ ...
    numel(Z_24TimeSteps_FR3.U_FR3{k});
end

U_sum24t_FR4 = zeros(height(Z_24TimeSteps_FR4),1);
col_names24tU_FR4 = Z_24TimeSteps_FR4.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR4)-1
col_to_sum24tU_FR4 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tU_FR4,x), ...
        Z_24TimeSteps_FR4.U_FR4{k+1}, 'UniformOutput', false).'),1);
U_sum24t_FR4(k) = nansum(Z_24TimeSteps_FR4{k,col_to_sum24tU_FR4})/ ...
    numel(Z_24TimeSteps_FR4.U_FR4{k});
end

U_sum24t_FR5 = zeros(height(Z_24TimeSteps_FR5),1);
col_names24tU_FR5 = Z_24TimeSteps_FR5.Properties.VariableNames;

for k = 1:height(Z_24TimeSteps_FR5)-1
col_to_sum24tU_FR5 = any(cell2mat( ...
        cellfun(@(x) strcmp(col_names24tU_FR5,x), ...
        Z_24TimeSteps_FR5.U_FR5{k+1}, 'UniformOutput', false).'),1);
U_sum24t_FR5(k) = nansum(Z_24TimeSteps_FR5{k,col_to_sum24tU_FR5})/ ...
    numel(Z_24TimeSteps_FR5.U_FR5{k});
end

% Table that summarizes returns based on different momentum portfolios
MomPF = table(Z_4TimeSteps.Date, Z.L, Z.U, L_sum4t, U_sum4t, L_sum12t,
... U_sum12t, L_sum24t, U_sum24t, 'VariableNames', {'Date', 'L', 'U',
... 'L_sum4t', 'U_sum4t', 'L_sum12t', 'U_sum12t', 'L_sum24t', ...
    'U_sum24t'});

% Same for front-running strategies
MomPF_FR1 = table(Z_4TimeSteps_FR1.Date, Z_FR1.L_FR1, Z_FR1.U_FR1, ...
    L_sum4t_FR1, U_sum4t_FR1, L_sum12t_FR1, U_sum12t_FR1, L_sum24t_FR1,
... U_sum24t_FR1, 'VariableNames', {'Date', 'L_FR1', 'U_FR1', ...
    'L_sum4t_FR1', 'U_sum4t_FR1', 'L_sum12t_FR1', 'U_sum12t_FR1', ...
    'L_sum24t_FR1', 'U_sum24t_FR1'});

MomPF_FR2 = table(Z_4TimeSteps_FR2.Date, Z_FR2.L_FR2, Z_FR2.U_FR2, ...
    L_sum4t_FR2, U_sum4t_FR2, L_sum12t_FR2, U_sum12t_FR2, L_sum24t_FR2,
... U_sum24t_FR2, 'VariableNames', {'Date', 'L_FR2', 'U_FR2', ...
```

```
    'L_sum4t_FR2', 'U_sum4t_FR2', 'L_sum12t_FR2', 'U_sum12t_FR2', ...
    'L_sum24t_FR2', 'U_sum24t_FR2'});

MomPF_FR3 = table(Z_4TimeSteps_FR3.Date, Z_FR3.L_FR3, Z_FR3.U_FR3, ...
    L_sum4t_FR3, U_sum4t_FR3, L_sum12t_FR3, U_sum12t_FR3, L_sum24t_FR3,
... U_sum24t_FR3, 'VariableNames', {'Date', 'L_FR3', 'U_FR3', ...
    'L_sum4t_FR3', 'U_sum4t_FR3', 'L_sum12t_FR3', 'U_sum12t_FR3', ...
    'L_sum24t_FR3', 'U_sum24t_FR3'});

MomPF_FR4 = table(Z_4TimeSteps_FR4.Date, Z_FR4.L_FR4, Z_FR4.U_FR4, ...
    L_sum4t_FR4, U_sum4t_FR4, L_sum12t_FR4, U_sum12t_FR4, L_sum24t_FR4,
... U_sum24t_FR4, 'VariableNames', {'Date', 'L_FR4', 'U_FR4', ...
    'L_sum4t_FR4', 'U_sum4t_FR4', 'L_sum12t_FR4', 'U_sum12t_FR4', ...
    'L_sum24t_FR4', 'U_sum24t_FR4'});

MomPF_FR5 = table(Z_4TimeSteps_FR5.Date, Z_FR5.L_FR5, Z_FR5.U_FR5, ...
    L_sum4t_FR5, U_sum4t_FR5, L_sum12t_FR5, U_sum12t_FR5, L_sum24t_FR5,
... U_sum24t_FR5, 'VariableNames', {'Date', 'L_FR5', 'U_FR5', ...
    'L_sum4t_FR5', 'U_sum4t_FR5', 'L_sum12t_FR5', 'U_sum12t_FR5', ...
    'L_sum24t_FR5', 'U_sum24t_FR5'});

% Profitability of different momentum strategies:
% (-1) hereafter indicates that we short the loser portfolio and (0.5)
% means that we are weighing winner and loser portfolio in an equal
% proportion
MomHold4Weeks = (-1)*MomPF.L_sum4t*0.5 + MomPF.U_sum4t*0.5;
MomHold12Weeks = (-1)*MomPF.L_sum12t*0.5 + MomPF.U_sum12t*0.5;
MomHold24Weeks = (-1)*MomPF.L_sum24t*0.5 + MomPF.U_sum24t*0.5;

% Same token for front-running strategies
MomHold4Weeks_FR1 = (-1)*MomPF_FR1.L_sum4t_FR1*0.5 + ...
    MomPF_FR1.U_sum4t_FR1*0.5;
MomHold12Weeks_FR1 = (-1)*MomPF_FR1.L_sum12t_FR1*0.5 + ...
    MomPF_FR1.U_sum12t_FR1*0.5;
MomHold24Weeks_FR1 = (-1)*MomPF_FR1.L_sum24t_FR1*0.5 + ...
    MomPF_FR1.U_sum24t_FR1*0.5;

MomHold4Weeks_FR2 = (-1)*MomPF_FR2.L_sum4t_FR2*0.5 + ...
    MomPF_FR2.U_sum4t_FR2*0.5;
MomHold12Weeks_FR2 = (-1)*MomPF_FR2.L_sum12t_FR2*0.5 + ...
    MomPF_FR2.U_sum12t_FR2*0.5;
MomHold24Weeks_FR2 = (-1)*MomPF_FR2.L_sum24t_FR2*0.5 + ...
    MomPF_FR2.U_sum24t_FR2*0.5;

MomHold4Weeks_FR3 = (-1)*MomPF_FR3.L_sum4t_FR3*0.5 + ...
    MomPF_FR3.U_sum4t_FR3*0.5;
MomHold12Weeks_FR3 = (-1)*MomPF_FR3.L_sum12t_FR3*0.5 + ...
    MomPF_FR3.U_sum12t_FR3*0.5;
MomHold24Weeks_FR3 = (-1)*MomPF_FR3.L_sum24t_FR3*0.5 + ...
    MomPF_FR3.U_sum24t_FR3*0.5;

MomHold4Weeks_FR4 = (-1)*MomPF_FR4.L_sum4t_FR4*0.5 + ...
    MomPF_FR4.U_sum4t_FR4*0.5;
MomHold12Weeks_FR4 = (-1)*MomPF_FR4.L_sum12t_FR4*0.5 + ...
    MomPF_FR4.U_sum12t_FR4*0.5;
MomHold24Weeks_FR4 = (-1)*MomPF_FR4.L_sum24t_FR4*0.5 + ...
    MomPF_FR4.U_sum24t_FR4*0.5;
```

```
MomHold4Weeks_FR5 = (-1)*MomPF_FR5.L_sum4t_FR5*0.5 + ...
    MomPF_FR5.U_sum4t_FR5*0.5;
MomHold12Weeks_FR5 = (-1)*MomPF_FR5.L_sum12t_FR5*0.5 + ...
    MomPF_FR5.U_sum12t_FR5*0.5;
MomHold24Weeks_FR5 = (-1)*MomPF_FR5.L_sum24t_FR5*0.5 + ...
    MomPF_FR5.U_sum24t_FR5*0.5;

MomHold4Weeks(1:3,:) = nan;
MomHold4Weeks(554:554,:) = nan;
MomHold4Weeks_FR1(1:3,:) = nan;
MomHold4Weeks_FR1(554:554,:) = nan;
MomHold4Weeks_FR2(1:3,:) = nan;
MomHold4Weeks_FR2(554:554,:) = nan;
MomHold4Weeks_FR3(1:3,:) = nan;
MomHold4Weeks_FR3(554:554,:) = nan;
MomHold4Weeks_FR4(1:3,:) = nan;
MomHold4Weeks_FR4(554:554,:) = nan;
MomHold4Weeks_FR5(1:3,:) = nan;
MomHold4Weeks_FR5(554:554,:) = nan;

MomHold12Weeks(1:11,:) = nan;
MomHold12Weeks(554:554,:) = nan;
MomHold12Weeks_FR1(1:11,:) = nan;
MomHold12Weeks_FR1(554:554,:) = nan;
MomHold12Weeks_FR2(1:11,:) = nan;
MomHold12Weeks_FR2(554:554,:) = nan;
MomHold12Weeks_FR3(1:11,:) = nan;
MomHold12Weeks_FR3(554:554,:) = nan;
MomHold12Weeks_FR4(1:11,:) = nan;
MomHold12Weeks_FR4(554:554,:) = nan;
MomHold12Weeks_FR5(1:11,:) = nan;
MomHold12Weeks_FR5(554:554,:) = nan;

MomHold24Weeks(1:23,:) = nan;
MomHold24Weeks(554:554,:) = nan;
MomHold24Weeks_FR1(1:23,:) = nan;
MomHold24Weeks_FR1(554:554,:) = nan;
MomHold24Weeks_FR2(1:23,:) = nan;
MomHold24Weeks_FR2(554:554,:) = nan;
MomHold24Weeks_FR3(1:23,:) = nan;
MomHold24Weeks_FR3(554:554,:) = nan;
MomHold24Weeks_FR4(1:23,:) = nan;
MomHold24Weeks_FR4(554:554,:) = nan;
MomHold24Weeks_FR5(1:23,:) = nan;
MomHold24Weeks_FR5(554:554,:) = nan;

% Time Series Momentum: The following constitutes an adjusted version
% of momentum investing: We only short the loser portfolio if its
% aggregate return is negative. (If aggregate return in loser portfolio
% positive, then we gong long 100% winner portfolio).
% In the same fashion, we only go long the winner portfolio if its past
% aggregate return is positive. (If aggregate return in the winner
% portfolio is negative, then we go short 100% loser portfolio).

% Prepare pre-defined matrix container with correct dimension
MomHold4Weeks_Dynamic = zeros(554,1);
```

```
idx1 = (MomPF.L_sum4t < 0) & (MomPF.U_sum4t > 0);
MomHold4Weeks_Dynamic(idx1) = (-1)*MomPF.L_sum4t(idx1)*0.5 + ...
    MomPF.U_sum4t(idx1)*0.5;
idx2 = (MomPF.L_sum4t < 0) & (MomPF.U_sum4t < 0);
MomHold4Weeks_Dynamic(idx2) = (-1)*MomPF.L_sum4t(idx2);
idx3 = (MomPF.L_sum4t > 0) & (MomPF.U_sum4t > 0);
MomHold4Weeks_Dynamic(idx3) = 1*MomPF.U_sum4t(idx3);
idx4 = (MomPF.L_sum4t > 0) & (MomPF.U_sum4t < 0);
MomHold4Weeks_Dynamic(idx4) = MomPF.L_sum4t(idx4)*0.5 + ...
    (-1)*MomPF.U_sum4t(idx4)*0.5;
idx5 = (MomPF.L_sum4t == 0) & (MomPF.U_sum4t == 0);
MomHold4Weeks_Dynamic(idx5) = nan;

MomHold12Weeks_Dynamic = zeros(554,1);

idx6 = (MomPF.L_sum12t < 0) & (MomPF.U_sum12t > 0);
MomHold12Weeks_Dynamic(idx6) = (-1)*MomPF.L_sum12t(idx6)*0.5 + ...
    MomPF.U_sum12t(idx6)*0.5;
idx7 = (MomPF.L_sum12t < 0) & (MomPF.U_sum12t < 0);
MomHold12Weeks_Dynamic(idx7) = (-1)*MomPF.L_sum12t(idx7);
idx8 = (MomPF.L_sum12t > 0) & (MomPF.U_sum12t > 0);
MomHold12Weeks_Dynamic(idx8) = 1*MomPF.U_sum12t(idx8);
idx9 = (MomPF.L_sum12t > 0) & (MomPF.U_sum12t < 0);
MomHold12Weeks_Dynamic(idx9) = MomPF.L_sum12t(idx9)*0.5 + ...
    (-1)*MomPF.U_sum12t(idx9)*0.5;
idx10 = (MomPF.L_sum12t == 0) & (MomPF.U_sum12t == 0);
MomHold12Weeks_Dynamic(idx10) = nan;

MomHold24Weeks_Dynamic = zeros(554,1);

idx11 = (MomPF.L_sum24t < 0) & (MomPF.U_sum24t > 0);
MomHold24Weeks_Dynamic(idx11) = (-1)*MomPF.L_sum24t(idx11)*0.5 + ...
    MomPF.U_sum24t(idx11)*0.5;
idx12 = (MomPF.L_sum24t < 0) & (MomPF.U_sum24t < 0);
MomHold24Weeks_Dynamic(idx12) = (-1)*MomPF.L_sum24t(idx12);
idx13 = (MomPF.L_sum24t > 0) & (MomPF.U_sum24t > 0);
MomHold24Weeks_Dynamic(idx13) = 1*MomPF.U_sum24t(idx13);
idx14 = (MomPF.L_sum24t > 0) & (MomPF.U_sum24t < 0);
MomHold24Weeks_Dynamic(idx14) = MomPF.L_sum24t(idx14)*0.5 + ...
    (-1)*MomPF.U_sum24t(idx14)*0.5;
idx15 = (MomPF.L_sum24t == 0) & (MomPF.U_sum24t == 0);
MomHold24Weeks_Dynamic(idx15) = nan;

% Import Rf and Rm data as separate column vectors (column 2 and 3 of
% file 'RmAndRf.xlsx'. N.b.: the date dimensions of Rm and Rf are
% designed as to match the date dimension of already existing data
Rf([555:end],:) = [];
Rm([555:end],:) = [];

% Stated Rf's, even though marked as "weekly" in Bloomberg, are in
% annualized form so we divide by 52 to get real weekly Rf's.
% Multiplying by 0.01 gets us into decimal form. Market return (Rm) is
% already in weekly format.
Rf = Rf/52*0.01;
Rm = Rm*0.01;
```

```
% Comparing different momentum strategies against long-only broad
% market index
MomVsMarket = table(Z_4TimeSteps.Date, MomHold4Weeks, MomHold12Weeks,
... MomHold24Weeks, Rf, Rm, 'VariableNames', {'Date', 'MomHold4Weeks',
... 'MomHold12Weeks', 'MomHold24Weeks', 'Rf', 'Rm'});
MomVsMarket.Date = datetime(MomVsMarket.Date, 'ConvertFrom', 'Excel',
... 'format', 'd-MMM-y');
MomVsMarket.MomHold4Weeks(1:3,:) = nan;
MomVsMarket.MomHold12Weeks(1:11,:) = nan;
MomVsMarket.MomHold24Weeks(1:23,:) = nan;
MomVsMarket.Rf(554:554,:) = nan;
MomVsMarket.Rm(554:554,:) = nan;

% The following algorithm is making market returns congruent with that
% of the 4-week momentum strategies because we need to calculate the 4-
% week market return in order to compare it to the 4-week momentum
% strategy
[rowsMom4, columnsMom4] = size(MomVsMarket);
kernel4tMom = [0;0;0;1;1;1;1];
onesVectorMom4 = ones(rowsMom4, 1);
trailingSum4tMom = zeros(rowsMom4, columnsMom4);

for col1 = 6 : 6
    % Extract all rows from this column
    thisColumnMom4 = MomVsMarket{:, col1};
    cellSum4tMom = conv(onesVectorMom4, kernel4tMom, 'same');
    valuesSum4tMom = conv(thisColumnMom4, kernel4tMom, 'same');
    trailingSum4tMom(:, col1) = valuesSum4tMom;
end
trailingSum4tMom(:,1:5)=[];
MomVsMarket.Rm4Weeks = trailingSum4tMom;
MomVsMarket.Rm4Weeks(1:3,:) = nan;

% Same for risk-free rate (Rf 4 Weeks)
[rowsMom4_rf, columnsMom4_rf] = size(MomVsMarket);
onesVectorMom4_rf = ones(rowsMom4_rf, 1);
trailingSum4tMom_rf = zeros(rowsMom4_rf, columnsMom4_rf);

for col2 = 5 : 5
    thisColumnMom4_rf = MomVsMarket{:, col2};
    cellSum4tMom_rf = conv(onesVectorMom4_rf, kernel4tMom, 'same');
    valuesSum4tMom_rf = conv(thisColumnMom4_rf, kernel4tMom, 'same');
    trailingSum4tMom_rf(:, col2) = valuesSum4tMom_rf;
end
trailingSum4tMom_rf(:,1:4)=[];
trailingSum4tMom_rf(:,2:3)=[];
MomVsMarket.Rf4Weeks = trailingSum4tMom_rf;
MomVsMarket.Rf4Weeks(1:3,:) = nan;

% Make market returns congruent with that of the 12-week momentum
% strategy
[rowsMom12, columnsMom12] = size(MomVsMarket);
kernel12tMom = [0;0;0;0;0;0;0;0;0;0;0;1;1;1;1;1;1;1;1;1;1;1;1];
onesVectorMom12 = ones(rowsMom12, 1);
trailingSum12tMom = zeros(rowsMom12, columnsMom12);

for col3 = 6 : 6
```

```
    thisColumnMom12 = MomVsMarket{:, col3};
    cellSum12tMom = conv(onesVectorMom12, kernel12tMom, 'same');
    valuesSum12tMom = conv(thisColumnMom12, kernel12tMom, 'same');
    trailingSum12tMom(:, col3) = valuesSum12tMom;
end
trailingSum12tMom(:,1:5)=[];
trailingSum12tMom(:,2:3) = [];
MomVsMarket.Rm12Weeks = trailingSum12tMom;
MomVsMarket.Rm12Weeks(1:11,:) = nan;

% Same for risk-free rate (Rf 12 Weeks)
[rowsMom12_rf, columnsMom12_rf] = size(MomVsMarket);
onesVectorMom12_rf = ones(rowsMom12_rf, 1);
trailingSum12tMom_rf = zeros(rowsMom12_rf, columnsMom12_rf);

for col4 = 5 : 5
    thisColumnMom12_rf = MomVsMarket{:, col4};
    cellSum12tMom_rf = conv(onesVectorMom12, kernel12tMom, 'same');
    valuesSum12tMom_rf = conv(thisColumnMom12_rf, kernel12tMom,
'same');
    trailingSum12tMom_rf(:, col4) = valuesSum12tMom_rf;
end
trailingSum12tMom_rf(:,1:4)=[];
trailingSum12tMom_rf(:,2:5)=[];
MomVsMarket.Rf12Weeks = trailingSum12tMom_rf;
MomVsMarket.Rf12Weeks(1:11,:) = nan;

% Make market returns congruent with that of the 24-week momentum
strategy
[rowsMom24, columnsMom24] = size(MomVsMarket);
kernel24tMom = [0;0;0;0;0;0;0;0;0;0;0;0;...
    0;0;0;0;0;0;0;0;0;0;0;1;1;1;1;1;1;1;1;1;1;1;1;...
    1;1;1;1;1;1;1;1;1;1;1;1]; % Kernel that computes trailing 24 values
onesVectorMom24 = ones(rowsMom24, 1);
trailingSum24tMom = zeros(rowsMom24, columnsMom24);

for col5 = 6 : 6
    thisColumnMom24 = MomVsMarket{:, col5}; % Extract all rows from
    % this column.
    cellSum24tMom = conv(onesVectorMom24, kernel24tMom, 'same');
    valuesSum24tMom = conv(thisColumnMom24, kernel24tMom, 'same');
    trailingSum24tMom(:, col5) = valuesSum24tMom;
end
trailingSum24tMom(:,1:5)=[];
trailingSum24tMom(:,2:5)=[];
MomVsMarket.Rm24Weeks = trailingSum24tMom;
MomVsMarket.Rm24Weeks(1:23,:) = nan;

% Same for risk-free rate (Rf 24 Weeks)
[rowsMom24_rf, columnsMom24_rf] = size(MomVsMarket);
onesVectorMom24_rf = ones(rowsMom24_rf, 1);
trailingSum24tMom_rf = zeros(rowsMom24_rf, columnsMom24_rf);

for col6 = 5 : 5
    thisColumnMom24_rf = MomVsMarket{:, col6};
    cellSum24tMom_rf = conv(onesVectorMom24_rf, kernel24tMom, 'same');
    valuesSum24tMom_rf = conv(thisColumnMom24_rf, kernel24tMom,
```

```matlab
'same');
    trailingSum24tMom_rf(:, col6) = valuesSum24tMom_rf;
end
trailingSum24tMom_rf(:,1:4)=[];
trailingSum24tMom_rf(:,2:7)=[];
MomVsMarket.Rf24Weeks = trailingSum24tMom_rf;
MomVsMarket.Rf24Weeks(1:23,:) = nan;



% Part B: The "week-effect" and "Month-effect" of Momentum
% ----------------------------------------------------------------------


% B.1 "Week effect"

% The following code groups momentum strategies into different date
% containers. This allows us to make inferences and analysis about
% different starting points of momentum investing within any month

% Rationale: At first, create a binary output matrix and then start the
% extraction
container26th_31st = MomVsMarket.Date.Day >= 26 & ...
    MomVsMarket.Date.Day <= 31;
Mom26th_31st = MomVsMarket(container26th_31st, :);

container21st_25th = MomVsMarket.Date.Day >= 21 & ...
    MomVsMarket.Date.Day <= 25;
Mom21st_25th = MomVsMarket(container21st_25th, :);

container16th_20th = MomVsMarket.Date.Day >= 16 & ...
    MomVsMarket.Date.Day <= 20;
Mom16th_20th = MomVsMarket(container16th_20th, :);

container11th_15th = MomVsMarket.Date.Day >= 11 & ...
    MomVsMarket.Date.Day <= 15;
Mom11th_15th = MomVsMarket(container11th_15th, :);

container6th_10th = MomVsMarket.Date.Day >= 6 & ...
    MomVsMarket.Date.Day <= 10;
Mom6th_10th = MomVsMarket(container6th_10th, :);

container1st_5th = MomVsMarket.Date.Day >= 1 & ...
    MomVsMarket.Date.Day <= 5;
Mom1st_5th = MomVsMarket(container1st_5th, :);


% B.2 "Month-Effect"

% Starting point: extract data for any month of the year
% January
containerJAN = MomVsMarket.Date.Month == 1;
MomJAN = MomVsMarket(containerJAN, :);

% February
```

```
containerFEB = MomVsMarket.Date.Month == 2;
MomFEB = MomVsMarket(containerFEB, :);

% March
containerMAR = MomVsMarket.Date.Month == 3;
MomMAR = MomVsMarket(containerMAR, :);

% April
containerAPR = MomVsMarket.Date.Month == 4;
MomAPR = MomVsMarket(containerAPR, :);

% May
containerMAY = MomVsMarket.Date.Month == 5;
MomMAY = MomVsMarket(containerMAY, :);

% June
containerJUN = MomVsMarket.Date.Month == 6;
MomJUN = MomVsMarket(containerJUN, :);

% July
containerJUL = MomVsMarket.Date.Month == 7;
MomJUL = MomVsMarket(containerJUL, :);

% August
containerAUG = MomVsMarket.Date.Month == 8;
MomAUG = MomVsMarket(containerAUG, :);

% September
containerSEP = MomVsMarket.Date.Month == 9;
MomSEP = MomVsMarket(containerSEP, :);

% October
containerOCT = MomVsMarket.Date.Month == 10;
MomOCT = MomVsMarket(containerOCT, :);

% November
containerNOV = MomVsMarket.Date.Month == 11;
MomNOV = MomVsMarket(containerNOV, :);

% December
containerDEC = MomVsMarket.Date.Month == 12;
MomDEC = MomVsMarket(containerDEC, :);



% Part C: Front-Running Month-end Momentum Strategies
% ---------------------------------------------------------------------


% The idea behind this is to start the holding period by 1, 2, 3, 4 and
% 5 weeks prior to the month-end strategies

% Firstly, extract month-end data points: Month-end is defined by any
% data between (and including) the 25th and 31st
containerMonthEnd = Z.Date.Day >= 25 & ...
```

```
    Z.Date.Day <= 31;
Rf_MonthEnd = Rf(containerMonthEnd, :);
Rm_MonthEnd = Rm(containerMonthEnd, :);

% All month-end data are M x N matrices with length M = 117

% Comparing momentum base strategies to its front-running strategies
Z_4TimeSteps.Date = T.Date(1:554,:);
NormalVsFrontRun4w = table(Z_4TimeSteps.Date, MomHold4Weeks, ...
    MomHold4Weeks_FR1, MomHold4Weeks_FR2, MomHold4Weeks_FR3, ...
    MomHold4Weeks_FR4, MomHold4Weeks_FR5, 'VariableNames', {'Date', ...
    'MomHold4Weeks', 'Mom4_FR1', 'Mom4_FR2', 'Mom4_FR3', 'Mom4_FR4',
    'Mom4_FR5'});
MonthEnd4 = NormalVsFrontRun4w(containerMonthEnd, :);
NormalVsFrontRun4w_n = NormalVsFrontRun4w(containerMonthEnd, :);
MonthEnd4.DiffFR1 = NormalVsFrontRun4w_n.Mom4_FR1 - ...
    NormalVsFrontRun4w_n.MomHold4Weeks;
MonthEnd4.DiffFR2 = NormalVsFrontRun4w_n.Mom4_FR2 - ...
    NormalVsFrontRun4w_n.MomHold4Weeks;
MonthEnd4.DiffFR3 = NormalVsFrontRun4w_n.Mom4_FR3 - ...
    NormalVsFrontRun4w_n.MomHold4Weeks;
MonthEnd4.DiffFR4 = NormalVsFrontRun4w_n.Mom4_FR4 - ...
    NormalVsFrontRun4w_n.MomHold4Weeks;
MonthEnd4.DiffFR5 = NormalVsFrontRun4w_n.Mom4_FR5 - ...
    NormalVsFrontRun4w_n.MomHold4Weeks;

Z_12TimeSteps.Date = T.Date(1:554,:);
NormalVsFrontRun12w = table(Z_12TimeSteps.Date, MomHold12Weeks, ...
    MomHold12Weeks_FR1, MomHold12Weeks_FR2, MomHold12Weeks_FR3, ...
    MomHold12Weeks_FR4, MomHold12Weeks_FR5, 'VariableNames', {'Date',
    ... 'MomHold12Weeks', 'Mom12_FR1', 'Mom12_FR2', 'Mom12_FR3', ...
    'Mom12_FR4', 'Mom12_FR5'});
MonthEnd12 = NormalVsFrontRun12w(containerMonthEnd, :);
NormalVsFrontRun12w_n = NormalVsFrontRun12w(containerMonthEnd, :);
MonthEnd12.DiffFR1 = NormalVsFrontRun12w_n.Mom12_FR1 - ...
    NormalVsFrontRun12w_n.MomHold12Weeks;
MonthEnd12.DiffFR2 = NormalVsFrontRun12w_n.Mom12_FR2 - ...
    NormalVsFrontRun12w_n.MomHold12Weeks;
MonthEnd12.DiffFR3 = NormalVsFrontRun12w_n.Mom12_FR3 - ...
    NormalVsFrontRun12w_n.MomHold12Weeks;
MonthEnd12.DiffFR4 = NormalVsFrontRun12w_n.Mom12_FR4 - ...
    NormalVsFrontRun12w_n.MomHold12Weeks;
MonthEnd12.DiffFR5 = NormalVsFrontRun12w_n.Mom12_FR5 - ...
    NormalVsFrontRun12w_n.MomHold12Weeks;

Z_24TimeSteps.Date = T.Date(1:554,:);
NormalVsFrontRun24w = table(Z_24TimeSteps.Date, MomHold24Weeks, ...
    MomHold24Weeks_FR1, MomHold24Weeks_FR2, MomHold24Weeks_FR3, ...
    MomHold24Weeks_FR4, MomHold24Weeks_FR5, 'VariableNames', {'Date',
    ...'MomHold24Weeks', 'Mom24_FR1', 'Mom24_FR2', 'Mom24_FR3', ...
    'Mom24_FR4', 'Mom24_FR5'});
MonthEnd24 = NormalVsFrontRun24w(containerMonthEnd, :);
NormalVsFrontRun24w_n = NormalVsFrontRun24w(containerMonthEnd, :);
MonthEnd24.DiffFR1 = NormalVsFrontRun24w_n.Mom24_FR1 - ...
    NormalVsFrontRun24w_n.MomHold24Weeks;
MonthEnd24.DiffFR2 = NormalVsFrontRun24w_n.Mom24_FR2 - ...
    NormalVsFrontRun24w_n.MomHold24Weeks;
```

```
MonthEnd24.DiffFR3 = NormalVsFrontRun24w_n.Mom24_FR3 - ...
    NormalVsFrontRun24w_n.MomHold24Weeks;
MonthEnd24.DiffFR4 = NormalVsFrontRun24w_n.Mom24_FR4 - ...
    NormalVsFrontRun24w_n.MomHold24Weeks;
MonthEnd24.DiffFR5 = NormalVsFrontRun24w_n.Mom24_FR5 - ...
    NormalVsFrontRun24w_n.MomHold24Weeks;

% Extract data and show month-end form only
MomVsMarket_new = MomVsMarket(containerMonthEnd, :);
Rf_MonthEnd = Rf(containerMonthEnd, :);

% Beta's
% Momentum Hold 4 Weeks (entire period)
AA = MomVsMarket.MomHold4Weeks - MomVsMarket.Rf4Weeks;
BB = MomVsMarket.Rm4Weeks - MomVsMarket.Rf4Weeks;
mdl = LinearModel.fit(BB,AA)

% Momentum Hold 4 weeks (Month-End)
AA1 = MonthEnd4.MomHold4Weeks - MomVsMarket_new.Rf4Weeks;
BB1 = MomVsMarket_new.Rm4Weeks - MomVsMarket_new.Rf4Weeks;
mdl1 = LinearModel.fit(BB1,AA1)

% Momentum Hold 4 weeks (FR by 1 week)
AA2 = MonthEnd4.Mom4_FR1 - MomVsMarket_new.Rf4Weeks;
mdl2 = LinearModel.fit(BB1,AA2)

% Momentum Hold 4 weeks (FR by 2 weeks)
AA3 = MonthEnd4.Mom4_FR2 - MomVsMarket_new.Rf4Weeks;
mdl3 = LinearModel.fit(BB1,AA3)

% Momentum Hold 4 weeks (FR by 3 weeks)
AA4 = MonthEnd4.Mom4_FR3 - MomVsMarket_new.Rf4Weeks;
mdl4 = LinearModel.fit(BB1,AA4)

% Momentum Hold 4 weeks (FR by 4 weeks)
AA5 = MonthEnd4.Mom4_FR4 - MomVsMarket_new.Rf4Weeks;
mdl5 = LinearModel.fit(BB1,AA5)

% Momentum Hold 4 weeks (FR by 5 weeks)
AA6 = MonthEnd4.Mom4_FR5 - MomVsMarket_new.Rf4Weeks;
mdl6 = LinearModel.fit(BB1,AA6)

% Beta's
% Momentum Hold 12 Weeks (entire period)
AAA = MomVsMarket.MomHold12Weeks - MomVsMarket.Rf12Weeks;
BBB = MomVsMarket.Rm12Weeks - MomVsMarket.Rf12Weeks;
mdl7 = LinearModel.fit(BBB,AAA)

% Momentum Hold 12 Weeks (Month-End)
AAA1 = MonthEnd12.MomHold12Weeks - MomVsMarket_new.Rf12Weeks;
BBB1 = MomVsMarket_new.Rm12Weeks - MomVsMarket_new.Rf12Weeks;
mdl8 = LinearModel.fit(BBB1,AAA1)

% Momentum Hold 12 Weeks (FR by 1 week)
AAA2 = MonthEnd12.Mom12_FR1 - MomVsMarket_new.Rf12Weeks;
mdl9 = LinearModel.fit(BBB1,AAA2)
```

```
% Momentum Hold 12 Weeks (FR by 2 weeks)
AAA3 = MonthEnd12.Mom12_FR2 - MomVsMarket_new.Rf12Weeks;
mdl10 = LinearModel.fit(BBB1,AAA3)

% Momentum Hold 12 Weeks (FR by 3 weeks)
AAA4 = MonthEnd12.Mom12_FR3 - MomVsMarket_new.Rf12Weeks;
mdl11 = LinearModel.fit(BBB1,AAA4)

% Momentum Hold 12 Weeks (FR by 4 weeks)
AAA5 = MonthEnd12.Mom12_FR4 - MomVsMarket_new.Rf12Weeks;
mdl12 = LinearModel.fit(BBB1,AAA5)

% Momentum Hold 12 Weeks (FR by 5 weeks)
AAA6 = MonthEnd12.Mom12_FR5-MomVsMarket_new.Rf12Weeks;
mdl13 = LinearModel.fit(BBB1,AAA6)

% Beta's
% Momentum Hold 24 Weeks (entire period)
AAAA = MomVsMarket.MomHold24Weeks - MomVsMarket.Rf24Weeks;
BBBB = MomVsMarket.Rm24Weeks - MomVsMarket.Rf24Weeks;
mdl14 = LinearModel.fit(BBBB,AAAA)

% Momentum Hold 24 Weeks (Month-End)
AAAA1 = MonthEnd24.MomHold24Weeks - MomVsMarket_new.Rf24Weeks;
BBBB1 = MomVsMarket_new.Rm24Weeks - MomVsMarket_new.Rf24Weeks;
mdl15 = LinearModel.fit(BBBB1,AAAA1)

% Momentum Hold 24 Weeks (FR by 1 week)
AAAA2 = MonthEnd24.Mom24_FR1 - MomVsMarket_new.Rf24Weeks;
mdl16 = LinearModel.fit(BBBB1,AAAA2)

% Momentum Hold 24 Weeks (FR by 2 weeks)
AAAA3 = MonthEnd24.Mom24_FR2 - MomVsMarket_new.Rf24Weeks;
mdl17 = LinearModel.fit(BBBB1,AAAA3)

% Momentum Hold 24 Weeks (FR by 3 weeks)
AAAA4 = MonthEnd24.Mom24_FR3 - MomVsMarket_new.Rf24Weeks;
mdl18 = LinearModel.fit(BBBB1,AAAA4)

% Momentum Hold 24 Weeks (FR by 4 weeks)
AAAA5 = MonthEnd24.Mom24_FR4 - MomVsMarket_new.Rf24Weeks;
mdl19 = LinearModel.fit(BBBB1,AAAA5)

% Momentum Hold 24 Weeks (FR by 5 weeks)
AAAA6 = MonthEnd24.Mom24_FR5 - MomVsMarket_new.Rf24Weeks;
mdl20 = LinearModel.fit(BBBB1,AAAA6)

% Overview Table for Beta's
BetaNormVsFR_OT = [{mdl.Coefficients.Estimate(2) ...
    mdl1.Coefficients.Estimate(2) mdl2.Coefficients.Estimate(2) ...
    mdl3.Coefficients.Estimate(2) mdl4.Coefficients.Estimate(2) ...
    mdl5.Coefficients.Estimate(2) mdl6.Coefficients.Estimate(2)}; { ...
    mdl7.Coefficients.Estimate(2) mdl8.Coefficients.Estimate(2) ...
    mdl9.Coefficients.Estimate(2) mdl10.Coefficients.Estimate(2) ...
    mdl11.Coefficients.Estimate(2) mdl12.Coefficients.Estimate(2) ...
```

```
    mdl13.Coefficients.Estimate(2)}; {mdl14.Coefficients.Estimate(2)
    ... mdl15.Coefficients.Estimate(2) mdl16.Coefficients.Estimate(2)
    ... mdl17.Coefficients.Estimate(2) mdl18.Coefficients.Estimate(2)
    ... mdl19.Coefficients.Estimate(2) ...
    mdl20.Coefficients.Estimate(2)}];
BetaNormVsFR = cell2table(BetaNormVsFR_OT);
BetaNormVsFR.Properties.RowNames = ...
    {'4-week Momentum', '12-week Momentum', '24-week Momentum'};
BetaNormVsFR.Properties.VariableNames = ...
    {'NormalCase' 'MonthEnd', 'FR_1week', 'FR_2weeks', 'FR_3weeks',
'FR_4weeks', ...
    'FR_5weeks'}
write(BetaNormVsFR, 'BetaNormVsFR.xlsx');



% Part D: Dynamic Momentum (Time Series Momentum)
% ---------------------------------------------------------------------

% I define Dynamic Momentum Strategies as an adjusted version to the
% above momentum strategy, which simply bought the winner portfolio and
% shorted the loser portfolio, regardless of whether the loser (winner)
% portfolio had a positive or negative past aggregate return.
% The dynamic momentum strategy shorts the loser portfolio only if its
% past 52-week aggregate return is negative. If the past aggregate
% return of the loser portfolio is positive, we invest 100% in the
% winner portfolio. In the same fashion, if the past 52-weel aggregate
% return of the winner portfolio is negative, we go short 100% the
% loser portfolio.

% Some preparations
MomVsMarket_Dyn = table(Z_4TimeSteps.Date, MomHold4Weeks_Dynamic, ...
    MomHold12Weeks_Dynamic, MomHold24Weeks_Dynamic, 'VariableNames',
... {'Date', 'MomHold4Weeks_Dyn', 'MomHold12Weeks_Dyn', ...
    'MomHold24Weeks_Dyn'});
MomVsMarket_Dyn.Date = datetime(MomVsMarket_Dyn.Date, 'ConvertFrom',
... 'Excel', 'format', 'd-MMM-y');
MomVsMarket_Dyn.MomHold4Weeks_Dyn(1:3,:) = nan;
MomVsMarket_Dyn.MomHold12Weeks_Dyn(1:11,:) = nan;
MomVsMarket_Dyn.MomHold24Weeks_Dyn(1:23,:) = nan;

% Compare Static vs. Dynamic Momentum Strategies
MomVsMarket_DynVsStatic = table(Z_4TimeSteps.Date, MomHold4Weeks, ...
    MomHold4Weeks_Dynamic, MomHold12Weeks, MomHold12Weeks_Dynamic, ...
    MomHold24Weeks, MomHold24Weeks_Dynamic, 'VariableNames', {'Date',
... 'MomHold4Weeks', 'MomHold4Weeks_Dyn', 'MomHold12Weeks', ...
    'MomHold12Weeks_Dyn', 'MomHold24Weeks', 'MomHold24Weeks_Dyn'});
MomVsMarket_DynVsStatic.Diff4 =
MomVsMarket_DynVsStatic.MomHold4Weeks_Dyn - ...
    MomVsMarket_DynVsStatic.MomHold4Weeks;
MomVsMarket_DynVsStatic.Diff12 =
MomVsMarket_DynVsStatic.MomHold12Weeks_Dyn - ...
    MomVsMarket_DynVsStatic.MomHold12Weeks;
MomVsMarket_DynVsStatic.Diff24 =
MomVsMarket_DynVsStatic.MomHold24Weeks_Dyn - ...
    MomVsMarket_DynVsStatic.MomHold24Weeks;
```

```
% 2-sided T-tests on differences in means: Outcome with all three tests
% is that the null hypothesis ("means are equal") is rejected at the
% 1% significance level. Thus, we are able to say that the Dynamic
% Momentum Strategy is statistically and significantly more profitable
% than the Static Strategy
[h10, p10, ci10, stats10] = ttest2( ...
    MomVsMarket_DynVsStatic.MomHold4Weeks_Dyn, ...
    MomVsMarket_DynVsStatic.MomHold4Weeks, 'Vartype','unequal', ...
    'alpha', 0.01);
[h11, p11, ci11, stats11] = ttest2( ...
    MomVsMarket_DynVsStatic.MomHold12Weeks_Dyn, ...
    MomVsMarket_DynVsStatic.MomHold12Weeks, 'Vartype','unequal', ...
    'alpha', 0.01);
[h12, p12, ci12, stats12] = ttest2( ...
    MomVsMarket_DynVsStatic.MomHold24Weeks_Dyn, ...
    MomVsMarket_DynVsStatic.MomHold24Weeks, 'Vartype','unequal', ...
    'alpha', 0.01);

Ttest4wDynSta = {p10; stats10.tstat; h10};
Ttest12wDynSta = {p11; stats11.tstat; h11};
Ttest24wDynSta = {p12; stats12.tstat; h12};

CC = [{Ttest4wDynSta{1,1} Ttest12wDynSta{1,1} Ttest24wDynSta{1,1}}; ...
    {Ttest4wDynSta{2,1} Ttest12wDynSta{2,1} Ttest24wDynSta{2,1}}; ...
    {Ttest4wDynSta{3,1} Ttest12wDynSta{3,1} Ttest24wDynSta{3,1}}];
TstatOverviewDynSta = cell2table(CC);
TstatOverviewDynSta.Properties.VariableNames = {'Momentum_4Weeks' ...
    'Momentum_12Weeks' 'Momentum_24Weeks'};
TstatOverviewDynSta.Properties.RowNames = {'p_value' 't_stat' ...
    'Outcome_Hyp_Test'};
writetable(TstatOverviewDynSta, 'TstatOverviewDynSta.xlsx')



% PART E: ANALYSIS, DESCRIPTIVE STATISTICS AND VISUALIZATION
% ----------------------------------------------------------------------

% E.1 Vanilla (“Base”) Momentum Strategy


% Descriptive Statistics Market return
MeanRmAnnualized = nanmean(MomVsMarket.Rm)*52;
StdDevRmAnnualized = nanstd(MomVsMarket.Rm)*sqrt(52);
StackedMeanStdRmAnnualized = {MeanRmAnnualized StdDevRmAnnualized};

% Since market return low, let's split market return into pre- and
% post-crisis (as well as inter-crisis)
MeanRmAnnualizedPre = nanmean(MomVsMarket.Rm(420:end,:))*52;
MeanRmAnnualizedInter = nanmean(MomVsMarket.Rm(345:419,:))*52;
MeanRmAnnualizedPost = nanmean(MomVsMarket.Rm(1:344,:))*52;

% Same for Std. Dev.
StdDevRmAnnualizedPre = nanstd(MomVsMarket.Rm(420:end,:))*sqrt(52);
StdDevRmAnnualizedInter = nanstd(MomVsMarket.Rm(345:419,:))*sqrt(52);
StdDevRmAnnualizedPost = nanstd(MomVsMarket.Rm(1:344,:))*sqrt(52);
```

```
% Table summarizing above
MeanAndStdDevPrePost_Annualized_OT = [{MeanRmAnnualizedPre ...
    MeanRmAnnualizedInter MeanRmAnnualizedPost}; {StdDevRmAnnualizedPre
...
    StdDevRmAnnualizedInter StdDevRmAnnualizedPost}];
MeanAndStdDevPrePost_Annualized = cell2table( ...
    MeanAndStdDevPrePost_Annualized_OT);
MeanAndStdDevPrePost_Annualized.Properties.RowNames = ...
    {'Annualized Mean', 'Annualized Std. Dev.'};
MeanAndStdDevPrePost_Annualized.Properties.VariableNames = ...
    {'Pre_Crisis', 'Inter_Crisis', 'Post_Crisis'}
write(MeanAndStdDevPrePost_Annualized,
'MeanAndStdDevPrePost_AnnualizedOK.xlsx');

% Descriptive Statistics Momentum 4-weeks
DesStat4 = table(MomVsMarket.MomHold4Weeks, MomVsMarket.Rm4Weeks, ...
     'VariableNames', {'MomHold4Weeks', 'Rm4Weeks'});
DesStat4.Diff = DesStat4.MomHold4Weeks - DesStat4.Rm4Weeks;
MeanMom4 = nanmean(DesStat4.MomHold4Weeks);
MeanRm4 = nanmean(DesStat4.Rm4Weeks);
MedianMom4 = nanmedian(DesStat4.MomHold4Weeks);
MedianRm4 = nanmedian(DesStat4.Rm4Weeks);
VarMom4 = nanvar(DesStat4.MomHold4Weeks);
VarRm4 = nanvar(DesStat4.Rm4Weeks);
StdDevMom4 = nanstd(DesStat4.MomHold4Weeks);
StdDevRm4 = nanstd(DesStat4.Rm4Weeks);
KurtMom4 = kurtosis(DesStat4.MomHold4Weeks);
KurtRm4 = kurtosis(DesStat4.Rm4Weeks);
SkewMom4 = skewness(DesStat4.MomHold4Weeks);
SkewRm4 = skewness(DesStat4.Rm4Weeks);
BetaMom4 = nancov(DesStat4.MomHold4Weeks,DesStat4.Rm4Weeks)./nanvar...
    (DesStat4.Rm4Weeks);
DesStatMom4Sum = {MeanMom4*13, StdDevMom4*sqrt(13)};

% Descriptive Statistics Momentum 12-weeks
DesStat12 = table(MomVsMarket.MomHold12Weeks, MomVsMarket.Rm12Weeks,
... 'VariableNames', {'MomHold12Weeks', 'Rm12Weeks'});
DesStat12.Diff = DesStat12.MomHold12Weeks-DesStat12.Rm12Weeks;
MeanMom12 = nanmean(DesStat12.MomHold12Weeks);
MeanRm12 = nanmean(DesStat12.Rm12Weeks);
MedianMom12 = nanmedian(DesStat12.MomHold12Weeks);
MedianRm12 = nanmedian(DesStat12.Rm12Weeks);
VarMom12 = nanvar(DesStat12.MomHold12Weeks);
VarRm12 = nanvar(DesStat12.Rm12Weeks);
StdDevMom12 = nanstd(DesStat12.MomHold12Weeks);
StdDevRm12 = nanstd(DesStat12.Rm12Weeks);
KurtMom12 = kurtosis(DesStat12.MomHold12Weeks);
KurtRm12 = kurtosis(DesStat12.Rm12Weeks);
SkewMom12 = skewness(DesStat12.MomHold12Weeks);
SkewRm12 = skewness(DesStat12.Rm12Weeks);
BetaMom12 =
nancov(DesStat12.MomHold12Weeks,DesStat12.Rm12Weeks)./nanvar...
    (DesStat12.Rm12Weeks);
DesStatMom12Sum = {MeanMom12*(13/3), StdDevMom12*sqrt(13/3)};

% Descriptive Statistics Momentum 24-weeks
DesStat24 = table(MomVsMarket.MomHold24Weeks, MomVsMarket.Rm24Weeks,
... 'VariableNames', {'MomHold24Weeks', 'Rm24Weeks'});
```

```
DesStat24.Diff = DesStat24.MomHold24Weeks-DesStat24.Rm24Weeks;
MeanMom24 = nanmean(DesStat24.MomHold24Weeks);
MeanRm24 = nanmean(DesStat24.Rm24Weeks);
MedianMom24 = nanmedian(DesStat24.MomHold24Weeks);
MedianRm24 = nanmedian(DesStat24.Rm24Weeks);
VarMom24 = nanvar(DesStat24.MomHold24Weeks);
VarRm24 = nanvar(DesStat24.Rm24Weeks);
StdDevMom24 = nanstd(DesStat24.MomHold24Weeks);
StdDevRm24 = nanstd(DesStat24.Rm24Weeks);
KurtMom24 = kurtosis(DesStat24.MomHold24Weeks);
KurtRm24 = kurtosis(DesStat24.Rm24Weeks);
SkewMom24 = skewness(DesStat24.MomHold24Weeks);
SkewRm24 = skewness(DesStat24.Rm24Weeks);
BetaMom24 =
nancov(DesStat24.MomHold24Weeks,DesStat24.Rm24Weeks)./nanvar...
    (DesStat24.Rm24Weeks);
DesStatMom24Sum = {MeanMom24*(13/6), StdDevMom24*(13/6)};

% Overview table Annualized Returns Market vs. Mom4, Mom12 and Mom24
MeanAndStdDevRmVsMom_Annualized_OT = [{nanmean(MomVsMarket.Rm)*52 ...
    nanmean(MomVsMarket.MomHold4Weeks)*13 nanmean( ...
    MomVsMarket.MomHold12Weeks)*(13/3) nanmean( ...
    MomVsMarket.MomHold24Weeks)*(13/6)};
{nanstd(MomVsMarket.Rm)*sqrt(52) ...
    nanstd(MomVsMarket.MomHold4Weeks)*sqrt(13) nanstd( ...
    MomVsMarket.MomHold12Weeks)*sqrt(13/3) nanstd( ...
    MomVsMarket.MomHold24Weeks)*sqrt(13/6)}];
MeanAndStdDevRmVsMom_Annualized = cell2table( ...
    MeanAndStdDevRmVsMom_Annualized_OT);
MeanAndStdDevRmVsMom_Annualized.Properties.RowNames = ...
    {'Annualized Mean', 'Annualized Std. Dev.'};
MeanAndStdDevRmVsMom_Annualized.Properties.VariableNames = ...
    {'MarketReturn', 'MomHold4Weeks', 'MomHold12Weeks',
'MomHold24Weeks'}
write(MeanAndStdDevRmVsMom_Annualized, ...
    'MeanAndStdDevRmVsMom_Annualized.xlsx');

% Skewness and Kurtosis of Momentum 4w, 12w and 24w (Table overview)
SkewAndKurt_OT = [{SkewMom4 SkewMom12 SkewMom24}; {KurtMom4 KurtMom12
... KurtMom24}];
SkewAndKurt_Norm = cell2table( ...
    SkewAndKurt_OT);
SkewAndKurt_Norm.Properties.RowNames = ...
    {'Skewness', 'Kurtosis'};
SkewAndKurt_Norm.Properties.VariableNames = ...
    {'MomHold4Weeks', 'MomHold12Weeks', 'MomHold24Weeks'};
write(SkewAndKurt_Norm, 'SkewAndKurt_Norm.xlsx');

% Single Bar Chart Momentum 4-week strategy
figure1 = bar(MomVsMarket.Date, MomVsMarket.MomHold4Weeks*13*100);
sDate = datenum(MomVsMarket.Date(1));
% set start date for x-axis eDate = datenum(dates(end));
% set end date for x-axis xData = linspace(sDate,eDate,n);
xlabel('Date'); %add x label
ylabel('Return (%)'); %add y label
box off;
grid off;
xlim auto;
```

```
ylim auto;
ytick = get(gca,'YTick');
sprintf('%.2f|',ytick);
title('Annualized Momentum Returns (4-Week Holding Period)');
print('figure1', '-djpeg');

% Single Bar Chart Momentum 12-week strategy
figure2 = bar(MomVsMarket.Date, MomVsMarket.MomHold12Weeks*(13/3)*100);
sDate = datenum(MomVsMarket.Date(1)); %set start date for x-axis
% datenum(dates(end)); %set end date for x-axis xData =
linspace(sDate,eDate,n);
xlabel('Date'); %add x label
ylabel('Return (%)'); %add y label
box off;
grid off;
xlim auto;
ylim auto;
ytick = get(gca,'YTick');
sprintf('%.2f|',ytick);
title('Annualized Momentum Returns (12-Week Holding Period)');
print('figure2', '-djpeg');

% Single Bar Chart Momentum 24-week strategy
figure3 = bar(MomVsMarket.Date, MomVsMarket.MomHold24Weeks*100*(13/6));
sDate = datenum(MomVsMarket.Date(1)); %set start date for x-axis
% datenum(dates(end)); %set end date for x-axis ...
% xData = linspace(sDate,eDate,n);
xlabel('Date'); %add x label
ylabel('Return (%)'); %add y label
box off;
grid off;
xlim auto;
ylim auto;
ytick = get(gca,'YTick');
sprintf('%.2f|',ytick);
title('Annualized Momentum Returns (24-Week Holding Period)');
print('figure3', '-djpeg');

% Creating subplots 3x1 Matrix Form
subplot(3,1,1)
plot(MomVsMarket.Date, MomVsMarket.MomHold4Weeks*(13)*100)
title('4-Week Momentum')
ylim([-330 220])
ylabel('Return (%)')
subplot(3,1,2)
plot(MomVsMarket.Date, MomVsMarket.MomHold12Weeks*(13/3)*100)
title('12-Week Momentum')
ylim([-200 140])
ylabel('Return (%)')
subplot(3,1,3)
plot(MomVsMarket.Date, MomVsMarket.MomHold24Weeks*(13/6)*100)
title('24-Week Momentum')
ylim([-200 140])
ylabel('Return (%)');

% Grouped Bar Charts
fig = figure('Color','w');
```

```
baroverlay = bar(MomVsMarket.Date,
[MomVsMarket.MomHold4Weeks*13*100,...
   MomVsMarket.MomHold12Weeks*(13/3)*100,
MomVsMarket.MomHold24Weeks*(13/6)*100],'grouped');
alpha(0.95);
legend('Momentum 4-weeks', 'Momentum 12-weeks', 'Momentum 24-weeks');
ylabel('Profitability (%)');
ylim([-300 250]);
xlabel('Time');
title('Profitability over Time');
ax = get(gca);
set(baroverlay(1),'FaceColor', 'magenta' ,'BarWidth',2);
%set the second bar chart style
set(baroverlay(2),'FaceColor','green','BarWidth',2);
%set the third bar chart style
set(baroverlay(3),'FaceColor','black','BarWidth',2);

% Stacked histogram overlay to compare the three momentum visually
h1 = histogram(MomVsMarket.MomHold4Weeks*13*100, 95);
hold on
h2 = histogram(MomVsMarket.MomHold12Weeks*(13/3)*100, 95);
hold on
h3 = histogram(MomVsMarket.MomHold24Weeks*(13/6)*100, 95);
h1.FaceColor = 'white';
h2.FaceColor = 'green';
h3.FaceColor = 'magenta';
ylabel('Probability');
xlabel('Annualized Returns in %');
title('Histogram Overlay of Momentum Returns');
legend({'Momentum 4-week holding', ...
    'Momentum 12-week holding', ...
    'Momentum 24-week holding'},...
    'FontSize', 13);

% Stacked histogram overlay to compare Momentum (4 weeks) strategy to
% 4-week market returns /// not reported in main section of thesis
hh1 = histogram(MomVsMarket.MomHold4Weeks, 90);
hold on
hh2 = histogram(MomVsMarket.Rm4Weeks, 90);
hold on
hh1.Normalization = 'probability';
hh1.BinWidth = 0.0075;
hh1.FaceColor = 'blue';
hh2.Normalization = 'probability';
hh2.BinWidth = 0.0075;
hh2.FaceColor = 'y';
ylabel('Probability');
xlabel('Return in 1/100');
axis([-0.3,0.2,0,0.12]);
title('Weekly Market and Momentum Returns (4 weeks) Histogram');
legend('4-Week Momentum Returns', ...
    '4-Week Market Returns');

% Stacked histogram overlay to compare Momentum (12 weeks) strategy to
% 12-week market returns // not reported in main section of thesis
hh3 = histogram(MomVsMarket.MomHold12Weeks, 90);
hold on
hh4 = histogram(MomVsMarket.Rm12Weeks, 90);
```

```
hh3.Normalization = 'probability';
hh3.BinWidth = 0.0075;
hh3.FaceColor = 'blue';
hh4.Normalization = 'probability';
hh4.BinWidth = 0.0075;
hh4.FaceColor = 'y';
ylabel('Probability');
xlabel('Return in 1/100');
axis([-0.45,0.35,0,0.1]);
title('Weekly Market and Momentum Returns (12 weeks) Histogram');
legend('12-Week Momentum Returns', ...
    '12-Week Market Returns');

% Stacked histogram overlay to compare Momentum (24 weeks) strategy to
% 24-week market returns // not reported in main section of thesis
hh5 = histogram(MomVsMarket.MomHold24Weeks, 75);
hold on
hh6 = histogram(MomVsMarket.Rm, 75);
hh5.Normalization = 'probability';
hh5.BinWidth = 0.0075;
hh5.FaceColor = 'blue';
hh6.Normalization = 'probability';
hh6.BinWidth = 0.0075;
hh6.FaceColor = 'y';
ylabel('Probability');
xlabel('Return in 1/100');
axis([-0.5,0.3,0,0.12]);
title('Weekly Market and Momentum Returns (24 weeks) Histogram');
legend('24-Week Momentum Returns','24-Week Market Returns');

% Time Series Cumulative Returns over 10-year horizon // not reported
% in main section of thesis
TS_Rm = cumsum(MomVsMarket.Rm*52,1,'reverse', 'omitnan');
TS_Mom4 = cumsum(MomVsMarket.MomHold4Weeks*13,1, 'reverse', 'omitnan');
TS_Mom12 = cumsum(MomVsMarket.MomHold12Weeks*(13/3),1,'reverse',
'omitnan');
TS_Mom24 = cumsum(MomVsMarket.MomHold24Weeks*(13/6),1,'reverse',
'omitnan');
TS_t = MomVsMarket.Date;
TimeSeries = table(TS_t, TS_Rm, TS_Mom4, TS_Mom12, TS_Mom24);
plot(TimeSeries.TS_t, TimeSeries.TS_Rm, '--b');
hold on
plot(TimeSeries.TS_t, TimeSeries.TS_Mom4, 'ok');
hold on
plot(TimeSeries.TS_t, TimeSeries.TS_Mom12, '-g');
hold on
plot(TimeSeries.TS_t, TimeSeries.TS_Mom24, '*m');
grid on
xlabel({'Date'}, 'FontSize', 12);
ylabel({'Cumulative Returns in %'}, 'FontSize', 12);
title({'Cumulative Returns over Time'}, 'FontSize',12);
ylim([-30 40]);
legend({'Rm','Momentum 4 weeks', 'Momentum 12 weeks', ...
    'Momentum 24 weeks'}, 'FontSize',12);

% Time Series Spread of loser and winner PF (4-week strategy)
TS_Mom4_L = cumsum(MomPF.L_sum4t,1,'reverse', 'omitnan');
TS_Mom4_U = cumsum(MomPF.U_sum4t,1,'reverse', 'omitnan');
```

```
TimeSeriesUandL = table(TS_t, MomPF.L_sum4t, MomPF.U_sum4t, ...
    MomPF.L_sum12t, MomPF.U_sum12t, MomPF.L_sum24t, MomPF.U_sum24t);
plot(TimeSeriesUandL.TS_t, TS_Mom4_L, '--b');
hold on
plot(TimeSeriesUandL.TS_t, TS_Mom4_U, '-k');
grid on
xlabel({'Date'}, 'FontSize', 12);
ylabel({'Cumulative Returns in %'}, 'FontSize', 12);
title({'Loser and Winner Portfolio over Time (4-Week Momentum)'},
'FontSize',12);
ylim([-5 10]);
legend({'Loser PF','Winner PF'}, 'FontSize',12);

% Time Series Spread of loser and winner PF (12-week strategy)
TS_Mom12_L = cumsum(MomPF.L_sum12t,1,'reverse', 'omitnan');
TS_Mom12_U = cumsum(MomPF.U_sum12t,1,'reverse', 'omitnan');
plot(TimeSeriesUandL.TS_t, TS_Mom12_L, '--b');
hold on
plot(TimeSeriesUandL.TS_t, TS_Mom12_U, '-k');
grid on
xlabel({'Date'}, 'FontSize', 12);
ylabel({'Cumulative Returns in %'}, 'FontSize', 12);
title({'Loser and Winner Portfolio over Time (12-Week Momentum)'}, ...
    'FontSize',12);
ylim([-10 25]);
legend({'Loser PF','Winner PF'}, 'FontSize',12);

% Time Series Cumulative Returns of loser and winner PF (24-week
strategy)
TS_Mom24_L = cumsum(MomPF.L_sum24t,1,'reverse', 'omitnan');
TS_Mom24_U = cumsum(MomPF.U_sum24t,1,'reverse', 'omitnan');
plot(TimeSeriesUandL.TS_t, TS_Mom24_L, '--b');
hold on
plot(TimeSeriesUandL.TS_t, TS_Mom24_U, '-k');
grid on
xlabel({'Date'}, 'FontSize', 12);
ylabel({'Cumulative Returns in %'}, 'FontSize', 12);
title({'Loser and Winner Portfolio over Time (24-Week Momentum)'}, ...
    'FontSize',12);
ylim([-15 50]);
legend({'Loser PF','Winner PF'}, 'FontSize',12);

% Time Series Overlay // not reported in main section of thesis
TS_Mom4_Dyn = cumsum(MomHold4Weeks_Dynamic,1, 'reverse', 'omitnan');
TimeSeriesZ = table(TS_t, TS_Mom4, TS_Mom4_Dyn);
plot(TimeSeriesZ.TS_t, TimeSeriesZ.TS_Mom4, '--b');
hold on
plot(TimeSeriesZ.TS_t, TimeSeriesZ.TS_Mom4_Dyn, '-m');
grid on
xlabel({'Date'}, 'FontSize', 12);
ylabel({'Cumulative Returns in %'}, 'FontSize', 12);
title({'Mom4 vs. Mom4 (dynamic) over Time'}, 'FontSize',12);
ylim([-3 36]);
legend({'Momentum 4 weeks', 'Momentum 4 weeks (dynamic)', ...
    'Momentum 24 weeks'}, 'FontSize',12);

% Ex-post Sharpe Ratios: Trend-following strategies are expected to
```

```
% have low Sharpe Ratios by nature
SharpeMom4 = sharpe(MomVsMarket.MomHold4Weeks*13,
MomVsMarket.Rf4Weeks*13);
SharpeMom12 = sharpe(MomVsMarket.MomHold12Weeks*(13/3),
MomVsMarket.Rf12Weeks*(13/3));
SharpeMom24 = sharpe(MomVsMarket.MomHold24Weeks*(13/6),
MomVsMarket.Rf24Weeks*(13/6));
SharpeRm = sharpe(MomVsMarket.Rm, MomVsMarket.Rf);

% Annualized Sharpe Ratio in a table overview
SharpeStacked = {SharpeMom4 SharpeMom12 SharpeMom24};
Stacked = [SharpeStacked];
SharpeAnnualized = cell2table(Stacked, 'RowNames', ...
    {'Sharpe Ratio'});
SharpeAnnualized.Properties.VariableNames = {'Mom4' 'Mom12' 'Mom24'};
write(SharpeAnnualized, 'SharpeAnnualized.xlsx');

% Regression Model for estimating beta [and alpha]
% Formula: (R[PF]-Rf) = alpha(i) + ß(i)(Rm-Rf) + e(i)
% A = (Rm-Rf) = predictor variable (n x p vector)
% b = (R[PF]-Rf) = response variable (n x 1 vector)
% // not reported in main section of this study
A = MomVsMarket.Rm4Weeks - MomVsMarket.Rf4Weeks;
b = MomVsMarket.MomHold4Weeks - MomVsMarket.Rf4Weeks;
mdl = LinearModel.fit(A, b)

A1 = MomVsMarket.Rm12Weeks - MomVsMarket.Rf12Weeks;
b1 = MomVsMarket.MomHold12Weeks - MomVsMarket.Rf12Weeks;
mdl1 = LinearModel.fit(A1, b1)

A2 = MomVsMarket.Rm24Weeks - MomVsMarket.Rf24Weeks;
b2 = MomVsMarket.MomHold24Weeks - MomVsMarket.Rf24Weeks;
mdl2 = LinearModel.fit(A2, b2)

% Not reported in main section of this research paper
% Beta's are split into 3 categories (pre-, inter- and post-crisis) and
% extracted via Matlab's Linear Regression function.
% Pre-crisis is defined as any data before and including July 2008; we
% achieve this by the indexing (420:end,:).
% Inter-crisis is defined as any data between July 2008 and January
% 2010; we achieve this by the indexing (345:419,:).
% Post-crisis is defined as any data after and including January 2010;
% we achieve this by the indexing (1:344,:).
A_pre = MomVsMarket.Rm4Weeks(420:end,:) -
MomVsMarket.Rf4Weeks(420:end,:);
b_pre = MomVsMarket.MomHold4Weeks(420:end,:) - MomVsMarket.Rf4Weeks(
... 420:end,:);
mdl_pre = LinearModel.fit(A_pre, b_pre)

A_post = MomVsMarket.Rm4Weeks(1:344,:) - MomVsMarket.Rf4Weeks(1:344,:);
b_post = MomVsMarket.MomHold4Weeks(1:344,:) -
MomVsMarket.Rf4Weeks(1:344,:);
mdl_post = LinearModel.fit(A_post, b_post)

A_crisis = MomVsMarket.Rm4Weeks(345:419,:) -
MomVsMarket.Rf4Weeks(345:419,:);
b_crisis = MomVsMarket.MomHold4Weeks(345:419,:) -
```

```
MomVsMarket.Rf4Weeks(345:419,:);
mdl_crisis = LinearModel.fit(A_crisis, b_crisis)

A1_pre = MomVsMarket.Rm12Weeks(420:end,:) -
MomVsMarket.Rf12Weeks(420:end,:);
b1_pre = MomVsMarket.MomHold12Weeks(420:end,:) - MomVsMarket.Rf12Weeks(
...
    420:end,:);
mdl1_pre = LinearModel.fit(A1_pre, b1_pre)

A1_post = MomVsMarket.Rm12Weeks(1:344,:) -
MomVsMarket.Rf12Weeks(1:344,:);
b1_post = MomVsMarket.MomHold12Weeks(1:344,:) -
MomVsMarket.Rf12Weeks(1:344,:);
mdl1_post = LinearModel.fit(A1_post, b1_post)

A1_crisis = MomVsMarket.Rm12Weeks(345:419,:) -
MomVsMarket.Rf12Weeks(345:419,:);
b1_crisis = MomVsMarket.MomHold12Weeks(345:419,:) -
MomVsMarket.Rf12Weeks(345:419,:);
mdl1_crisis = LinearModel.fit(A1_crisis, b1_crisis)

A2_pre = MomVsMarket.Rm24Weeks(420:end,:) -
MomVsMarket.Rf24Weeks(420:end,:);
b2_pre = MomVsMarket.MomHold24Weeks(420:end,:) - MomVsMarket.Rf24Weeks(
...
    420:end,:);
mdl2_pre = LinearModel.fit(A2_pre, b2_pre)

A2_post = MomVsMarket.Rm24Weeks(1:344,:) -
MomVsMarket.Rf24Weeks(1:344,:);
b2_post = MomVsMarket.MomHold24Weeks(1:344,:) -
MomVsMarket.Rf24Weeks(1:344,:);
mdl2_post = LinearModel.fit(A2_post, b2_post)

A2_crisis = MomVsMarket.Rm24Weeks(345:419,:) -
MomVsMarket.Rf24Weeks(345:419,:);
b2_crisis = MomVsMarket.MomHold24Weeks(345:419,:) -
MomVsMarket.Rf24Weeks(345:419,:);
mdl2_crisis = LinearModel.fit(A2_crisis, b2_crisis)

% Create an overtiew table // not reported in main section of study
XX=[{mdl_pre.Coefficients.Estimate(2) mdl1_pre.Coefficients.Estimate(2)
... mdl2_pre.Coefficients.Estimate(2)}; ...
    {mdl_crisis.Coefficients.Estimate(2)
mdl1_crisis.Coefficients.Estimate(2) ...
    mdl2_crisis.Coefficients.Estimate(2)}; ...
    {mdl_post.Coefficients.Estimate(2)
mdl1_post.Coefficients.Estimate(2) ...
    mdl2_post.Coefficients.Estimate(2)}];
BetaPrePostCrisis=cell2table(XX);
BetaPrePostCrisis.Properties.VariableNames= {'Mom4' ...
    'Mom12' 'Mom24'};
BetaPrePostCrisis.Properties.RowNames = {'Pre-Crisis Beta' 'Crisis
Beta' 'Post-Crisis Beta'}
write(BetaPrePostCrisis, 'BetaPrePostCrisis.xlsx');
```

```
% Beta Calculation for Winner and Loser Portfolio (entire period)
% 4-Week Scenario (Loser)
G1 = MomVsMarket.Rm4Weeks - MomVsMarket.Rf4Weeks;
G2 = MomPF.L_sum4t - MomVsMarket.Rf4Weeks;
mdlL4 = LinearModel.fit(G1, G2)

% 4-Week Scenario (Winner)
G3 = MomVsMarket.Rm4Weeks - MomVsMarket.Rf4Weeks;
G4 = MomPF.U_sum4t - MomVsMarket.Rf4Weeks;
mdlW4 = LinearModel.fit(G3, G4)

% 12-Week Scenario (Loser)
G5 = MomVsMarket.Rm12Weeks - MomVsMarket.Rf12Weeks;
G6 = MomPF.L_sum12t - MomVsMarket.Rf12Weeks;
mdlL12 = LinearModel.fit(G5, G6)

% 12-Week Scenario (Winner)
G7 = MomVsMarket.Rm12Weeks - MomVsMarket.Rf12Weeks;
G8 = MomPF.U_sum12t - MomVsMarket.Rf12Weeks;
mdlW12 = LinearModel.fit(G7, G8)

% 24-Week Scenario (Loser)
G9 = MomVsMarket.Rm24Weeks - MomVsMarket.Rf24Weeks;
G10 = MomPF.L_sum24t - MomVsMarket.Rf24Weeks;
mdlL24 = LinearModel.fit(G9, G10)

% 24-Week Scenario (Winner)
G11 = MomVsMarket.Rm24Weeks - MomVsMarket.Rf24Weeks;
G12 = MomPF.U_sum24t - MomVsMarket.Rf24Weeks;
mdlW24 = LinearModel.fit(G11, G12)

% Overview (Beta W and L PF over entire period)
JJ = [{mdlL4.Coefficients.Estimate(2) mdlL12.Coefficients.Estimate(2)
... mdlL24.Coefficients.Estimate(2)}; ...
    {mdlL4.Rsquared.Adjusted mdlL12.Rsquared.Adjusted ...
    mdlL24.Rsquared.Adjusted};
    {mdlW4.Coefficients.Estimate(2) mdlW12.Coefficients.Estimate(2) ...
    mdlW24.Coefficients.Estimate(2)};
    {mdlW4.Rsquared.Adjusted mdlW12.Rsquared.Adjusted ...
    mdlW24.Rsquared.Adjusted};];
BetaWinnerLoser = cell2table(JJ);
BetaWinnerLoser.Properties.VariableNames= {'Mom4' ...
    'Mom12' 'Mom24'};
BetaWinnerLoser.Properties.RowNames = {'Loser PF beta' ...
    'Loser PF Adj. R^2' 'Winner PF' 'Winner PF Adj. R^2'}
write(BetaWinnerLoser, 'BetaWinnerLoser.xlsx');

% Beta Calculation for Winner and Loser Portfolio (distinction between
% pre-crisis, crisis and post-crisis)
% How can we do that? A simple yet elegant way is by indexing
% 4-Week Scenario (Loser)
G13 = MomVsMarket.Rm4Weeks(420:end,:) -
MomVsMarket.Rf4Weeks(420:end,:);
G14 = MomPF.L_sum4t(420:end,:) - MomVsMarket.Rf4Weeks(420:end,:);
mdlL4_pre = LinearModel.fit(G13, G14)

G15 = MomVsMarket.Rm4Weeks(345:419,:) -
```

```
MomVsMarket.Rf4Weeks(345:419,:);
G16 = MomPF.L_sum4t(345:419,:) - MomVsMarket.Rf4Weeks(345:419,:);
mdlL4_crisis = LinearModel.fit(G15, G16)

G17 = MomVsMarket.Rm4Weeks(1:344,:) - MomVsMarket.Rf4Weeks(1:344,:);
G18 = MomPF.L_sum4t(1:344,:) - MomVsMarket.Rf4Weeks(1:344,:);
mdlL4_post = LinearModel.fit(G17, G18)

% 4-Week Scenario (Winner)
G19 = MomVsMarket.Rm4Weeks(420:end,:) -
MomVsMarket.Rf4Weeks(420:end,:);
G20 = MomPF.U_sum4t(420:end,:) - MomVsMarket.Rf4Weeks(420:end,:);
mdlW4_pre = LinearModel.fit(G19, G20)

G21 = MomVsMarket.Rm4Weeks(345:419,:) -
MomVsMarket.Rf4Weeks(345:419,:);
G22 = MomPF.U_sum4t(345:419,:) - MomVsMarket.Rf4Weeks(345:419,:);
mdlW4_crisis = LinearModel.fit(G21, G22)

G23 = MomVsMarket.Rm4Weeks(1:344,:) - MomVsMarket.Rf4Weeks(1:344,:);
G24 = MomPF.U_sum4t(1:344,:) - MomVsMarket.Rf4Weeks(1:344,:);
mdlW4_post = LinearModel.fit(G23, G24)

% 12-Week Scenario (Loser)
G25 = MomVsMarket.Rm12Weeks(420:end,:) -
MomVsMarket.Rf12Weeks(420:end,:);
G26 = MomPF.L_sum12t(420:end,:) - MomVsMarket.Rf12Weeks(420:end,:);
mdlL12_pre = LinearModel.fit(G25, G26)

G27 = MomVsMarket.Rm12Weeks(345:419,:) -
MomVsMarket.Rf12Weeks(345:419,:);
G28 = MomPF.L_sum12t(345:419,:) - MomVsMarket.Rf12Weeks(345:419,:);
mdlL12_crisis = LinearModel.fit(G27, G28)

G29 = MomVsMarket.Rm12Weeks(1:344,:) - MomVsMarket.Rf12Weeks(1:344,:);
G30 = MomPF.L_sum12t(1:344,:) - MomVsMarket.Rf12Weeks(1:344,:);
mdlL12_post = LinearModel.fit(G29, G30)

% 12-Week Scenario (Winner)
G31 = MomVsMarket.Rm12Weeks(420:end,:) -
MomVsMarket.Rf12Weeks(420:end,:);
G32 = MomPF.U_sum12t(420:end,:) - MomVsMarket.Rf12Weeks(420:end,:);
mdlW12_pre = LinearModel.fit(G31, G32)

G33 = MomVsMarket.Rm12Weeks(345:419,:) -
MomVsMarket.Rf12Weeks(345:419,:);
G34 = MomPF.U_sum12t(345:419,:) - MomVsMarket.Rf12Weeks(345:419,:);
mdlW12_crisis = LinearModel.fit(G33, G34)

G35 = MomVsMarket.Rm12Weeks(1:344,:) - MomVsMarket.Rf12Weeks(1:344,:);
G36 = MomPF.U_sum12t(1:344,:) - MomVsMarket.Rf12Weeks(1:344,:);
mdlW12_post = LinearModel.fit(G35, G36)

% 24-Week Scenario (Loser)
G37 = MomVsMarket.Rm24Weeks(420:end,:) -
MomVsMarket.Rf24Weeks(420:end,:);
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```
G38 = MomPF.L_sum24t(420:end,:) - MomVsMarket.Rf24Weeks(420:end,:);
mdlL24_pre = LinearModel.fit(G37, G38)

G39 = MomVsMarket.Rm24Weeks(345:419,:) -
MomVsMarket.Rf24Weeks(345:419,:);
G40 = MomPF.L_sum24t(345:419,:) - MomVsMarket.Rf24Weeks(345:419,:);
mdlL24_crisis = LinearModel.fit(G39, G40)

G41 = MomVsMarket.Rm24Weeks(1:344,:) - MomVsMarket.Rf24Weeks(1:344,:);
G42 = MomPF.L_sum24t(1:344,:) - MomVsMarket.Rf24Weeks(1:344,:);
mdlL24_post = LinearModel.fit(G41, G42)

% 24-Week Scenario (Winner)
G43 = MomVsMarket.Rm24Weeks(420:end,:) -
MomVsMarket.Rf24Weeks(420:end,:);
G44 = MomPF.U_sum24t(420:end,:) - MomVsMarket.Rf24Weeks(420:end,:);
mdlW24_pre = LinearModel.fit(G43, G44)

G45 = MomVsMarket.Rm24Weeks(345:419,:) -
MomVsMarket.Rf24Weeks(345:419,:);
G46 = MomPF.U_sum24t(345:419,:) - MomVsMarket.Rf24Weeks(345:419,:);
mdlW24_crisis = LinearModel.fit(G45, G46)

G47 = MomVsMarket.Rm24Weeks(1:344,:) - MomVsMarket.Rf24Weeks(1:344,:);
G48 = MomPF.U_sum24t(1:344,:) - MomVsMarket.Rf24Weeks(1:344,:);
mdlW24_post = LinearModel.fit(G47, G48)

% Create overview table
OO = [{mdlL4_pre.Coefficients.Estimate(2)
mdlL12_pre.Coefficients.Estimate(2) ...
    mdlL24_pre.Coefficients.Estimate(2)}; ...
    {mdlW4_pre.Coefficients.Estimate(2)
mdlW12_pre.Coefficients.Estimate(2) ...
    mdlW24_pre.Coefficients.Estimate(2)};
    {mdlL4_crisis.Coefficients.Estimate(2)
mdlL12_crisis.Coefficients.Estimate(2) ...
    mdlL24_crisis.Coefficients.Estimate(2)}; ...
    {mdlW4_crisis.Coefficients.Estimate(2)
mdlW12_crisis.Coefficients.Estimate(2) ...
    mdlW24_crisis.Coefficients.Estimate(2)};
    {mdlL4_post.Coefficients.Estimate(2)
mdlL12_post.Coefficients.Estimate(2) ...
    mdlL24_post.Coefficients.Estimate(2)}; ...
    {mdlW4_post.Coefficients.Estimate(2)
mdlW12_post.Coefficients.Estimate(2) ...
    mdlW24_post.Coefficients.Estimate(2)}];
BetaWinnerLoserPreCrisisPost = cell2table(OO);
BetaWinnerLoserPreCrisisPost.Properties.VariableNames= {'Mom4' ...
    'Mom12' 'Mom24'};
BetaWinnerLoserPreCrisisPost.Properties.RowNames = {'Loser_PF_Pre' ...
    'Winner_PF_Pre' 'Loser_PF_Crisis' 'Winner_PF_Crisis' ...
    'Loser_PF_Post' 'Winner_PF_Post'}
write(BetaWinnerLoserPreCrisisPost,
'BetaWinnerLoserPreCrisisPost.xlsx');
```

```
% E.2 Week-effect
% --------------------------------------------------------------------

% Descriptive Statistics "Week-Effect" Momentum 1st-5th
MeanMom4_1st_5th = nanmean(Mom1st_5th.MomHold4Weeks);
MeanMom12_1st_5th = nanmean(Mom1st_5th.MomHold12Weeks);
MeanMom24_1st_5th = nanmean(Mom1st_5th.MomHold24Weeks);
MedianMom4_1st_5th = nanmedian(Mom1st_5th.MomHold4Weeks);
MedianMom12_1st_5th = nanmedian(Mom1st_5th.MomHold12Weeks);
MedianMom24_1st_5th = nanmedian(Mom1st_5th.MomHold24Weeks);
StdDevMom4_1st_5th = nanstd(Mom1st_5th.MomHold4Weeks);
StdDevMom12_1st_5th = nanstd(Mom1st_5th.MomHold12Weeks);
StdDevMom24_1st_5th = nanstd(Mom1st_5th.MomHold24Weeks);
KurtMom4_1st_5th = kurtosis(Mom1st_5th.MomHold4Weeks);
KurtMom12_1st_5th = kurtosis(Mom1st_5th.MomHold12Weeks);
KurtMom24_1st_5th = kurtosis(Mom1st_5th.MomHold24Weeks);
SkewMom4_1st_5th = skewness(Mom1st_5th.MomHold4Weeks);
SkewMom12_1st_5th = skewness(Mom1st_5th.MomHold12Weeks);
SkewMom24_1st_5th = skewness(Mom1st_5th.MomHold24Weeks);
BetaMom4_1st_5th =
nancov(Mom1st_5th.MomHold4Weeks,Mom1st_5th.Rm4Weeks)./nanvar...
    (Mom1st_5th.Rm4Weeks);
BetaMom12_1st_5th =
nancov(Mom1st_5th.MomHold12Weeks,Mom1st_5th.Rm12Weeks)./nanvar...
    (Mom1st_5th.Rm12Weeks);
BetaMom24_1st_5th =
nancov(Mom1st_5th.MomHold24Weeks,Mom1st_5th.Rm24Weeks)./nanvar...
    (Mom1st_5th.Rm24Weeks);
DesStatMom4_1st_5th = {MeanMom4_1st_5th*13, MedianMom4_1st_5th*13, ...
    StdDevMom4_1st_5th*sqrt(13), KurtMom4_1st_5th, SkewMom4_1st_5th,
... BetaMom4_1st_5th(2,1)};
DesStatMom12_1st_5th = {MeanMom12_1st_5th*(13/3), ...
    MedianMom12_1st_5th*(13/3), StdDevMom12_1st_5th*sqrt(13/3),
KurtMom12_1st_5th,...
    SkewMom12_1st_5th, BetaMom12_1st_5th(2,1)};
DesStatMom24_1st_5th = {MeanMom24_1st_5th*(13/6),
MedianMom24_1st_5th*(13/6), ...
    StdDevMom24_1st_5th*sqrt(13/6), KurtMom24_1st_5th,
SkewMom24_1st_5th, ...
    BetaMom24_1st_5th(2,1)};
DesStatSummary_1st_5th = table(DesStatMom4_1st_5th',...
    DesStatMom12_1st_5th', DesStatMom24_1st_5th', ...
    'RowNames', {'Mean', 'Median', 'Std. Dev.',...
    'Kurtosis', 'Skewness', 'Portfolio Beta'});
DesStatSummary_1st_5th.Properties.VariableNames = {'Mom4' 'Mom12'
'Mom24'}
write(DesStatSummary_1st_5th, 'DesStatSummary_1st_5th.xlsx');

% Descriptive Statistics "Week-Effect" Momentum 6th-10th
MeanMom4_6th_10th = nanmean(Mom6th_10th.MomHold4Weeks);
MeanMom12_6th_10th = nanmean(Mom6th_10th.MomHold12Weeks);
MeanMom24_6th_10th = nanmean(Mom6th_10th.MomHold24Weeks);
MedianMom4_6th_10th = nanmedian(Mom6th_10th.MomHold4Weeks);
MedianMom12_6th_10th = nanmedian(Mom6th_10th.MomHold12Weeks);
MedianMom24_6th_10th = nanmedian(Mom6th_10th.MomHold24Weeks);
StdDevMom4_6th_10th = nanstd(Mom6th_10th.MomHold4Weeks);
StdDevMom12_6th_10th = nanstd(Mom6th_10th.MomHold12Weeks);
StdDevMom24_6th_10th = nanstd(Mom6th_10th.MomHold24Weeks);
```

```
KurtMom4_6th_10th = kurtosis(Mom6th_10th.MomHold4Weeks);
KurtMom12_6th_10th = kurtosis(Mom6th_10th.MomHold12Weeks);
KurtMom24_6th_10th = kurtosis(Mom6th_10th.MomHold24Weeks);
SkewMom4_6th_10th = skewness(Mom6th_10th.MomHold4Weeks);
SkewMom12_6th_10th = skewness(Mom6th_10th.MomHold12Weeks);
SkewMom24_6th_10th = skewness(Mom6th_10th.MomHold24Weeks);
BetaMom4_6th_10th =
nancov(Mom6th_10th.MomHold4Weeks,Mom6th_10th.Rm4Weeks)./nanvar...
    (Mom6th_10th.Rm4Weeks);
BetaMom12_6th_10th =
nancov(Mom6th_10th.MomHold12Weeks,Mom6th_10th.Rm12Weeks)./nanvar...
    (Mom6th_10th.Rm12Weeks);
BetaMom24_6th_10th =
nancov(Mom6th_10th.MomHold24Weeks,Mom6th_10th.Rm24Weeks)./nanvar...
    (Mom6th_10th.Rm24Weeks);
DesStatMom4_6th_10th = {MeanMom4_6th_10th*13, MedianMom4_6th_10th*13,
StdDevMom4_6th_10th*sqrt(13), KurtMom4_6th_10th*13,...
    SkewMom4_6th_10th*13, BetaMom4_6th_10th(2,1)};
DesStatMom12_6th_10th = {MeanMom12_6th_10th*(13/3),
MedianMom12_6th_10th*(13/3), StdDevMom12_6th_10th*sqrt(13/3),
KurtMom12_6th_10th,...
    SkewMom12_6th_10th*(13/3), BetaMom12_6th_10th(2,1)};
DesStatMom24_6th_10th = {MeanMom24_6th_10th*(13/6),
MedianMom24_6th_10th*(13/6), StdDevMom24_6th_10th*sqrt(13/6),
KurtMom24_6th_10th,...
    SkewMom24_6th_10th, BetaMom24_6th_10th(2,1)};
DesStatSummary_6th_10th = table(DesStatMom4_6th_10th',...
    DesStatMom12_6th_10th', DesStatMom24_6th_10th', ...
    'RowNames', {'Mean', 'Median', 'Std. Dev.',...
    'Kurtosis', 'Skewness', 'Portfolio Beta'});
DesStatSummary_6th_10th.Properties.VariableNames = {'Mom4' 'Mom12'
'Mom24'}
write(DesStatSummary_6th_10th, 'DesStatSummary_6th_10th.xlsx');

% Descriptive Statistics "Week-Effect" Momentum 11th-15th
MeanMom4_11th_15th = nanmean(Mom11th_15th.MomHold4Weeks);
MeanMom12_11th_15th = nanmean(Mom11th_15th.MomHold12Weeks);
MeanMom24_11th_15th = nanmean(Mom11th_15th.MomHold24Weeks);
MedianMom4_11th_15th = nanmedian(Mom11th_15th.MomHold4Weeks);
MedianMom12_11th_15th = nanmedian(Mom11th_15th.MomHold12Weeks);
MedianMom24_11th_15th = nanmedian(Mom11th_15th.MomHold24Weeks);
StdDevMom4_11th_15th = nanstd(Mom11th_15th.MomHold4Weeks);
StdDevMom12_11th_15th = nanstd(Mom11th_15th.MomHold12Weeks);
StdDevMom24_11th_15th = nanstd(Mom11th_15th.MomHold24Weeks);
KurtMom4_11th_15th = kurtosis(Mom11th_15th.MomHold4Weeks);
KurtMom12_11th_15th = kurtosis(Mom11th_15th.MomHold12Weeks);
KurtMom24_11th_15th = kurtosis(Mom11th_15th.MomHold24Weeks);
SkewMom4_11th_15th = skewness(Mom11th_15th.MomHold4Weeks);
SkewMom12_11th_15th = skewness(Mom11th_15th.MomHold12Weeks);
SkewMom24_11th_15th = skewness(Mom11th_15th.MomHold24Weeks);
BetaMom4_11th_15th =
nancov(Mom11th_15th.MomHold4Weeks,Mom11th_15th.Rm4Weeks)./nanvar...
    (Mom11th_15th.Rm4Weeks);
BetaMom12_11th_15th =
nancov(Mom11th_15th.MomHold12Weeks,Mom11th_15th.Rm12Weeks)./nanvar...
    (Mom11th_15th.Rm12Weeks);
BetaMom24_11th_15th =
nancov(Mom11th_15th.MomHold24Weeks,Mom11th_15th.Rm24Weeks)./nanvar...
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```
    (Mom11th_15th.Rm24Weeks);
DesStatMom4_11th_15th = {MeanMom4_11th_15th*13,
MedianMom4_11th_15th*13, ...
    StdDevMom4_11th_15th*sqrt(13), KurtMom4_11th_15th,
SkewMom4_11th_15th, ...
    BetaMom4_11th_15th(2,1)};
DesStatMom12_11th_15th = {MeanMom12_11th_15th*(13/3), ...
    MedianMom12_11th_15th*(13/3), StdDevMom12_11th_15th*sqrt(13/3), ...
    KurtMom12_11th_15th, SkewMom12_11th_15th,
BetaMom12_11th_15th(2,1)};
DesStatMom24_11th_15th = {MeanMom24_11th_15th*(13/6), ...
    MedianMom24_11th_15th*(13/6), StdDevMom24_11th_15th*sqrt(13/6), ...
    KurtMom24_11th_15th, SkewMom24_11th_15th,
BetaMom24_11th_15th(2,1)};
DesStatSummary_11th_15th = table(DesStatMom4_11th_15th',...
    DesStatMom12_11th_15th', DesStatMom24_11th_15th', ...
    'RowNames', {'Mean', 'Median', 'Std. Dev.',...
    'Kurtosis', 'Skewness', 'Portfolio Beta'});
DesStatSummary_11th_15th.Properties.VariableNames = {'Mom4' 'Mom12'
'Mom24'}
write(DesStatSummary_11th_15th, 'DesStatSummary_11th_15th.xlsx');

% Descriptive Statistics "Week-Effect" Momentum 16th-20th
MeanMom4_16th_20th = nanmean(Mom16th_20th.MomHold4Weeks);
MeanMom12_16th_20th = nanmean(Mom16th_20th.MomHold12Weeks);
MeanMom24_16th_20th = nanmean(Mom16th_20th.MomHold24Weeks);
MedianMom4_16th_20th = nanmedian(Mom16th_20th.MomHold4Weeks);
MedianMom12_16th_20th = nanmedian(Mom16th_20th.MomHold12Weeks);
MedianMom24_16th_20th = nanmedian(Mom16th_20th.MomHold24Weeks);
StdDevMom4_16th_20th = nanstd(Mom16th_20th.MomHold4Weeks);
StdDevMom12_16th_20th = nanstd(Mom16th_20th.MomHold12Weeks);
StdDevMom24_16th_20th = nanstd(Mom16th_20th.MomHold24Weeks);
KurtMom4_16th_20th = kurtosis(Mom16th_20th.MomHold4Weeks);
KurtMom12_16th_20th = kurtosis(Mom16th_20th.MomHold12Weeks);
KurtMom24_16th_20th = kurtosis(Mom16th_20th.MomHold24Weeks);
SkewMom4_16th_20th = skewness(Mom16th_20th.MomHold4Weeks);
SkewMom12_16th_20th = skewness(Mom16th_20th.MomHold12Weeks);
SkewMom24_16th_20th = skewness(Mom16th_20th.MomHold24Weeks);
BetaMom4_16th_20th =
nancov(Mom16th_20th.MomHold4Weeks,Mom16th_20th.Rm4Weeks)./nanvar...
    (Mom16th_20th.Rm4Weeks);
BetaMom12_16th_20th =
nancov(Mom16th_20th.MomHold12Weeks,Mom16th_20th.Rm12Weeks)./nanvar...
    (Mom16th_20th.Rm12Weeks);
BetaMom24_16th_20th =
nancov(Mom16th_20th.MomHold24Weeks,Mom16th_20th.Rm24Weeks)./nanvar...
    (Mom16th_20th.Rm24Weeks);
DesStatMom4_16th_20th = {MeanMom4_16th_20th*13,
MedianMom4_16th_20th*13, ...
    StdDevMom4_16th_20th*sqrt(13), KurtMom4_16th_20th,
SkewMom4_16th_20th, ...
    BetaMom4_16th_20th(2,1)};
DesStatMom12_16th_20th = {MeanMom12_16th_20th*(13/3), ...
    MedianMom12_16th_20th*(13/3), StdDevMom12_16th_20th*sqrt(13/3), ...
    KurtMom12_16th_20th, SkewMom12_16th_20th,
BetaMom12_16th_20th(2,1)};
DesStatMom24_16th_20th = {MeanMom24_16th_20th*(13/6), ...
    MedianMom24_16th_20th*(13/6), StdDevMom24_16th_20th*sqrt(13/6), ...
```

```
    KurtMom24_16th_20th, SkewMom24_16th_20th,
BetaMom24_16th_20th(2,1)};
DesStatSummary_16th_20th = table(DesStatMom4_16th_20th',...
    DesStatMom12_16th_20th', DesStatMom24_16th_20th', ...
    'RowNames', {'Mean', 'Median', 'Std. Dev.',...
    'Kurtosis', 'Skewness', 'Portfolio Beta'});
DesStatSummary_16th_20th.Properties.VariableNames = {'Mom4' 'Mom12'
'Mom24'}
write(DesStatSummary_16th_20th, 'DesStatSummary_16th_20th.xlsx');

% Descriptive Statistics "Week-Effect" Momentum 21st-25th
MeanMom4_21st_25th = nanmean(Mom21st_25th.MomHold4Weeks);
MeanMom12_21st_25th = nanmean(Mom21st_25th.MomHold12Weeks);
MeanMom24_21st_25th = nanmean(Mom21st_25th.MomHold24Weeks);
MedianMom4_21st_25th = nanmedian(Mom21st_25th.MomHold4Weeks);
MedianMom12_21st_25th = nanmedian(Mom21st_25th.MomHold12Weeks);
MedianMom24_21st_25th = nanmedian(Mom21st_25th.MomHold24Weeks);
StdDevMom4_21st_25th = nanstd(Mom21st_25th.MomHold4Weeks);
StdDevMom12_21st_25th = nanstd(Mom21st_25th.MomHold12Weeks);
StdDevMom24_21st_25th = nanstd(Mom21st_25th.MomHold24Weeks);
KurtMom4_21st_25th = kurtosis(Mom21st_25th.MomHold4Weeks);
KurtMom12_21st_25th = kurtosis(Mom21st_25th.MomHold12Weeks);
KurtMom24_21st_25th = kurtosis(Mom21st_25th.MomHold24Weeks);
SkewMom4_21st_25th = skewness(Mom21st_25th.MomHold4Weeks);
SkewMom12_21st_25th = skewness(Mom21st_25th.MomHold12Weeks);
SkewMom24_21st_25th = skewness(Mom21st_25th.MomHold24Weeks);
BetaMom4_21st_25th =
nancov(Mom21st_25th.MomHold4Weeks,Mom21st_25th.Rm4Weeks)./nanvar...
    (Mom21st_25th.Rm4Weeks);
BetaMom12_21st_25th =
nancov(Mom21st_25th.MomHold12Weeks,Mom21st_25th.Rm12Weeks)./nanvar...
    (Mom21st_25th.Rm12Weeks);
BetaMom24_21st_25th =
nancov(Mom21st_25th.MomHold24Weeks,Mom21st_25th.Rm24Weeks)./nanvar...
    (Mom21st_25th.Rm24Weeks);
DesStatMom4_21st_25th = {MeanMom4_21st_25th*13,
MedianMom4_21st_25th*13, ...
    StdDevMom4_21st_25th*sqrt(13), KurtMom4_21st_25th,
SkewMom4_21st_25th, ...
    BetaMom4_21st_25th(2,1)};
DesStatMom12_21st_25th = {MeanMom12_21st_25th*(13/3), ...
    MedianMom12_21st_25th*(13/3), StdDevMom12_21st_25th*sqrt(13/3),
KurtMom12_21st_25th,...
    SkewMom12_21st_25th, BetaMom12_21st_25th(2,1)};
DesStatMom24_21st_25th = {MeanMom24_21st_25th*(13/6), ...
    MedianMom24_21st_25th*(13/6), StdDevMom24_21st_25th*sqrt(13/6), ...
    KurtMom24_21st_25th, SkewMom24_21st_25th,
BetaMom24_21st_25th(2,1)};
DesStatSummary_21st_25th = table(DesStatMom4_21st_25th',...
    DesStatMom12_21st_25th', DesStatMom24_21st_25th', ...
    'RowNames', {'Mean', 'Median', 'Std. Dev.',...
    'Kurtosis', 'Skewness', 'Portfolio Beta'});
DesStatSummary_21st_25th.Properties.VariableNames = {'Mom4' 'Mom12'
'Mom24'}
write(DesStatSummary_21st_25th, 'DesStatSummary_21st_25th.xlsx');

% Descriptive Statistics "Week-Effect" Momentum 26th-31st
MeanMom4_26th_31st = nanmean(Mom26th_31st.MomHold4Weeks);
```

```
MeanMom12_26th_31st = nanmean(Mom26th_31st.MomHold12Weeks);
MeanMom24_26th_31st = nanmean(Mom26th_31st.MomHold24Weeks);
MedianMom4_26th_31st = nanmedian(Mom26th_31st.MomHold4Weeks);
MedianMom12_26th_31st = nanmedian(Mom26th_31st.MomHold12Weeks);
MedianMom24_26th_31st = nanmedian(Mom26th_31st.MomHold24Weeks);
StdDevMom4_26th_31st = nanstd(Mom26th_31st.MomHold4Weeks);
StdDevMom12_26th_31st = nanstd(Mom26th_31st.MomHold12Weeks);
StdDevMom24_26th_31st = nanstd(Mom26th_31st.MomHold24Weeks);
KurtMom4_26th_31st = kurtosis(Mom26th_31st.MomHold4Weeks);
KurtMom12_26th_31st = kurtosis(Mom26th_31st.MomHold12Weeks);
KurtMom24_26th_31st = kurtosis(Mom26th_31st.MomHold24Weeks);
SkewMom4_26th_31st = skewness(Mom26th_31st.MomHold4Weeks);
SkewMom12_26th_31st = skewness(Mom26th_31st.MomHold12Weeks);
SkewMom24_26th_31st = skewness(Mom26th_31st.MomHold24Weeks);
BetaMom4_26th_31st =
nancov(Mom26th_31st.MomHold4Weeks,Mom26th_31st.Rm4Weeks)./nanvar...
    (Mom26th_31st.Rm4Weeks);
BetaMom12_26th_31st =
nancov(Mom26th_31st.MomHold12Weeks,Mom26th_31st.Rm12Weeks)./nanvar...
    (Mom26th_31st.Rm12Weeks);
BetaMom24_26th_31st =
nancov(Mom26th_31st.MomHold24Weeks,Mom26th_31st.Rm24Weeks)./nanvar...
    (Mom26th_31st.Rm24Weeks);
DesStatMom4_26th_31st = {MeanMom4_26th_31st*13,
MedianMom4_26th_31st*13, ...
    StdDevMom4_26th_31st*sqrt(13), KurtMom4_26th_31st,
SkewMom4_26th_31st, ...
    BetaMom4_26th_31st(2,1)};
DesStatMom12_26th_31st = {MeanMom12_26th_31st*(13/3), ...
    MedianMom12_26th_31st*(13/3), StdDevMom12_26th_31st*sqrt(13/3), ...
    KurtMom12_26th_31st, SkewMom12_26th_31st,
BetaMom12_26th_31st(2,1)};
DesStatMom24_26th_31st = {MeanMom24_26th_31st*(13/6), ...
    MedianMom24_26th_31st*(13/6), StdDevMom24_26th_31st*sqrt(13/6), ...
    KurtMom24_26th_31st, SkewMom24_26th_31st,
BetaMom24_26th_31st(2,1)};
DesStatSummary_26th_31st = table(DesStatMom4_26th_31st',...
    DesStatMom12_26th_31st', DesStatMom24_26th_31st', ...
    'RowNames', {'Mean', 'Median', 'Std. Dev.',...
    'Kurtosis', 'Skewness', 'Portfolio Beta'});
DesStatSummary_26th_31st.Properties.VariableNames = {'Mom4' 'Mom12'
'Mom24'}
write(DesStatSummary_26th_31st, 'DesStatSummary_26th_31st.xlsx');

% Summary Annualized Mean ("Week-effect")
YY=[{MeanMom4_1st_5th*13 MeanMom4_6th_10th*13 MeanMom4_11th_15th*13 ...
    MeanMom4_16th_20th*13 MeanMom4_21st_25th*13
MeanMom4_26th_31st*13};...
    {MeanMom12_1st_5th*(13/3) MeanMom12_6th_10th*(13/3)
MeanMom12_11th_15th*(13/3) ...
    MeanMom12_16th_20th*(13/3) MeanMom12_21st_25th*(13/3)
MeanMom12_26th_31st*(13/3)};...
    {MeanMom24_1st_5th*(13/6) MeanMom24_6th_10th*(13/6)
MeanMom24_11th_15th*(13/6) ...
    MeanMom24_16th_20th*(13/6) MeanMom24_21st_25th*(13/6)
MeanMom24_26th_31st*(13/6)}];
WeeklyMeanOverview_annualized=cell2table(YY);
WeeklyMeanOverview_annualized.Properties.VariableNames= {'From_1st_5th'
```

```
... 'From_6th_10th' 'From_11th_15th' 'From_16th_20th' 'From_21st_25th'
... 'From_26th_31st'};
WeeklyMeanOverview_annualized.Properties.RowNames = {'4Weeks' '12Weeks'
'24Weeks'}
writetable(WeeklyMeanOverview_annualized,
'WeeklyMeanOverview_annualized.xlsx')

% Summary Annualized Standard Deviation (Week-effect)
YY1=[{StdDevMom4_1st_5th*sqrt(13) StdDevMom4_6th_10th*sqrt(13)
StdDevMom4_11th_15th*sqrt(13) ...
    StdDevMom4_16th_20th*sqrt(13) StdDevMom4_21st_25th*sqrt(13)
StdDevMom4_26th_31st*sqrt(13)};...
    {StdDevMom12_1st_5th*sqrt(13/3) StdDevMom12_6th_10th*sqrt(13/3)
StdDevMom12_11th_15th*sqrt(13/3) ...
    StdDevMom12_16th_20th*sqrt(13/3) StdDevMom12_21st_25th*sqrt(13/3)
StdDevMom12_26th_31st*sqrt(13/3)};...
    {StdDevMom24_1st_5th*sqrt(13/6) StdDevMom24_6th_10th*sqrt(13/6)
StdDevMom24_11th_15th*sqrt(13/6) ...
    StdDevMom24_16th_20th*sqrt(13/6) StdDevMom24_21st_25th*sqrt(13/6)
StdDevMom24_26th_31st*sqrt(13/6)}];
WeeklyStdDevOverview_annualized=cell2table(YY1);
WeeklyStdDevOverview_annualized.Properties.VariableNames =
{'From_1st_5th' ...
    'From_6th_10th' 'From_11th_15th' 'From_16th_20th' 'From_21st_25th'
... 'From_26th_31st'};
WeeklyStdDevOverview_annualized.Properties.RowNames = {'4Weeks'
'12Weeks' '24Weeks'}
writetable(WeeklyStdDevOverview_annualized,
'WeeklyStdDevOverview_annualized.xlsx')

% Summary Beta (Week-effect)
YY2=[{BetaMom4_1st_5th(1,2) BetaMom4_6th_10th(1,2)
BetaMom4_11th_15th(1,2) ...
    BetaMom4_16th_20th(1,2) BetaMom4_21st_25th(1,2)
BetaMom4_26th_31st(1,2)};...
    {BetaMom12_1st_5th(1,2) BetaMom12_6th_10th(1,2)
BetaMom12_11th_15th(1,2) ...
    BetaMom12_16th_20th(1,2) BetaMom12_21st_25th(1,2)
BetaMom12_26th_31st(1,2)};...
    {BetaMom24_1st_5th(1,2) BetaMom24_6th_10th(1,2)
BetaMom24_11th_15th(1,2) ...
    BetaMom24_16th_20th(1,2) BetaMom24_21st_25th(1,2)
BetaMom24_26th_31st(1,2)}];
WeeklyBetaOverview=cell2table(YY2);
WeeklyBetaOverview.Properties.VariableNames = {'From_1st_5th' ...
    'From_6th_10th' 'From_11th_15th' 'From_16th_20th' 'From_21st_25th'
... 'From_26th_31st'};
WeeklyBetaOverview.Properties.RowNames = {'4Weeks' '12Weeks'
'24Weeks'};
writetable(WeeklyBetaOverview, 'WeeklyBetaOverview.xlsx')

% Ex-post Sharpe Ratios in a week-to-week overview
% Sharpe Ratio Momentum 1st-5th
Sharpe1st_5th_4w = sharpe(Mom1st_5th.MomHold4Weeks(2:end,:), ...
    Mom1st_5th.Rf4Weeks(2:end,:)); % 0.1223
Sharpe1st_5th_12w = sharpe(Mom1st_5th.MomHold12Weeks(4:end,:), ...
    Mom1st_5th.Rf12Weeks(4:end,:)); % 0.3102
Sharpe1st_5th_24w = sharpe(Mom1st_5th.MomHold24Weeks(6:end,:), ...
```

```
    Mom1st_5th.Rf24Weeks(6:end,:)); % 0.2467

% Sharpe Ratio Momentum 6th-10th
Sharpe6th_10th_4w = sharpe(Mom6th_10th.MomHold4Weeks(:,:), ...
    Mom6th_10th.Rf4Weeks(:,:)); % 0.1045
Sharpe6th_10th_12w = sharpe(Mom6th_10th.MomHold12Weeks(3:end,:), ...
    Mom6th_10th.Rf12Weeks(3:end,:)); % 0.1212
Sharpe6th_10th_24w = sharpe(Mom6th_10th.MomHold24Weeks(5:end,:), ...
    Mom6th_10th.Rf24Weeks(5:end,:)); % 0.1062

% Sharpe Ratio Momentum 11th-15th
Sharpe11th_15th_4w = sharpe(Mom11th_15th.MomHold4Weeks(:,:), ...
    Mom11th_15th.Rf4Weeks(:,:)); % 0.1962
Sharpe11th_15th_12w = sharpe(Mom11th_15th.MomHold12Weeks(2:end,:), ...
    Mom11th_15th.Rf12Weeks(2:end,:)); % 0.1718
Sharpe11th_15th_24w = sharpe(Mom11th_15th.MomHold24Weeks(5:end,:), ...
    Mom11th_15th.Rf24Weeks(5:end,:)); % 0.1541

% Sharpe Ratio Momentum 16th-20th
Sharpe16th_20th_4w = sharpe(Mom16th_20th.MomHold4Weeks(:,:), ...
    Mom16th_20th.Rf4Weeks(:,:)); % 0.0629
Sharpe16th_20th_12w = sharpe(Mom16th_20th.MomHold12Weeks(2:end,:), ...
    Mom16th_20th.Rf12Weeks(2:end,:)); % 0.1616
Sharpe16th_20th_24w = sharpe(Mom16th_20th.MomHold24Weeks(4:end,:), ...
    Mom16th_20th.Rf24Weeks(4:end,:)); % 0.1735

% Sharpe Ratio Momentum 21st-25th
Sharpe21st_25th_4w = sharpe(Mom21st_25th.MomHold4Weeks(2:end,:), ...
    Mom21st_25th.Rf4Weeks(2:end,:)); % 0.2663
Sharpe21st_25th_12w = sharpe(Mom21st_25th.MomHold12Weeks(3:end,:), ...
    Mom21st_25th.Rf12Weeks(3:end,:)); % 0.3412
Sharpe21st_25th_24w = sharpe(Mom21st_25th.MomHold24Weeks(5:end,:), ...
    Mom21st_25th.Rf24Weeks(5:end,:)); % 0.3654

% Sharpe Ratio Momentum 26th-31st
Sharpe26th_31st_4w = sharpe(Mom26th_31st.MomHold4Weeks(2:end,:), ...
    Mom26th_31st.Rf4Weeks(2:end,:)); % 0.1267
Sharpe26th_31st_12w = sharpe(Mom26th_31st.MomHold12Weeks(3:end,:), ...
    Mom26th_31st.Rf12Weeks(3:end,:)); % 0.0746
Sharpe26th_31st_24w = sharpe(Mom26th_31st.MomHold24Weeks(4:end,:), ...
    Mom26th_31st.Rf24Weeks(4:end,:)); % 0.1101

% Annualized Sharpe Ratio summary in matrix form (Week effect)
ZZ=[{Sharpe1st_5th_4w*sqrt(13) Sharpe6th_10th_4w*sqrt(13)
Sharpe11th_15th_4w*sqrt(13) ...
    Sharpe16th_20th_4w*sqrt(13) Sharpe21st_25th_4w*sqrt(13)
Sharpe26th_31st_4w*sqrt(13)};...
    {Sharpe1st_5th_12w*sqrt(13/3) Sharpe6th_10th_12w*sqrt(13/3)
Sharpe11th_15th_12w*sqrt(13/3) ...
    Sharpe16th_20th_12w*sqrt(13/3) Sharpe21st_25th_12w*sqrt(13/3)
Sharpe26th_31st_12w*sqrt(13/3)};...
    {Sharpe1st_5th_24w*sqrt(13/6) Sharpe6th_10th_24w*sqrt(13/6)
Sharpe11th_15th_24w*sqrt(13/6) ...
    Sharpe16th_20th_24w*sqrt(13/6) Sharpe21st_25th_24w*sqrt(13/6)
Sharpe26th_31st_24w*sqrt(13/6)}];
WeeklySharpOverview=cell2table(ZZ);
WeeklySharpOverview.Properties.VariableNames= {'From_1st_5th' ...
```

```
    'From_6th_10th' 'From_11th_15th' 'From_16th_20th' 'From_21st_25th'
... 'From_26th_31st'};
WeeklySharpOverview.Properties.RowNames = {'4Weeks' '12Weeks'
'24Weeks'}
writetable(WeeklySharpOverview, 'WeeklySharpOverview.xlsx')

% Now we still want to test the differences in mean. To do this we will
% run the Kruskal-Wallis test

% Matrix alignments and preparatory work 4-Week scenarios
Mom1st_5th_4wAdj = Mom1st_5th.MomHold4Weeks;
Mom1st_5th_4wAdj(92:101,:) = nan;

Mom6th_10th_4wAdj = Mom6th_10th.MomHold4Weeks;
Mom6th_10th_4wAdj(90:101,:) = nan;

Mom11th_15th_4wAdj = Mom11th_15th.MomHold4Weeks;
Mom11th_15th_4wAdj(93:101,:) = nan;

Mom16th_20th_4wAdj = Mom16th_20th.MomHold4Weeks;
Mom16th_20th_4wAdj(93:101,:) = nan;

Mom21st_25th_4wAdj = Mom21st_25th.MomHold4Weeks;
Mom21st_25th_4wAdj(90:101,:) = nan;

Mom26th_31st_4wAdj = Mom26th_31st.MomHold4Weeks;

% Matrix alignments and preparatory work 12-Week scenarios
Mom1st_5th_12wAdj = Mom1st_5th.MomHold12Weeks;
Mom1st_5th_12wAdj(92:101,:) = nan;

Mom6th_10th_12wAdj = Mom6th_10th.MomHold12Weeks;
Mom6th_10th_12wAdj(90:101,:) = nan;

Mom11th_15th_12wAdj = Mom11th_15th.MomHold12Weeks;
Mom11th_15th_12wAdj(93:101,:) = nan;

Mom16th_20th_12wAdj = Mom16th_20th.MomHold12Weeks;
Mom16th_20th_12wAdj(93:101,:) = nan;

Mom21st_25th_12wAdj = Mom21st_25th.MomHold12Weeks;
Mom21st_25th_12wAdj(90:101,:) = nan;

Mom26th_31st_12wAdj = Mom26th_31st.MomHold12Weeks;

% Matrix alignments and preparatory work 12-Week scenarios
Mom1st_5th_24wAdj = Mom1st_5th.MomHold24Weeks;
Mom1st_5th_24wAdj(92:101,:) = nan;

Mom6th_10th_24wAdj = Mom6th_10th.MomHold24Weeks;
Mom6th_10th_24wAdj(90:101,:) = nan;

Mom11th_15th_24wAdj = Mom11th_15th.MomHold24Weeks;
Mom11th_15th_24wAdj(93:101,:) = nan;
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```
Mom16th_20th_24wAdj = Mom16th_20th.MomHold24Weeks;
Mom16th_20th_24wAdj(93:101,:) = nan;

Mom21st_25th_24wAdj = Mom21st_25th.MomHold24Weeks;
Mom21st_25th_24wAdj(90:101,:) = nan;

Mom26th_31st_24wAdj = Mom26th_31st.MomHold24Weeks;

% A-priori Kruskal-Wallis test assumption: checking whether the group
% distributions have similar shapes
% 4-Week Momentum
skew4KW_1st_5th = skewness(Mom1st_5th.MomHold4Weeks);
histogram(Mom1st_5th.MomHold4Weeks, 95); % negatively skewed

skew4KW_6th_10th = skewness(Mom6th_10th.MomHold4Weeks);
histogram(Mom6th_10th.MomHold4Weeks, 95); % negatively skewed

skew4KW_11th_15th = skewness(Mom11th_15th.MomHold4Weeks);
histogram(Mom11th_15th.MomHold4Weeks, 95); % negatively skewed

skew4KW_16th_20th = skewness(Mom16th_20th.MomHold4Weeks);
histogram(Mom16th_20th.MomHold4Weeks, 95); % negatively skewed

skew4KW_21st_25th = skewness(Mom21st_25th.MomHold4Weeks);
histogram(Mom21st_25th.MomHold4Weeks, 95); % negatively skewed -0.3198
/ rather centered d'wise

skew4KW_26th_31st = skewness(Mom26th_31st.MomHold4Weeks);
histogram(Mom26th_31st.MomHold4Weeks, 95); % negatively skewed

% 12-Week Momentum
skew12KW_1st_5th = skewness(Mom1st_5th.MomHold12Weeks); % -0.4981
histogram(Mom1st_5th.MomHold12Weeks, 95); % negatively skewed

skew12KW_6th_10th = skewness(Mom6th_10th.MomHold12Weeks) % -1.4098
histogram(Mom6th_10th.MomHold12Weeks, 95); % negatively skewed

skew12KW_11th_15th = skewness(Mom11th_15th.MomHold12Weeks) % -2.3715
histogram(Mom11th_15th.MomHold12Weeks, 95); % negatively skewed

skew12KW_16th_20th = skewness(Mom16th_20th.MomHold12Weeks) % -2.0119
histogram(Mom16th_20th.MomHold12Weeks, 95); % negatively skewed

skew12KW_21st_25th = skewness(Mom21st_25th.MomHold12Weeks) % +0.3916
histogram(Mom21st_25th.MomHold12Weeks, 95); % positively skewed

skew12KW_26th_31st = skewness(Mom26th_31st.MomHold12Weeks) % -1.6132
histogram(Mom26th_31st.MomHold12Weeks, 95); % negatively skewed

% 24-Week Momentum
skew24KW_1st_5th = skewness(Mom1st_5th.MomHold24Weeks) % -1.4918
histogram(Mom1st_5th.MomHold24Weeks, 95); % negatively skewed

skew24KW_6th_10th = skewness(Mom6th_10th.MomHold24Weeks) % -1.8620
histogram(Mom6th_10th.MomHold24Weeks, 95); % negatively skewed
```

```
skew24KW_11th_15th = skewness(Mom11th_15th.MomHold24Weeks) % -2.4853
histogram(Mom11th_15th.MomHold24Weeks, 95); % negatively skewed

skew24KW_16th_20th = skewness(Mom16th_20th.MomHold24Weeks) % -2.3949
histogram(Mom16th_20th.MomHold24Weeks, 95); % negatively skewed

skew24KW_21st_25th = skewness(Mom21st_25th.MomHold24Weeks) % -0.7179
histogram(Mom21st_25th.MomHold24Weeks, 95); % negatively skewed

skew24KW_26th_31st = skewness(Mom26th_31st.MomHold24Weeks) % -2.2518
histogram(Mom26th_31st.MomHold24Weeks, 95); % negatively skewed

% Overview
LL = [{skew4KW_1st_5th skew4KW_6th_10th skew4KW_11th_15th
skew4KW_16th_20th ...
    skew4KW_21st_25th skew4KW_26th_31st};...
    {skew12KW_1st_5th skew12KW_6th_10th skew12KW_11th_15th
skew12KW_16th_20th ...
    skew12KW_21st_25th skew12KW_26th_31st};...
    {skew24KW_1st_5th skew24KW_6th_10th skew24KW_11th_15th
skew24KW_16th_20th ...
    skew24KW_21st_25th skew24KW_26th_31st}];
SkewforKWtesting = cell2table(LL);
SkewforKWtesting.Properties.VariableNames = {'From_1st_5th' ...
    'From_6th_10th' 'From_11th_15th' 'From_16th_20th' 'From_21st_25th'
... 'From_26th_31st'};
SkewforKWtesting.Properties.RowNames = {'4Weeks' ...
    '12Weeks' '24Weeks'};
writetable(SkewforKWtesting, 'SkewforKWtestingWeekEffect.xlsx')

% Kruskal-Wallis Test for the 4-Week Momentum Scenario
KruskalWallis4w_WeekEffect = [Mom1st_5th_4wAdj*100, ...
    Mom6th_10th_4wAdj*100, Mom11th_15th_4wAdj*100, ...
    Mom16th_20th_4wAdj*100, Mom21st_25th_4wAdj*100, ...
    Mom26th_31st_4wAdj*100];
p_KW4w_WeekEffect = kruskalwallis(KruskalWallis4w_WeekEffect)
ylabel('% Return')
xlabel('Week Effect')
% result: p = 0.98

% Kruskal-Wallis Test for the 12-Week Momentum Scenario
KruskalWallis12w_WeekEffect = [Mom1st_5th_12wAdj*100, ...
    Mom6th_10th_12wAdj*100, Mom11th_15th_12wAdj*100, ...
    Mom16th_20th_12wAdj*100, Mom21st_25th_12wAdj*100, ...
    Mom26th_31st_12wAdj*100];
p_KW12w_WeekEffect = kruskalwallis(KruskalWallis12w_WeekEffect)
ylabel('% Return')
xlabel('Week-Effect')
% result: P = 0.88

% Kruskal-Wallis Test for the 24-Week Momentum Scenario
KruskalWallis24w_WeekEffect = [Mom1st_5th_24wAdj*100, ...
    Mom6th_10th_24wAdj*100, Mom11th_15th_24wAdj*100, ...
    Mom16th_20th_24wAdj*100, Mom21st_25th_24wAdj*100, ...
    Mom26th_31st_24wAdj*100];
p_KW24w_WeekEffect = kruskalwallis(KruskalWallis24w_WeekEffect)
```

```
ylabel('% Return')
xlabel('Week-Effect')
% result: P = 0.89

% Summary of p-values for Kruskal-Wallis test outcomes
KK = table(p_KW4w_WeekEffect, p_KW12w_WeekEffect, p_KW24w_WeekEffect);
KK.Properties.VariableNames = {'WeekEffect_4Mom_Setup' ...
    'WeekEffect_12Mom_Setup' 'WeekEffect_24Mom_Setup'};
KK.Properties.RowNames = {'p_value'};
writetable(KK, 'KW_WeekEffect.xlsx')



% E.3 Month-Effect
% ----------------------------------------------------------------------

% Idea: how well do momentum strategies work, depending on the month
% they are launched at?

% Descriptive Statistics January
MeanMom4_JAN = nanmean(MomJAN.MomHold4Weeks);
MeanMom12_JAN = nanmean(MomJAN.MomHold12Weeks);
MeanMom24_JAN = nanmean(MomJAN.MomHold24Weeks);
StdDevMom4_JAN = nanstd(MomJAN.MomHold4Weeks);
StdDevMom12_JAN = nanstd(MomJAN.MomHold12Weeks);
StdDevMom24_JAN = nanstd(MomJAN.MomHold24Weeks);

% Descriptive Statistics February
MeanMom4_FEB = nanmean(MomFEB.MomHold4Weeks);
MeanMom12_FEB = nanmean(MomFEB.MomHold12Weeks);
MeanMom24_FEB = nanmean(MomFEB.MomHold24Weeks);
StdDevMom4_FEB = nanstd(MomFEB.MomHold4Weeks);
StdDevMom12_FEB = nanstd(MomFEB.MomHold12Weeks);
StdDevMom24_FEB = nanstd(MomFEB.MomHold24Weeks);

% Descriptive Statistics March
MeanMom4_MAR = nanmean(MomMAR.MomHold4Weeks);
MeanMom12_MAR = nanmean(MomMAR.MomHold12Weeks);
MeanMom24_MAR = nanmean(MomMAR.MomHold24Weeks);
StdDevMom4_MAR = nanstd(MomMAR.MomHold4Weeks);
StdDevMom12_MAR = nanstd(MomMAR.MomHold12Weeks);
StdDevMom24_MAR = nanstd(MomMAR.MomHold24Weeks);

% Descriptive Statistics April
MeanMom4_APR = nanmean(MomAPR.MomHold4Weeks);
MeanMom12_APR = nanmean(MomAPR.MomHold12Weeks);
MeanMom24_APR = nanmean(MomAPR.MomHold24Weeks);
StdDevMom4_APR = nanstd(MomAPR.MomHold4Weeks);
StdDevMom12_APR = nanstd(MomAPR.MomHold12Weeks);
StdDevMom24_APR = nanstd(MomAPR.MomHold24Weeks);

% Descriptive Statistics May
MeanMom4_MAY = nanmean(MomMAY.MomHold4Weeks);
MeanMom12_MAY = nanmean(MomMAY.MomHold12Weeks);
MeanMom24_MAY = nanmean(MomMAY.MomHold24Weeks);
StdDevMom4_MAY = nanstd(MomMAY.MomHold4Weeks);
```

```
StdDevMom12_MAY = nanstd(MomMAY.MomHold12Weeks);
StdDevMom24_MAY = nanstd(MomMAY.MomHold24Weeks);

% Descriptive Statistics June
MeanMom4_JUN = nanmean(MomJUN.MomHold4Weeks);
MeanMom12_JUN = nanmean(MomJUN.MomHold12Weeks);
MeanMom24_JUN = nanmean(MomJUN.MomHold24Weeks);
StdDevMom4_JUN = nanstd(MomJUN.MomHold4Weeks);
StdDevMom12_JUN = nanstd(MomJUN.MomHold12Weeks);
StdDevMom24_JUN = nanstd(MomJUN.MomHold24Weeks);

% Descriptive Statistics July
MeanMom4_JUL = nanmean(MomJUL.MomHold4Weeks);
MeanMom12_JUL = nanmean(MomJUL.MomHold12Weeks);
MeanMom24_JUL = nanmean(MomJUL.MomHold24Weeks);
StdDevMom4_JUL = nanstd(MomJUL.MomHold4Weeks);
StdDevMom12_JUL = nanstd(MomJUL.MomHold12Weeks);
StdDevMom24_JUL = nanstd(MomJUL.MomHold24Weeks);

% Descriptive Statistics August
MeanMom4_AUG = nanmean(MomAUG.MomHold4Weeks);
MeanMom12_AUG = nanmean(MomAUG.MomHold12Weeks);
MeanMom24_AUG = nanmean(MomAUG.MomHold24Weeks);
StdDevMom4_AUG = nanstd(MomAUG.MomHold4Weeks);
StdDevMom12_AUG = nanstd(MomAUG.MomHold12Weeks);
StdDevMom24_AUG = nanstd(MomAUG.MomHold24Weeks);

% Descriptive Statistics September
MeanMom4_SEP = nanmean(MomSEP.MomHold4Weeks);
MeanMom12_SEP = nanmean(MomSEP.MomHold12Weeks);
MeanMom24_SEP = nanmean(MomSEP.MomHold24Weeks);
StdDevMom4_SEP = nanstd(MomSEP.MomHold4Weeks);
StdDevMom12_SEP = nanstd(MomSEP.MomHold12Weeks);
StdDevMom24_SEP = nanstd(MomSEP.MomHold24Weeks);

% Descriptive Statistics October
MeanMom4_OCT = nanmean(MomOCT.MomHold4Weeks);
MeanMom12_OCT = nanmean(MomOCT.MomHold12Weeks);
MeanMom24_OCT = nanmean(MomOCT.MomHold24Weeks);
StdDevMom4_OCT = nanstd(MomOCT.MomHold4Weeks);
StdDevMom12_OCT = nanstd(MomOCT.MomHold12Weeks);
StdDevMom24_OCT = nanstd(MomOCT.MomHold24Weeks);

% Descriptive Statistics November
MeanMom4_NOV = nanmean(MomNOV.MomHold4Weeks);
MeanMom12_NOV = nanmean(MomNOV.MomHold12Weeks);
MeanMom24_NOV = nanmean(MomNOV.MomHold24Weeks);
StdDevMom4_NOV = nanstd(MomNOV.MomHold4Weeks);
StdDevMom12_NOV = nanstd(MomNOV.MomHold12Weeks);
StdDevMom24_NOV = nanstd(MomNOV.MomHold24Weeks);

% Descriptive Statistics December
MeanMom4_DEC = nanmean(MomDEC.MomHold4Weeks);
MeanMom12_DEC = nanmean(MomDEC.MomHold12Weeks);
MeanMom24_DEC = nanmean(MomDEC.MomHold24Weeks);
StdDevMom4_DEC = nanstd(MomDEC.MomHold4Weeks);
StdDevMom12_DEC = nanstd(MomDEC.MomHold12Weeks);
```

```
StdDevMom24_DEC = nanstd(MomDEC.MomHold24Weeks);

% Annualizing of the findings (mean) and creating overview table
FF = [{MeanMom4_JAN*13 MeanMom4_FEB*13 MeanMom4_MAR*13 MeanMom4_APR*13
... MeanMom4_MAY*13 MeanMom4_JUN*13 MeanMom4_JUL*13 MeanMom4_AUG*13 ...
    MeanMom4_SEP*13 MeanMom4_OCT*13 MeanMom4_NOV*13
MeanMom4_DEC*13};...
    {MeanMom12_JAN*(13/3) MeanMom12_FEB*(13/3) MeanMom12_MAR*(13/3) ...
    MeanMom12_APR*(13/3) MeanMom12_MAY*(13/3) MeanMom12_JUN*(13/3) ...
    MeanMom12_JUL*(13/3) MeanMom12_AUG*(13/3) MeanMom12_SEP*(13/3) ...
    MeanMom12_OCT*(13/3) MeanMom12_NOV*(13/3) MeanMom12_DEC*(13/3)};...
    {MeanMom24_JAN*(13/6) MeanMom24_FEB*(13/6) MeanMom24_MAR*(13/6) ...
    MeanMom24_APR*(13/6) MeanMom24_MAY*(13/6) MeanMom24_JUN*(13/6) ...
    MeanMom24_JUL*(13/6) MeanMom24_AUG*(13/6) MeanMom24_SEP*(13/6) ...
    MeanMom24_OCT*(13/6) MeanMom24_NOV*(13/6) MeanMom24_DEC*(13/6)}];
MonthlyMeanOverview_annualized = cell2table(FF);
MonthlyMeanOverview_annualized.Properties.VariableNames = {'January'
... 'February' 'March' 'April' 'May' 'June' 'July' 'August' 'September'
... 'October' 'November' 'December'};
MonthlyMeanOverview_annualized.Properties.RowNames = {'4Weeks' ...
    '12Weeks' '24Weeks'};
writetable(MonthlyMeanOverview_annualized, ...
    'MonthlyMeanOverview_annualized.xlsx')

% Annualizing of the findings (std. dev.) and creating overview table
GG=[{StdDevMom4_JAN*sqrt(13) StdDevMom4_FEB*sqrt(13) ...
    StdDevMom4_MAR*sqrt(13) StdDevMom4_APR*sqrt(13) ...
    StdDevMom4_MAY*sqrt(13) StdDevMom4_JUN*sqrt(13) ...
    StdDevMom4_JUL*sqrt(13) StdDevMom4_AUG*sqrt(13) ...
    StdDevMom4_SEP*sqrt(13) StdDevMom4_OCT*sqrt(13) ...
    StdDevMom4_NOV*sqrt(13) StdDevMom4_DEC*sqrt(13)}; ...
    {StdDevMom12_JAN*sqrt(13/3) StdDevMom12_FEB*sqrt(13/3) ...
    StdDevMom12_MAR*sqrt(13/3) StdDevMom12_APR*sqrt(13/3) ...
    StdDevMom12_MAY*sqrt(13/3) StdDevMom12_JUN*sqrt(13/3) ...
    StdDevMom12_JUL*sqrt(13/3) StdDevMom12_AUG*sqrt(13/3) ...
    StdDevMom12_SEP*sqrt(13/3) StdDevMom12_OCT*sqrt(13/3) ...
    StdDevMom12_NOV*sqrt(13/3) StdDevMom12_DEC*sqrt(13/3)};...
    {StdDevMom24_JAN*sqrt(13/6) StdDevMom24_FEB*sqrt(13/6) ...
    StdDevMom24_MAR*sqrt(13/6) StdDevMom24_APR*sqrt(13/6) ...
    StdDevMom24_MAY*sqrt(13/6) StdDevMom24_JUN*sqrt(13/6) ...
    StdDevMom24_JUL*sqrt(13/6) StdDevMom24_AUG*sqrt(13/6) ...
    StdDevMom24_SEP*sqrt(13/6) StdDevMom24_OCT*sqrt(13/6) ...
    StdDevMom24_NOV*sqrt(13/6) StdDevMom24_DEC*sqrt(13/6)}];
MonthlyStdDevOverview_annualized=cell2table(GG);
MonthlyStdDevOverview_annualized.Properties.VariableNames= {'January'
... 'February' 'March' 'April' 'May' 'June' 'July' 'August' 'September'
... 'October' 'November' 'December'};
MonthlyStdDevOverview_annualized.Properties.RowNames = {'4Weeks' ...
    '12Weeks' '24Weeks'}
writetable(MonthlyStdDevOverview_annualized, ...
    'MonthlyStdDevOverview_annualized.xlsx')

% Beta's (Month-to-Month)
% For the sake of brevity, no distinction is made between pre- and
% post-crisis // Not shown in main section of thesis

% January
```

```
JANmkt_4w = MomJAN.Rm4Weeks - MomJAN.Rf4Weeks;
JAN_4w = MomJAN.MomHold4Weeks - MomJAN.Rf4Weeks;
JANmdl_4w = LinearModel.fit(JANmkt_4w, JAN_4w)

JANmkt_12w = MomJAN.Rm12Weeks - MomJAN.Rf12Weeks;
JAN_12w = MomJAN.MomHold12Weeks - MomJAN.Rf12Weeks;
JANmdl_12w = LinearModel.fit(JANmkt_12w, JAN_12w)

JANmkt_24w = MomJAN.Rm24Weeks - MomJAN.Rf24Weeks;
JAN_24w = MomJAN.MomHold24Weeks - MomJAN.Rf24Weeks;
JANmdl_24w = LinearModel.fit(JANmkt_24w, JAN_24w)

% February
FEBmkt_4w = MomFEB.Rm4Weeks - MomFEB.Rf4Weeks;
FEB_4w = MomFEB.MomHold4Weeks - MomFEB.Rf4Weeks;
FEBmdl_4w = LinearModel.fit(FEBmkt_4w, FEB_4w)

FEBmkt_12w = MomFEB.Rm12Weeks - MomFEB.Rf12Weeks;
FEB_12w = MomFEB.MomHold12Weeks - MomFEB.Rf12Weeks;
FEBmdl_12w = LinearModel.fit(FEBmkt_12w, FEB_12w)

FEBmkt_24w = MomFEB.Rm24Weeks - MomFEB.Rf24Weeks;
FEB_24w = MomFEB.MomHold24Weeks - MomFEB.Rf24Weeks;
FEBmdl_24w = LinearModel.fit(FEBmkt_24w, FEB_24w)

% March
MARmkt_4w = MomMAR.Rm4Weeks - MomMAR.Rf4Weeks;
MAR_4w = MomMAR.MomHold4Weeks - MomMAR.Rf4Weeks;
MARmdl_4w = LinearModel.fit(MARmkt_4w, MAR_4w)

MARmkt_12w = MomMAR.Rm12Weeks - MomMAR.Rf12Weeks;
MAR_12w = MomMAR.MomHold12Weeks - MomMAR.Rf12Weeks;
MARmdl_12w = LinearModel.fit(MARmkt_12w, MAR_12w)

MARmkt_24w = MomMAR.Rm24Weeks - MomMAR.Rf24Weeks;
MAR_24w = MomMAR.MomHold24Weeks - MomMAR.Rf24Weeks;
MARmdl_24w = LinearModel.fit(MARmkt_24w, MAR_24w)

% April
APRmkt_4w = MomAPR.Rm4Weeks - MomAPR.Rf4Weeks;
APR_4w = MomAPR.MomHold4Weeks - MomAPR.Rf4Weeks;
APRmdl_4w = LinearModel.fit(APRmkt_4w, APR_4w)

APRmkt_12w = MomAPR.Rm12Weeks - MomAPR.Rf12Weeks;
APR_12w = MomAPR.MomHold12Weeks - MomAPR.Rf12Weeks;
APRmdl_12w = LinearModel.fit(APRmkt_12w, APR_12w)

APRmkt_24w = MomAPR.Rm24Weeks - MomAPR.Rf24Weeks;
APR_24w = MomAPR.MomHold24Weeks - MomAPR.Rf24Weeks;
APRmdl_24w = LinearModel.fit(APRmkt_24w, APR_24w)

% May
MAYmkt_4w = MomMAY.Rm4Weeks - MomMAY.Rf4Weeks;
MAY_4w = MomMAY.MomHold4Weeks - MomMAY.Rf4Weeks;
MAYmdl_4w = LinearModel.fit(MAYmkt_4w, MAY_4w)
```

```
MAYmkt_12w = MomMAY.Rm12Weeks - MomMAY.Rf12Weeks;
MAY_12w = MomMAY.MomHold12Weeks - MomMAY.Rf12Weeks;
MAYmdl_12w = LinearModel.fit(MAYmkt_12w, MAY_12w)

MAYmkt_24w = MomMAY.Rm24Weeks - MomMAY.Rf24Weeks;
MAY_24w = MomMAY.MomHold24Weeks - MomMAY.Rf24Weeks;
MAYmdl_24w = LinearModel.fit(MAYmkt_24w, MAY_24w)

% June
JUNmkt_4w = MomJUN.Rm4Weeks - MomJUN.Rf4Weeks;
JUN_4w = MomJUN.MomHold4Weeks - MomJUN.Rf4Weeks;
JUNmdl_4w = LinearModel.fit(JUNmkt_4w, JUN_4w)

JUNmkt_12w = MomJUN.Rm12Weeks - MomJUN.Rf12Weeks;
JUN_12w = MomJUN.MomHold12Weeks - MomJUN.Rf12Weeks;
JUNmdl_12w = LinearModel.fit(JUNmkt_12w, JUN_12w)

JUNmkt_24w = MomJUN.Rm24Weeks - MomJUN.Rf24Weeks;
JUN_24w = MomJUN.MomHold24Weeks - MomJUN.Rf24Weeks;
JUNmdl_24w = LinearModel.fit(JUNmkt_24w, JUN_24w)

% July
JULmkt_4w = MomJUL.Rm4Weeks - MomJUL.Rf4Weeks;
JUL_4w = MomJUL.MomHold4Weeks - MomJUL.Rf4Weeks;
JULmdl_4w = LinearModel.fit(JULmkt_4w, JUL_4w)

JULmkt_12w = MomJUL.Rm12Weeks - MomJUL.Rf12Weeks;
JUL_12w = MomJUL.MomHold12Weeks - MomJUL.Rf12Weeks;
JULmdl_12w = LinearModel.fit(JULmkt_12w, JUL_12w)

JULmkt_24w = MomJUL.Rm24Weeks - MomJUL.Rf24Weeks;
JUL_24w = MomJUL.MomHold24Weeks - MomJUL.Rf24Weeks;
JULmdl_24w = LinearModel.fit(JULmkt_24w, JUL_24w)

% August
AUGmkt_4w = MomAUG.Rm4Weeks - MomAUG.Rf4Weeks;
AUG_4w = MomAUG.MomHold4Weeks - MomAUG.Rf4Weeks;
AUGmdl_4w = LinearModel.fit(AUGmkt_4w, AUG_4w)

AUGmkt_12w = MomAUG.Rm12Weeks - MomAUG.Rf12Weeks;
AUG_12w = MomAUG.MomHold12Weeks - MomAUG.Rf12Weeks;
AUGmdl_12w = LinearModel.fit(AUGmkt_12w, AUG_12w)

AUGmkt_24w = MomAUG.Rm24Weeks - MomAUG.Rf24Weeks;
AUG_24w = MomAUG.MomHold24Weeks - MomAUG.Rf24Weeks;
AUGmdl_24w = LinearModel.fit(AUGmkt_24w, AUG_24w)

% September
SEPmkt_4w = MomSEP.Rm4Weeks - MomSEP.Rf4Weeks;
SEP_4w = MomSEP.MomHold4Weeks - MomSEP.Rf4Weeks;
SEPmdl_4w = LinearModel.fit(SEPmkt_4w, SEP_4w)

SEPmkt_12w = MomSEP.Rm12Weeks - MomSEP.Rf12Weeks;
SEP_12w = MomSEP.MomHold12Weeks - MomSEP.Rf12Weeks;
SEPmdl_12w = LinearModel.fit(SEPmkt_12w, SEP_12w)
```

```
SEPmkt_24w = MomSEP.Rm24Weeks - MomSEP.Rf24Weeks;
SEP_24w = MomSEP.MomHold24Weeks - MomSEP.Rf24Weeks;
SEPmdl_24w = LinearModel.fit(SEPmkt_24w, SEP_24w)

% October
OCTmkt_4w = MomOCT.Rm4Weeks - MomOCT.Rf4Weeks;
OCT_4w = MomOCT.MomHold4Weeks - MomOCT.Rf4Weeks;
OCTmdl_4w = LinearModel.fit(OCTmkt_4w, OCT_4w)

OCTmkt_12w = MomOCT.Rm12Weeks - MomOCT.Rf12Weeks;
OCT_12w = MomOCT.MomHold12Weeks - MomOCT.Rf12Weeks;
OCTmdl_12w = LinearModel.fit(OCTmkt_12w, OCT_12w)

OCTmkt_24w = MomOCT.Rm24Weeks - MomOCT.Rf24Weeks;
OCT_24w = MomOCT.MomHold24Weeks - MomOCT.Rf24Weeks;
OCTmdl_24w = LinearModel.fit(OCTmkt_24w, OCT_24w)

% November
NOVmkt_4w = MomNOV.Rm4Weeks - MomNOV.Rf4Weeks;
NOV_4w = MomNOV.MomHold4Weeks - MomNOV.Rf4Weeks;
NOVmdl_4w = LinearModel.fit(NOVmkt_4w, NOV_4w)

NOVmkt_12w = MomNOV.Rm12Weeks - MomNOV.Rf12Weeks;
NOV_12w = MomNOV.MomHold12Weeks - MomNOV.Rf12Weeks;
NOVmdl_12w = LinearModel.fit(NOVmkt_12w, NOV_12w)

NOVmkt_24w = MomNOV.Rm24Weeks - MomNOV.Rf24Weeks;
NOV_24w = MomNOV.MomHold24Weeks - MomNOV.Rf24Weeks;
NOVmdl_24w = LinearModel.fit(NOVmkt_24w, NOV_24w)

% December
DECmkt_4w = MomDEC.Rm4Weeks - MomDEC.Rf4Weeks;
DEC_4w = MomDEC.MomHold4Weeks - MomDEC.Rf4Weeks;
DECmdl_4w = LinearModel.fit(DECmkt_4w, DEC_4w)

DECmkt_12w = MomDEC.Rm12Weeks - MomDEC.Rf12Weeks;
DEC_12w = MomDEC.MomHold12Weeks - MomDEC.Rf12Weeks;
DECmdl_12w = LinearModel.fit(DECmkt_12w, DEC_12w)

DECmkt_24w = MomDEC.Rm24Weeks - MomDEC.Rf24Weeks;
DEC_24w = MomDEC.MomHold24Weeks - MomDEC.Rf24Weeks;
DECmdl_24w = LinearModel.fit(DECmkt_24w, DEC_24w)

% Report in an overtiew table // don't show in main section of thesis
HH=[{JANmdl_4w.Coefficients.Estimate(2)
FEBmdl_4w.Coefficients.Estimate(2) ...
    MARmdl_4w.Coefficients.Estimate(2)
APRmdl_4w.Coefficients.Estimate(2) ...
    MAYmdl_4w.Coefficients.Estimate(2)
JUNmdl_4w.Coefficients.Estimate(2) ...
    JULmdl_4w.Coefficients.Estimate(2)
AUGmdl_4w.Coefficients.Estimate(2) ...
    SEPmdl_4w.Coefficients.Estimate(2)
OCTmdl_4w.Coefficients.Estimate(2) ...
    NOVmdl_4w.Coefficients.Estimate(2)
DECmdl_4w.Coefficients.Estimate(2)}; ...
```

```
    {JANmdl_12w.Coefficients.Estimate(2)
FEBmdl_12w.Coefficients.Estimate(2) ...
    MARmdl_12w.Coefficients.Estimate(2)
APRmdl_12w.Coefficients.Estimate(2) ...
    MAYmdl_12w.Coefficients.Estimate(2)
JUNmdl_12w.Coefficients.Estimate(2) ...
    JULmdl_12w.Coefficients.Estimate(2)
AUGmdl_12w.Coefficients.Estimate(2) ...
    SEPmdl_12w.Coefficients.Estimate(2)
OCTmdl_12w.Coefficients.Estimate(2) ...
    NOVmdl_12w.Coefficients.Estimate(2)
DECmdl_12w.Coefficients.Estimate(2)}; ...
    {JANmdl_24w.Coefficients.Estimate(2)
FEBmdl_24w.Coefficients.Estimate(2) ...
    MARmdl_24w.Coefficients.Estimate(2)
APRmdl_24w.Coefficients.Estimate(2) ...
    MAYmdl_24w.Coefficients.Estimate(2)
JUNmdl_24w.Coefficients.Estimate(2) ...
    JULmdl_24w.Coefficients.Estimate(2)
AUGmdl_24w.Coefficients.Estimate(2) ...
    SEPmdl_24w.Coefficients.Estimate(2)
OCTmdl_24w.Coefficients.Estimate(2) ...
    NOVmdl_24w.Coefficients.Estimate(2)
DECmdl_24w.Coefficients.Estimate(2)}];
BetaMonthToMonth=cell2table(HH);
BetaMonthToMonth.Properties.VariableNames= {'January' 'February'
'March' 'April' 'May' 'June' 'July' 'August' 'September' 'October'
'November' 'December'};
BetaMonthToMonth.Properties.RowNames = {'4-Week Momentum' '12-Week
Momentum' ...
    '24-Week Momentum'}
write(BetaMonthToMonth, 'BetaMonthToMonth.xlsx');


% Sharpe Ratios (Month-to-Month)
% January
SharpeJAN_4w = sharpe(MomJAN.MomHold4Weeks(1:end,:), ...
    MomJAN.Rf4Weeks(1:end,:)); % returns negative SR (!)
SharpeJAN_12w = sharpe(MomJAN.MomHold12Weeks(1:end,:), ...
    MomJAN.Rf12Weeks(1:end,:)); % returns negative SR (!)
SharpeJAN_24w = sharpe(MomJAN.MomHold24Weeks(1:end,:), ...
    MomJAN.Rf24Weeks(1:end,:)); % positive SR here

% February
SharpeFEB_4w = sharpe(MomFEB.MomHold4Weeks(1:end,:), ...
    MomFEB.Rf4Weeks(1:end,:));
SharpeFEB_12w = sharpe(MomFEB.MomHold12Weeks(1:end,:), ...
    MomFEB.Rf12Weeks(1:end,:));
SharpeFEB_24w = sharpe(MomFEB.MomHold24Weeks(1:end,:), ...
    MomFEB.Rf24Weeks(1:end,:));

% March
SharpeMAR_4w = sharpe(MomMAR.MomHold4Weeks(1:end,:), ...
    MomMAR.Rf4Weeks(1:end,:));
SharpeMAR_12w = sharpe(MomMAR.MomHold12Weeks(1:end,:), ...
    MomMAR.Rf12Weeks(1:end,:));
SharpeMAR_24w = sharpe(MomMAR.MomHold24Weeks(5:end,:), ...
```

```
    MomMAR.Rf24Weeks(5:end,:));

% April
SharpeAPR_4w = sharpe(MomAPR.MomHold4Weeks(1:end,:), ...
    MomAPR.Rf4Weeks(1:end,:));
SharpeAPR_12w = sharpe(MomAPR.MomHold12Weeks(1:end,:), ...
    MomAPR.Rf12Weeks(1:end,:));
SharpeAPR_24w = sharpe(MomAPR.MomHold24Weeks(6:end,:), ...
    MomAPR.Rf24Weeks(6:end,:));

% May
SharpeMAY_4w = sharpe(MomMAY.MomHold4Weeks(1:end,:), ...
    MomMAY.Rf4Weeks(1:end,:));
SharpeMAY_12w = sharpe(MomMAY.MomHold12Weeks(2:end,:), ...
    MomMAY.Rf12Weeks(2:end,:));
SharpeMAY_24w = sharpe(MomMAY.MomHold24Weeks(5:end,:), ...
    MomMAY.Rf24Weeks(5:end,:));

% June
SharpeJUN_4w = sharpe(MomJUN.MomHold4Weeks(1:end,:), ...
    MomJUN.Rf4Weeks(1:end,:));
SharpeJUN_12w = sharpe(MomJUN.MomHold12Weeks(5:end,:), ...
    MomJUN.Rf12Weeks(5:end,:));
SharpeJUN_24w = sharpe(MomJUN.MomHold24Weeks(5:end,:), ...
    MomJUN.Rf24Weeks(5:end,:));

% July
SharpeJUL_4w = sharpe(MomJUL.MomHold4Weeks(3:end,:), ...
    MomJUL.Rf4Weeks(3:end,:));
SharpeJUL_12w = sharpe(MomJUL.MomHold12Weeks(6:end,:), ...
    MomJUL.Rf12Weeks(6:end,:));
SharpeJUL_24w = sharpe(MomJUL.MomHold24Weeks(6:end,:), ...
    MomJUL.Rf24Weeks(6:end,:));

% August
SharpeAUG_4w = sharpe(MomAUG.MomHold4Weeks(2:end,:), ...
    MomAUG.Rf4Weeks(2:end,:));
SharpeAUG_12w = sharpe(MomAUG.MomHold12Weeks(2:end,:), ...
    MomAUG.Rf12Weeks(2:end,:));
SharpeAUG_24w = sharpe(MomAUG.MomHold24Weeks(2:end,:), ...
    MomAUG.Rf24Weeks(2:end,:));

% September
SharpeSEP_4w = sharpe(MomSEP.MomHold4Weeks(1:end,:), ...
    MomSEP.Rf4Weeks(1:end,:));
SharpeSEP_12w = sharpe(MomSEP.MomHold12Weeks(1:end,:), ...
    MomSEP.Rf12Weeks(1:end,:));
SharpeSEP_24w = sharpe(MomSEP.MomHold24Weeks(1:end,:), ...
    MomSEP.Rf24Weeks(1:end,:));

% October
SharpeOCT_4w = sharpe(MomOCT.MomHold4Weeks(1:end,:), ...
    MomOCT.Rf4Weeks(1:end,:));
SharpeOCT_12w = sharpe(MomOCT.MomHold12Weeks(1:end,:), ...
    MomOCT.Rf12Weeks(1:end,:));
SharpeOCT_24w = sharpe(MomOCT.MomHold24Weeks(1:end,:), ...
    MomOCT.Rf24Weeks(1:end,:));
```

```
% November
SharpeNOV_4w = sharpe(MomNOV.MomHold4Weeks(1:end,:), ...
    MomNOV.Rf4Weeks(1:end,:));
SharpeNOV_12w = sharpe(MomNOV.MomHold12Weeks(1:end,:), ...
    MomNOV.Rf12Weeks(1:end,:));
SharpeNOV_24w = sharpe(MomNOV.MomHold24Weeks(1:end,:), ...
    MomNOV.Rf24Weeks(1:end,:));

% December
SharpeDEC_4w = sharpe(MomDEC.MomHold4Weeks(1:end,:), ...
    MomDEC.Rf4Weeks(1:end,:));
SharpeDEC_12w = sharpe(MomDEC.MomHold12Weeks(1:end,:), ...
    MomDEC.Rf12Weeks(1:end,:));
SharpeDEC_24w = sharpe(MomDEC.MomHold24Weeks(1:end,:), ...
    MomDEC.Rf24Weeks(1:end,:));

% Month-to-Month Sharpe Ratio (annualized) summary in matrix form
II=[{SharpeJAN_4w*sqrt(13) SharpeFEB_4w*sqrt(13) SharpeMAR_4w*sqrt(13)
... SharpeAPR_4w*sqrt(13) SharpeMAY_4w*sqrt(13) SharpeJUN_4w*sqrt(13)
... SharpeJUL_4w*sqrt(13) SharpeAUG_4w*sqrt(13) SharpeSEP_4w*sqrt(13)
... SharpeOCT_4w*sqrt(13) SharpeNOV_4w*sqrt(13)
    SharpeDEC_4w*sqrt(13)};...
    {SharpeJAN_12w*sqrt(13/3) SharpeFEB_12w*sqrt(13/3) ...
    SharpeMAR_12w*sqrt(13/3) SharpeAPR_12w*sqrt(13/3) ...
    SharpeMAY_12w*sqrt(13/3) SharpeJUN_12w*sqrt(13/3) ...
    SharpeJUL_12w*sqrt(13/3) SharpeAUG_12w*sqrt(13/3) ...
    SharpeSEP_12w*sqrt(13/3) SharpeOCT_12w*sqrt(13/3) ...
    SharpeNOV_12w*sqrt(13/3) SharpeDEC_12w*sqrt(13/3)};...
    {SharpeJAN_24w*sqrt(13/6) SharpeFEB_24w*sqrt(13/6) ...
    SharpeMAR_24w*sqrt(13/6) SharpeAPR_24w*sqrt(13/6) ...
    SharpeMAY_24w*sqrt(13/6) SharpeJUN_24w*sqrt(13/6) ...
    SharpeJUL_24w*sqrt(13/6) SharpeAUG_24w*sqrt(13/6) ...
    SharpeSEP_24w*sqrt(13/6) SharpeOCT_24w*sqrt(13/6) ...
    SharpeNOV_24w*sqrt(13/6) SharpeDEC_24w*sqrt(13/6)}];
MonthToMonthSharpeOverview = cell2table(II);
MonthToMonthSharpeOverview.Properties.VariableNames= {'January' ...
    'February' 'March' 'April' 'May' 'June' 'July' 'August' 'September'
... 'October' 'November' 'December'};
MonthToMonthSharpeOverview.Properties.RowNames = {'4Weeks' '12Weeks'
... '24Weeks'}
write(MonthToMonthSharpeOverview, 'MonthToMonthSharpeOverview.xlsx');


% ANOVA techniques test whether a set of group means (treatment
% effects) are equal or not. Rejection of the null hypothesis leads to
% the conclusion that not all group means are the same. This result,
% however, does not provide further information on which group means
% are different. Performing a series of t-tests to determine which
% pairs of means are significantly different is not recommended. When
% you perform multiple t-tests, the probability that the means appear
% significant, and significant difference results might be due to large
% number of tests. These t-tests use the data from the same sample,
% hence they are not independent. This fact makes it more difficult to
% quantify the level of significance for multiple tests.

% Prepare for ANOVA treatment
```

```
MomJAN_adj4w = MomJAN.MomHold4Weeks;
MomJAN_adj4w(48:49,:) = 0;
MomJAN_adj12w = MomJAN.MomHold12Weeks;
MomJAN_adj12w(48:49,:) = 0;
MomJAN_adj24w = MomJAN.MomHold24Weeks;
MomJAN_adj24w(48:49,:) = 0;

MomFEB_adj4w = MomFEB.MomHold4Weeks;
MomFEB_adj4w(46:49,:) = 0;
MomFEB_adj12w = MomFEB.MomHold12Weeks;
MomFEB_adj12w(46:49,:) = 0;
MomFEB_adj24w = MomFEB.MomHold24Weeks;
MomFEB_adj24w(46:49,:) = 0;

MomMAR_adj4w = MomMAR.MomHold4Weeks;
MomMAR_adj4w(49:49,:) = 0;
MomMAR_adj12w = MomMAR.MomHold12Weeks;
MomMAR_adj12w(49:49,:) = 0;
MomMAR_adj24w = MomMAR.MomHold24Weeks;
MomMAR_adj24w(49:49,:) = 0;

MomAPR_adj4w = MomAPR.MomHold4Weeks;
MomAPR_adj4w(48:49,:) = 0;
MomAPR_adj12w = MomAPR.MomHold12Weeks;
MomAPR_adj12w(48:49,:) = 0;
MomAPR_adj24w = MomAPR.MomHold24Weeks;
MomAPR_adj24w(48:49,:) = 0;

MomMAY_adj4w = MomMAY.MomHold4Weeks;
MomMAY_adj12w = MomMAY.MomHold12Weeks;
MomMAY_adj24w = MomMAY.MomHold24Weeks;

MomJUN_adj4w = MomJUN.MomHold4Weeks;
MomJUN_adj4w(48:49,:) = 0;
MomJUN_adj12w = MomJUN.MomHold12Weeks;
MomJUN_adj12w(48:49,:) = 0;
MomJUN_adj24w = MomJUN.MomHold24Weeks;
MomJUN_adj24w(48:49,:) = 0;

MomJUL_adj4w = MomJUL.MomHold4Weeks;
MomJUL_adj12w = MomJUL.MomHold12Weeks;
MomJUL_adj24w = MomJUL.MomHold24Weeks;

MomAUG_adj4w = MomAUG.MomHold4Weeks;
MomAUG_adj4w(47:49,:) = 0;
MomAUG_adj12w = MomAUG.MomHold12Weeks;
MomAUG_adj12w(47:49,:) = 0;
MomAUG_adj24w = MomAUG.MomHold24Weeks;
MomAUG_adj24w(47:49,:) = 0;

MomSEP_adj4w = MomSEP.MomHold4Weeks;
MomSEP_adj4w(43:49,:) = 0;
MomSEP_adj12w = MomSEP.MomHold12Weeks;
MomSEP_adj12w(43:49,:) = 0;
MomSEP_adj24w = MomSEP.MomHold24Weeks;
MomSEP_adj24w(43:49,:) = 0;
```

```
MomOCT_adj4w = MomOCT.MomHold4Weeks;
MomOCT_adj4w(46:49,:) = 0;
MomOCT_adj12w = MomOCT.MomHold12Weeks;
MomOCT_adj12w(46:49,:) = 0;
MomOCT_adj24w = MomOCT.MomHold24Weeks;
MomOCT_adj24w(46:49,:) = 0;

MomNOV_adj4w = MomNOV.MomHold4Weeks;
MomNOV_adj4w(44:49,:) = 0;
MomNOV_adj12w = MomNOV.MomHold12Weeks;
MomNOV_adj12w(44:49,:) = 0;
MomNOV_adj24w = MomNOV.MomHold24Weeks;
MomNOV_adj24w(44:49,:) = 0;

MomDEC_adj4w = MomDEC.MomHold4Weeks;
MomDEC_adj4w(47:49,:) = 0;
MomDEC_adj12w = MomDEC.MomHold12Weeks;
MomDEC_adj12w(47:49,:) = 0;
MomDEC_adj24w = MomDEC.MomHold24Weeks;
MomDEC_adj24w(47:49,:) = 0;

ANOVA_Table4w = table(MomJAN_adj4w, MomFEB_adj4w, MomMAR_adj4w, ...
    MomAPR_adj4w, MomMAY_adj4w, MomJUN_adj4w, MomJUL_adj4w, ...
    MomAUG_adj4w, MomSEP_adj4w, MomOCT_adj4w, MomNOV_adj4w,
MomDEC_adj4w);

ANOVA_Table12w = table(MomJAN_adj12w, MomFEB_adj12w, MomMAR_adj12w, ...
    MomAPR_adj12w, MomMAY_adj12w, MomJUN_adj12w, MomJUL_adj12w, ...
    MomAUG_adj12w, MomSEP_adj12w, MomOCT_adj12w, MomNOV_adj12w, ...
    MomDEC_adj12w);

ANOVA_Table24w = table(MomJAN_adj24w, MomFEB_adj24w, MomMAR_adj24w, ...
    MomAPR_adj24w, MomMAY_adj24w, MomJUN_adj24w, MomJUL_adj24w, ...
    MomAUG_adj24w, MomSEP_adj24w, MomOCT_adj24w, MomNOV_adj24w, ...
    MomDEC_adj24w)

% We use the One-Way ANOVA technique for between-sample variation.
% The boxplot outcome gives a detailed ouverview: red line represents
% median values
ANOVA_4w = [MomJAN_adj4w*100 MomFEB_adj4w*100 MomMAR_adj4w*100 ...
    MomAPR_adj4w*100 MomMAY_adj4w*100 MomJUN_adj4w*100 MomJUL_adj4w*100
... MomAUG_adj4w*100 MomSEP_adj4w*100 MomOCT_adj4w*100 MomNOV_adj4w*100
... MomDEC_adj4w*100];
months_names = {'Jan' 'Feb' 'Mar' 'Apr' 'May' 'Jun' 'Jul' 'Aug' 'Sep'
... 'Oct' 'Nov' 'Dec'};
[p_anova4,t_anova4,stats_anova4] = anova1(ANOVA_4w, months_names, ...
    'alpha', 0.01);
% result: p = 0 -> (we reject Ho) = at least one mean differs from
% another in a statistically significant way

ANOVA_12w = [MomJAN_adj12w*100 MomFEB_adj12w*100 MomMAR_adj12w*100 ...
    MomAPR_adj12w*100 MomMAY_adj12w*100 MomJUN_adj12w*100 ...
    MomJUL_adj12w*100 MomAUG_adj12w*100 MomSEP_adj12w*100 ...
    MomOCT_adj12w*100 MomNOV_adj12w*100 MomDEC_adj12w*100];
[p_anova12,t_anova12,stats_anova12] = anova1(ANOVA_12w, months_names,
... 'alpha', 0.01);
```

```
% result: p = 0 (we reject Ho) = same interpretation as above

ANOVA_24w = [MomJAN_adj24w*100 MomFEB_adj24w*100 MomMAR_adj24w*100 ...
    MomAPR_adj24w*100 MomMAY_adj24w*100 MomJUN_adj24w*100 ...
    MomJUL_adj24w*100 MomAUG_adj24w*100 MomSEP_adj24w*100 ...
    MomOCT_adj24w*100 MomNOV_adj24w*100 MomDEC_adj24w*100];
[p_anova24,t_anova24,stats_anova24] = anova1(ANOVA_24w, months_names,
... 'alpha', 0.01);
% result: p = 0.26 -> (we cannot reject Ho) = means are very similar

% Summarize F-stat and p-value in one table
NN=[{t_anova4(2:2,5) t_anova12(2:2,5) t_anova24(2:2,5)};...
    {t_anova4(2:2,6) t_anova12(2:2,6) t_anova24(2:2,6)}];
ANOVA_monthlyOverview = cell2table(NN);
ANOVA_monthlyOverview.Properties.VariableNames= {'Mom_4Weeks' ...
    'Mom_12Weeks' 'Mom_24Weeks'};
ANOVA_monthlyOverview.Properties.RowNames = {'F-stat' 'p-value'}
write(ANOVA_monthlyOverview, 'ANOVA_monthlyOverview.xlsx');

% The above ANOVA test has a big drawback: it assumes a normal
% distribution of returns. The following is a more realistic test that
% doesn't make this assumption. From the descriptive analysis above we
% have seen that the normal distribution of returns was very
% unrealistic and that almost every momentum strategy exhibits a
% negatively skewed distribution.

% “Kruskal-Wallis test for comparing distribution of multiple groups
% Outcome p=0 means that the null hypothesis (= all group have the same
% distribution) is rejected at the 1% significance level. This test is
% a non-parametric method for testing whether samples originate from
% the same distribution. It is used for comparing two or more
% independent samples of equal or different sample sizes. It extends
% the Mann-Whitney U test when there are more than two groups.
% Since it is a non-parametric method, the Kruskal-Wallis test does not
% assume a normal distribution of the residuals, unlike the analogous
% one-way analysis of variance.” The boxplots give a detailed overview.
% Red line represents median values
AAAAA = [MomJAN_adj4w*100, MomFEB_adj4w*100, MomMAR_adj4w*100, ...
    MomAPR_adj4w*100, MomMAY_adj4w*100, MomJUN_adj4w*100, ...
    MomJUL_adj4w*100, MomAUG_adj4w*100, MomSEP_adj4w*100, ...
    MomOCT_adj4w*100, MomNOV_adj4w*100, MomDEC_adj4w*100];
kruskalwallis(AAAAA)
ylabel('% Return')
xlabel('Months of the Year')
% result: p=0

BBBBB = [MomJAN_adj12w*100, MomFEB_adj12w*100, MomMAR_adj12w*100, ...
    MomAPR_adj12w*100, MomMAY_adj12w*100, MomJUN_adj12w*100, ...
    MomJUL_adj12w*100, MomAUG_adj12w*100, MomSEP_adj12w*100, ...
    MomOCT_adj12w*100, MomNOV_adj12w*100, MomDEC_adj12w*100];
kruskalwallis(BBBBB)
ylabel('% Return')
xlabel('Months of the Year')
% result: p=0

CCCCC = [MomJAN_adj24w*100, MomFEB_adj24w*100, MomMAR_adj24w*100, ...
    MomAPR_adj24w*100, MomMAY_adj24w*100, MomJUN_adj24w*100, ...
```

```
    MomJUL_adj24w*100, MomAUG_adj24w*100, MomSEP_adj24w*100, ...
    MomOCT_adj24w*100, MomNOV_adj24w*100, MomDEC_adj24w*100];
kruskalwallis(CCCCC)
ylabel('% Return')
xlabel('Months of the Year')
% result: p=0.1139

% Summary of Kruskal-Wallis analysis (Chi-Squared, p value etc.) made
% in Excel

% Check whether shape of distributions are the same among the different
% groups
% 4-Week Momentum
skew4KW_JAN = skewness(MomJAN.MomHold4Weeks) % -1.5329
histogram(MomJAN.MomHold4Weeks, 95) % negatively skewed

skew4KW_FEB = skewness(MomFEB.MomHold4Weeks) % 0.0575
histogram(MomFEB.MomHold4Weeks, 95) % positively skewed

skew4KW_MAR = skewness(MomMAR.MomHold4Weeks) % -2.0119
histogram(MomMAR.MomHold4Weeks, 95) % negatively skewed

skew4KW_APR = skewness(MomAPR.MomHold4Weeks) % -0.6554
histogram(MomAPR.MomHold4Weeks, 95) % negatively skewed

skew4KW_MAY = skewness(MomMAY.MomHold4Weeks) % -0.8654
histogram(MomMAY.MomHold4Weeks, 95) % negatively skewed

skew4KW_JUN = skewness(MomJUN.MomHold4Weeks) % -0.4198
histogram(MomJUN.MomHold4Weeks, 95) % negatively skewed

skew4KW_JUL = skewness(MomJUL.MomHold4Weeks) % 0.1742
histogram(MomJUL.MomHold4Weeks, 95) % positively skewed

skew4KW_AUG = skewness(MomAUG.MomHold4Weeks) % -0.3457
histogram(MomAUG.MomHold4Weeks, 95) % negatively skewed

skew4KW_SEP = skewness(MomSEP.MomHold4Weeks) % 0.1338
histogram(MomSEP.MomHold4Weeks, 95) % positively skewed

skew4KW_OCT = skewness(MomOCT.MomHold4Weeks) % 0.4704
histogram(MomOCT.MomHold4Weeks, 95) % positively skewed

skew4KW_NOV = skewness(MomNOV.MomHold4Weeks) % 0.8933
histogram(MomNOV.MomHold4Weeks, 95) % positively skewed

skew4KW_DEC = skewness(MomDEC.MomHold4Weeks) % -0.4949
histogram(MomDEC.MomHold4Weeks, 95) % negatively skewed

% 12-Week Momentum
skew12KW_JAN = skewness(MomJAN.MomHold12Weeks) % -0.8374
histogram(MomJAN.MomHold12Weeks, 95) % negatively skewed

skew12KW_FEB = skewness(MomFEB.MomHold12Weeks) % -1.1940
histogram(MomFEB.MomHold12Weeks, 95) % negatively skewed
```

```
skew12KW_MAR = skewness(MomMAR.MomHold12Weeks) % -1.5739
histogram(MomMAR.MomHold12Weeks, 95) % negatively skewed

skew12KW_APR = skewness(MomAPR.MomHold12Weeks) % -1.0703
histogram(MomAPR.MomHold12Weeks, 95) % negatively skewed

skew12KW_MAY = skewness(MomMAY.MomHold12Weeks) % 0.1490
histogram(MomMAY.MomHold12Weeks, 95) % positively skewed

skew12KW_JUN = skewness(MomJUN.MomHold12Weeks) % -0.1144
histogram(MomJUN.MomHold12Weeks, 95) % negatively skewed

skew12KW_JUL = skewness(MomJUL.MomHold12Weeks) % -0.6654
histogram(MomJUL.MomHold12Weeks, 95) % negatively skewed

skew12KW_AUG = skewness(MomAUG.MomHold12Weeks) % -0.3751
histogram(MomAUG.MomHold12Weeks, 95) % negatively skewed

skew12KW_SEP = skewness(MomSEP.MomHold12Weeks) % 0.5770
histogram(MomSEP.MomHold12Weeks, 95) % positively skewed

skew12KW_OCT = skewness(MomOCT.MomHold12Weeks) % 0.5182
histogram(MomOCT.MomHold12Weeks, 95) % positively skewed

skew12KW_NOV = skewness(MomNOV.MomHold12Weeks) % 0.0819
histogram(MomNOV.MomHold12Weeks, 95) % positively skewed

skew12KW_DEC = skewness(MomDEC.MomHold12Weeks) % -1.0659
histogram(MomDEC.MomHold12Weeks, 95) % negatively skewed

% 24-Week Momentum
skew24KW_JAN = skewness(MomJAN.MomHold24Weeks) % -1.6994
histogram(MomJAN.MomHold24Weeks, 95) % negatively skewed

skew24KW_FEB = skewness(MomFEB.MomHold24Weeks) % -1.4935
histogram(MomFEB.MomHold24Weeks, 95) % negatively skewed

skew24KW_MAR = skewness(MomMAR.MomHold24Weeks) % -2.0050
histogram(MomMAR.MomHold24Weeks, 95) % negatively skewed

skew24KW_APR = skewness(MomAPR.MomHold24Weeks) % -1.3459
histogram(MomAPR.MomHold24Weeks, 95) % negatively skewed

skew24KW_MAY = skewness(MomMAY.MomHold24Weeks) % -0.9364
histogram(MomMAY.MomHold24Weeks, 95) % positively skewed

skew24KW_JUN = skewness(MomJUN.MomHold24Weeks) % 0.1010
histogram(MomJUN.MomHold24Weeks, 95) % positively skewed

skew24KW_JUL = skewness(MomJUL.MomHold24Weeks) % 0.0467
histogram(MomJUL.MomHold24Weeks, 95) % positively skewed

skew24KW_AUG = skewness(MomAUG.MomHold24Weeks) % -0.5333
histogram(MomAUG.MomHold24Weeks, 95) % negatively skewed
```

```
skew24KW_SEP = skewness(MomSEP.MomHold12Weeks) % 0.5770
histogram(MomSEP.MomHold12Weeks, 95) % positively skewed

skew24KW_OCT = skewness(MomOCT.MomHold24Weeks) % -1.0348
histogram(MomOCT.MomHold24Weeks, 95) % negatively skewed

skew24KW_NOV = skewness(MomNOV.MomHold24Weeks) % -1.9766
histogram(MomNOV.MomHold24Weeks, 95) % negatively skewed

skew24KW_DEC = skewness(MomDEC.MomHold24Weeks) % -2.1054
histogram(MomDEC.MomHold24Weeks, 95) % negatively skewed

% Overview
MM = [{skew4KW_JAN skew4KW_FEB skew4KW_MAR skew4KW_APR skew4KW_MAY ...
    skew4KW_JUN skew4KW_JUL skew4KW_AUG skew4KW_SEP skew4KW_OCT ...
    skew4KW_NOV skew4KW_DEC};...
    {skew12KW_JAN skew12KW_FEB skew12KW_MAR skew12KW_APR skew12KW_MAY
... skew12KW_JUN skew12KW_JUL skew12KW_AUG skew12KW_SEP skew12KW_OCT
... skew12KW_NOV skew12KW_DEC};...
    {skew24KW_JAN skew24KW_FEB skew24KW_MAR skew24KW_APR skew24KW_MAY
... skew24KW_JUN skew24KW_JUL skew24KW_AUG skew24KW_SEP skew24KW_OCT
... skew24KW_NOV skew24KW_DEC}];
SkewforKWtesting_M = cell2table(MM);
SkewforKWtesting_M.Properties.VariableNames = {'January' 'February'
'March' 'April' 'May' 'June' 'July' 'August' 'September' 'October'
'November ' 'December'};
SkewforKWtesting_M.Properties.RowNames = {'4Weeks' ...
    '12Weeks' '24Weeks'};
writetable(SkewforKWtesting_M, 'SkewforKWtestingMonthEffect.xlsx')



% E.4 Front-Running
% ---------------------------------------------------------------------


% Annualized Means "Base" vs. Front-Running Strategies
Mean4wNorm = nanmean(MonthEnd4.MomHold4Weeks);   % 0.005
Mean4wFR1 = nanmean(MonthEnd4.Mom4_FR1); % 0.0039
Mean4wFR2 = nanmean(MonthEnd4.Mom4_FR2); % 0.0036
Mean4wFR3 = nanmean(MonthEnd4.Mom4_FR3); % 0.0037
Mean4wFR4 = nanmean(MonthEnd4.Mom4_FR4); % 0.0029
Mean4wFR5 = nanmean(MonthEnd4.Mom4_FR5); % 0.0043
MeanFrTable4w_annualized = table(Mean4wNorm*13, Mean4wFR1*13, ...
    Mean4wFR2*13, Mean4wFR3*13, Mean4wFR4*13, Mean4wFR5*13, ...
    'VariableNames', {'MeanNorm', 'MeanFR1', 'MeanFR2', 'MeanFR3', ...
    'MeanFR4', 'MeanFR5'});
Mean12wNorm = nanmean(MonthEnd12.MomHold12Weeks);
Mean12wFR1 = nanmean(MonthEnd12.Mom12_FR1);
Mean12wFR2 = nanmean(MonthEnd12.Mom12_FR2);
Mean12wFR3 = nanmean(MonthEnd12.Mom12_FR3);
Mean12wFR4 = nanmean(MonthEnd12.Mom12_FR4);
Mean12wFR5 = nanmean(MonthEnd12.Mom12_FR5);
MeanFrTable12w_annualized = table(Mean12wNorm*(13/3), ...
    Mean12wFR1*(13/3), Mean12wFR2*(13/3), Mean12wFR3*(13/3), ...
    Mean12wFR4*(13/3), Mean12wFR5*(13/3), 'VariableNames', {'MeanNorm',
```

```
... 'MeanFR1', 'MeanFR2', 'MeanFR3', 'MeanFR4', 'MeanFR5'});
Mean24wNorm = nanmean(MonthEnd24.MomHold24Weeks);
Mean24wFR1 = nanmean(MonthEnd24.Mom24_FR1);
Mean24wFR2 = nanmean(MonthEnd24.Mom24_FR2);
Mean24wFR3 = nanmean(MonthEnd24.Mom24_FR3);
Mean24wFR4 = nanmean(MonthEnd24.Mom24_FR4);
Mean24wFR5 = nanmean(MonthEnd24.Mom24_FR5);
MeanFrTable24w_annualized = table(Mean24wNorm*(13/6), ...
    Mean24wFR1*(13/6), Mean24wFR2*(13/6), Mean24wFR3*(13/6), ...
    Mean24wFR4*(13/6), Mean24wFR5*(13/6),'VariableNames', {'MeanNorm',
... 'MeanFR1', 'MeanFR2', 'MeanFR3', 'MeanFR4', 'MeanFR5'});

% Overview table
MeanFR_MonthEnd_Overview = [MeanFrTable4w_annualized; ...
    MeanFrTable12w_annualized; MeanFrTable24w_annualized];
MeanFR_MonthEnd_Overview.Properties.RowNames = {'4-Week Momentum' ...
    '12-Week Momentum' '24-Weeks Momentum'};
MeanFR_MonthEnd_Overview.Properties.VariableNames = {'MonthEnd' ...
    'FR_1Week' 'FR_2Weeks' 'FR_3Weeks' 'FR_4Weeks' 'FR_5Weeks'};
write(MeanFR_MonthEnd_Overview, 'MeanFR_MonthEnd_Overview.xlsx')

% Annualized Std. Dev. "Base" vs. Front-Running Strategies
StdDev4wNorm = nanstd(MonthEnd4.MomHold4Weeks);
StdDev4wFR1 = nanstd(MonthEnd4.Mom4_FR1);
StdDev4wFR2 = nanstd(MonthEnd4.Mom4_FR2);
StdDev4wFR3 = nanstd(MonthEnd4.Mom4_FR3);
StdDev4wFR4 = nanstd(MonthEnd4.Mom4_FR4);
StdDev4wFR5 = nanstd(MonthEnd4.Mom4_FR5);
StdDevFrTable4w_annualized = table(StdDev4wNorm*sqrt(13), ...
    StdDev4wFR1*sqrt(13), StdDev4wFR2*sqrt(13), StdDev4wFR3*sqrt(13),
... StdDev4wFR4*sqrt(13), StdDev4wFR5*sqrt(13), 'VariableNames', ...
    {'MonthEnd', 'FR_1Week', 'FR_2Weeks', 'FR_3Weeks', 'FR_4Weeks', ...
    'FR_5Weeks'});
StdDev12wNorm = nanstd(MonthEnd12.MomHold12Weeks);
StdDev12wFR1 = nanstd(MonthEnd12.Mom12_FR1);
StdDev12wFR2 = nanstd(MonthEnd12.Mom12_FR2);
StdDev12wFR3 = nanstd(MonthEnd12.Mom12_FR3);
StdDev12wFR4 = nanstd(MonthEnd12.Mom12_FR4);
StdDev12wFR5 = nanstd(MonthEnd12.Mom12_FR5);
StdDevFrTable12w_annualized = table(StdDev12wNorm*sqrt(13/3), ...
    StdDev12wFR1*sqrt(13/3), StdDev12wFR2*sqrt(13/3),
StdDev12wFR3*sqrt(13/3), ...
    StdDev12wFR4*sqrt(13/3), StdDev12wFR5*sqrt(13/3), 'VariableNames',
... {'MonthEnd', 'FR_1Week', 'FR_2Weeks', 'FR_3Weeks', 'FR_4Weeks', ...
    'FR_5Weeks'});
StdDev24wNorm = nanstd(MonthEnd24.MomHold24Weeks);
StdDev24wFR1 = nanstd(MonthEnd24.Mom24_FR1);
StdDev24wFR2 = nanstd(MonthEnd24.Mom24_FR2);
StdDev24wFR3 = nanstd(MonthEnd24.Mom24_FR3);
StdDev24wFR4 = nanstd(MonthEnd24.Mom24_FR4);
StdDev24wFR5 = nanstd(MonthEnd24.Mom24_FR5);
StdDevFrTable24w_annualized = table(StdDev24wNorm*sqrt(13/6), ...
    StdDev24wFR1*sqrt(13/6), StdDev24wFR2*sqrt(13/6),
StdDev24wFR3*sqrt(13/6), ...
    StdDev24wFR4*sqrt(13/6), StdDev24wFR5*sqrt(13/6),'VariableNames',
... {'MonthEnd', 'FR_1Week', 'FR_2Weeks', 'FR_3Weeks', 'FR_4Weeks', ...
    'FR_5Weeks'});
```

```matlab
% Overview table
StdDevFR_MonthEnd_Overview = [StdDevFrTable4w_annualized; ...
    StdDevFrTable12w_annualized; StdDevFrTable24w_annualized];
StdDevFR_MonthEnd_Overview.Properties.RowNames = {'4-Week Momentum' ...
    '12-Week Momentum' '24-Weeks Momentum'};
StdDevFR_MonthEnd_Overview.Properties.VariableNames = {'MonthEnd' ...
    'FR_1Week' 'FR_2Weeks' 'FR_3Weeks' 'FR_4Weeks' 'FR_5Weeks'};
write(StdDevFR_MonthEnd_Overview, 'StdDevFR_MonthEnd_Overview.xlsx')

% Skewness and Kurtosis of Momentum base strategies vs. FR cases
SkewMom4FR_Base = skewness(MonthEnd4.MomHold4Weeks);
SkewMom4FR_FR1 = skewness(MonthEnd4.Mom4_FR1);
SkewMom4FR_FR2 = skewness(MonthEnd4.Mom4_FR2);
SkewMom4FR_FR3 = skewness(MonthEnd4.Mom4_FR3);
SkewMom4FR_FR4 = skewness(MonthEnd4.Mom4_FR4);
SkewMom4FR_FR5 = skewness(MonthEnd4.Mom4_FR5);
KurtMom4FR_Base = kurtosis(MonthEnd4.MomHold4Weeks);
KurtMom4FR_FR1 = kurtosis(MonthEnd4.Mom4_FR1);
KurtMom4FR_FR2 = kurtosis(MonthEnd4.Mom4_FR2);
KurtMom4FR_FR3 = kurtosis(MonthEnd4.Mom4_FR3);
KurtMom4FR_FR4 = kurtosis(MonthEnd4.Mom4_FR4);
KurtMom4FR_FR5 = kurtosis(MonthEnd4.Mom4_FR5);

SkewMom12FR_Base = skewness(MonthEnd12.MomHold12Weeks);
SkewMom12FR_FR1 = skewness(MonthEnd12.Mom12_FR1);
SkewMom12FR_FR2 = skewness(MonthEnd12.Mom12_FR2);
SkewMom12FR_FR3 = skewness(MonthEnd12.Mom12_FR3);
SkewMom12FR_FR4 = skewness(MonthEnd12.Mom12_FR4);
SkewMom12FR_FR5 = skewness(MonthEnd12.Mom12_FR5);
KurtMom12FR_Base = kurtosis(MonthEnd12.MomHold12Weeks);
KurtMom12FR_FR1 = kurtosis(MonthEnd12.Mom12_FR1);
KurtMom12FR_FR2 = kurtosis(MonthEnd12.Mom12_FR2);
KurtMom12FR_FR3 = kurtosis(MonthEnd12.Mom12_FR3);
KurtMom12FR_FR4 = kurtosis(MonthEnd12.Mom12_FR4);
KurtMom12FR_FR5 = kurtosis(MonthEnd12.Mom12_FR5);

SkewMom24FR_Base = skewness(MonthEnd24.MomHold24Weeks);
SkewMom24FR_FR1 = skewness(MonthEnd24.Mom24_FR1);
SkewMom24FR_FR2 = skewness(MonthEnd24.Mom24_FR2);
SkewMom24FR_FR3 = skewness(MonthEnd24.Mom24_FR3);
SkewMom24FR_FR4 = skewness(MonthEnd24.Mom24_FR4);
SkewMom24FR_FR5 = skewness(MonthEnd24.Mom24_FR5);
KurtMom24FR_Base = kurtosis(MonthEnd24.MomHold24Weeks);
KurtMom24FR_FR1 = kurtosis(MonthEnd24.Mom24_FR1);
KurtMom24FR_FR2 = kurtosis(MonthEnd24.Mom24_FR2);
KurtMom24FR_FR3 = kurtosis(MonthEnd24.Mom24_FR3);
KurtMom24FR_FR4 = kurtosis(MonthEnd24.Mom24_FR4);
KurtMom24FR_FR5 = kurtosis(MonthEnd24.Mom24_FR5);


% Summary of Kurtosis and Skewness in table format
SkewFRvsBase_OT = [{SkewMom4FR_Base SkewMom4FR_FR1 SkewMom4FR_FR2 ...
    SkewMom4FR_FR3 SkewMom4FR_FR4 SkewMom4FR_FR5};...
    {SkewMom12FR_Base SkewMom12FR_FR1 SkewMom12FR_FR2 SkewMom12FR_FR3
... SkewMom12FR_FR4 SkewMom12FR_FR5};...
    {SkewMom24FR_Base SkewMom24FR_FR1 SkewMom24FR_FR2 SkewMom24FR_FR3
... SkewMom24FR_FR4 SkewMom24FR_FR5}];
```

```
SkewFRvsBase = cell2table(SkewFRvsBase_OT);
SkewFRvsBase.Properties.VariableNames = {'MonthEnd' ...
    'FR1' 'FR2' 'FR3' 'FR4' 'FR5'};
SkewFRvsBase.Properties.RowNames = {'4Weeks' '12Weeks' '24Weeks'}
write(SkewFRvsBase, 'SkewFRvsBase.xlsx')

KurtFRvsBase_OT = [{KurtMom4FR_Base KurtMom4FR_FR1 KurtMom4FR_FR2 ...
    KurtMom4FR_FR3 KurtMom4FR_FR4 KurtMom4FR_FR5}; ...
    {KurtMom12FR_Base KurtMom12FR_FR1 KurtMom12FR_FR2 KurtMom12FR_FR3
... KurtMom12FR_FR4 KurtMom12FR_FR5}; ...
    {KurtMom24FR_Base KurtMom24FR_FR1 KurtMom24FR_FR2 KurtMom24FR_FR3
... KurtMom24FR_FR4 KurtMom24FR_FR5}];
KurtFRvsBase=cell2table(KurtFRvsBase_OT);
KurtFRvsBase.Properties.VariableNames = {'MonthEnd' ...
    'FR1' 'FR2' 'FR3' 'FR4' 'FR5'};
KurtFRvsBase.Properties.RowNames = {'Mom_4Weeks' 'Mom_12Weeks' ...
    'Mom_24Weeks'}
write(KurtFRvsBase, 'KurtFRvsBase.xlsx')

% 2-sample t-Test for differences in mean (Null hypothesis is μ(A)-μ(B)
% = 0) Assumption: standard normal distribution (N(0,1))

% t-statistics for 4-week scenario (5% significance level)
% Purpose: testing significance of difference in means
% h = 0 indicates that ttest does not reject the null hypothesis
[h1, p1, ci1, stats1] = ttest2(MonthEnd4.Mom4_FR1*13, ...
    MonthEnd4.MomHold4Weeks*13, 'Vartype','unequal');
[h2, p2, ci2, stats2] = ttest2(MonthEnd4.Mom4_FR2*13, ...
    MonthEnd4.MomHold4Weeks*13, 'Vartype','unequal');
[h3, p3, ci3, stats3] = ttest2(MonthEnd4.Mom4_FR3*13, ...
    MonthEnd4.MomHold4Weeks*13, 'Vartype','unequal');
[h4, p4, ci4, stats4] = ttest2(MonthEnd4.Mom4_FR4*13, ...
    MonthEnd4.MomHold4Weeks*13, 'Vartype','unequal');
[h5, p5, ci5, stats5] = ttest2(MonthEnd4.Mom4_FR5*13, ...
    MonthEnd4.MomHold4Weeks*13, 'Vartype','unequal');
Ttest4wFR1_single = {p1; stats1.tstat; h1};
Ttest4wFR2_single = {p2; stats2.tstat; h2};
Ttest4wFR3_single = {p3; stats3.tstat; h3};
Ttest4wFR4_single = {p4; stats4.tstat; h4};
Ttest4wFR5_single = {p5; stats5.tstat; h5};

% t-statistics for 12-week scenario (5% significance level)
[h1_1, p1_1, ci1_1, stats1_1] = ttest2(MonthEnd12.Mom12_FR1*(13/3), ...
    MonthEnd12.MomHold12Weeks*(13/3), 'Vartype','unequal');
[h2_1, p2_1, ci2_1, stats2_1] = ttest2(MonthEnd12.Mom12_FR2*(13/3), ...
    MonthEnd12.MomHold12Weeks*(13/3), 'Vartype','unequal');
[h3_1, p3_1, ci3_1, stats3_1] = ttest2(MonthEnd12.Mom12_FR3*(13/3), ...
   MonthEnd12.MomHold12Weeks*(13/3), 'Vartype','unequal');
[h4_1, p4_1, ci4_1, stats4_1] = ttest2(MonthEnd12.Mom12_FR4*(13/3), ...
   MonthEnd12.MomHold12Weeks*(13/3), 'Vartype','unequal');
[h5_1, p5_1, ci5_1, stats5_1] = ttest2(MonthEnd12.Mom12_FR5*(13/3), ...
   MonthEnd12.MomHold12Weeks*(13/3), 'Vartype','unequal');
Ttest12wFR1_single = {p1_1; stats1_1.tstat; h1_1};
Ttest12wFR2_single = {p2_1; stats2_1.tstat; h2_1};
Ttest12wFR3_single = {p3_1; stats3_1.tstat; h3_1};
Ttest12wFR4_single = {p4_1; stats4_1.tstat; h4_1};
Ttest12wFR5_single = {p5_1; stats5_1.tstat; h5_1};
```

```
% T stats for 24-week scenario (5% significance level)
[h1_2, p1_2, ci1_2, stats1_2] = ttest2(MonthEnd24.Mom24_FR1*(13/6), ...
    MonthEnd24.MomHold24Weeks*(13/6), 'Vartype','unequal');
[h2_2, p2_2, ci2_2, stats2_2] = ttest2(MonthEnd24.Mom24_FR2*(13/6), ...
    MonthEnd24.MomHold24Weeks*(13/6), 'Vartype','unequal');
[h3_2, p3_2, ci3_2, stats3_2] = ttest2(MonthEnd24.Mom24_FR3*(13/6), ...
    MonthEnd24.MomHold24Weeks*(13/6), 'Vartype','unequal');
[h4_2, p4_2, ci4_2, stats4_2] = ttest2(MonthEnd24.Mom24_FR4*(13/6), ...
    MonthEnd24.MomHold24Weeks*(13/6), 'Vartype','unequal');
[h5_2, p5_2, ci5_2, stats5_2] = ttest2(MonthEnd24.Mom24_FR5*(13/6), ...
    MonthEnd24.MomHold24Weeks*(13/6), 'Vartype','unequal');
Ttest24wFR1_single = {p1_2; stats1_2.tstat; h1_2};
Ttest24wFR2_single = {p2_2; stats2_2.tstat; h2_2};
Ttest24wFR3_single = {p3_2; stats3_2.tstat; h3_2};
Ttest24wFR4_single = {p4_2; stats4_2.tstat; h4_2};
Ttest24wFR5_single = {p5_2; stats5_2.tstat; h5_2};

% Summarizing table for 5% significance level
VV=[{Ttest4wFR1_single{1,1} Ttest4wFR2_single{1,1}
Ttest4wFR3_single{1,1} ...
    Ttest4wFR4_single{1,1} Ttest4wFR5_single{1,1}};...
    {Ttest4wFR1_single{2,1} Ttest4wFR2_single{2,1}
Ttest4wFR3_single{2,1} ...
    Ttest4wFR4_single{2,1} Ttest4wFR5_single{2,1}};...
    {Ttest4wFR1_single{3,1} Ttest4wFR2_single{3,1}
Ttest4wFR3_single{3,1} ...
    Ttest4wFR4_single{3,1} Ttest4wFR5_single{3,1}};...
    {Ttest12wFR1_single{1,1} Ttest12wFR2_single{1,1}
Ttest12wFR3_single{1,1} ...
    Ttest12wFR4_single{1,1} Ttest12wFR5_single{1,1}};...
    {Ttest12wFR1_single{2,1} Ttest12wFR2_single{2,1}
Ttest12wFR3_single{2,1} ...
    Ttest12wFR4_single{2,1} Ttest12wFR5_single{2,1}};...
    {Ttest12wFR1_single{3,1} Ttest12wFR2_single{3,1}
Ttest12wFR3_single{3,1} ...
    Ttest12wFR4_single{3,1} Ttest12wFR5_single{3,1}};...
    {Ttest24wFR1_single{1,1} Ttest24wFR2_single{1,1}
Ttest24wFR3_single{1,1} ...
    Ttest24wFR4_single{1,1} Ttest24wFR5_single{1,1}};...
    {Ttest24wFR1_single{2,1} Ttest24wFR2_single{2,1}
Ttest24wFR3_single{2,1} ...
    Ttest24wFR4_single{2,1} Ttest24wFR5_single{2,1}};...
    {Ttest24wFR1_single{3,1} Ttest24wFR2_single{3,1}
Ttest24wFR3_single{3,1} ...
    Ttest24wFR4_single{3,1} Ttest24wFR5_single{3,1}}];
TstatOverview5perc=cell2table(VV);
TstatOverview5perc.Properties.VariableNames = {'FR_by_1w' 'FR_by_2w'
... 'FR_by_3w' 'FR_by_4w' 'FR_by_5w'};
TstatOverview5perc.Properties.RowNames = {'p_value_4Weeks'
't_stat_4weeks' ...
    'Outcome_Hyp_Test_4weeks' 'p_value_12Weeks' 't_stat_12weeks' ...
    'Outcome_Hyp_Test_12weeks' 'p_value_24Weeks' 't_stat_24weeks' ...
    'Outcome_Hyp_Test_24weeks'}
writetable(TstatOverview5perc, 'TstatOverview5perc.xlsx')

% Sharpe Ratios (base, FR1, FR2, FR3, FR4 and FR5)
Sharpe4wNorm = sharpe(MonthEnd4.MomHold4Weeks,
```

```
MomVsMarket_new.Rf4Weeks);
Sharpe4wFR1 = sharpe(MonthEnd4.Mom4_FR1, MomVsMarket_new.Rf4Weeks);
Sharpe4wFR2 = sharpe(MonthEnd4.Mom4_FR2, MomVsMarket_new.Rf4Weeks);
Sharpe4wFR3 = sharpe(MonthEnd4.Mom4_FR3, MomVsMarket_new.Rf4Weeks);
Sharpe4wFR4 = sharpe(MonthEnd4.Mom4_FR4, MomVsMarket_new.Rf4Weeks);
Sharpe4wFR5 = sharpe(MonthEnd4.Mom4_FR5, MomVsMarket_new.Rf4Weeks);

Sharpe12wNorm = sharpe(MonthEnd12.MomHold12Weeks, ...
    MomVsMarket_new.Rf12Weeks);
Sharpe12wFR1 = sharpe(MonthEnd12.Mom12_FR1, MomVsMarket_new.Rf12Weeks);
Sharpe12wFR2 = sharpe(MonthEnd12.Mom12_FR2, MomVsMarket_new.Rf12Weeks);
Sharpe12wFR3 = sharpe(MonthEnd12.Mom12_FR3, MomVsMarket_new.Rf12Weeks);
Sharpe12wFR4 = sharpe(MonthEnd12.Mom12_FR4, MomVsMarket_new.Rf12Weeks);
Sharpe12wFR5 = sharpe(MonthEnd12.Mom12_FR5, MomVsMarket_new.Rf12Weeks);

Sharpe24wNorm = sharpe(MonthEnd24.MomHold24Weeks, ...
    MomVsMarket_new.Rf24Weeks);
Sharpe24wFR1 = sharpe(MonthEnd24.Mom24_FR1, MomVsMarket_new.Rf24Weeks);
Sharpe24wFR2 = sharpe(MonthEnd24.Mom24_FR2, MomVsMarket_new.Rf24Weeks);
Sharpe24wFR3 = sharpe(MonthEnd24.Mom24_FR3, MomVsMarket_new.Rf24Weeks);
Sharpe24wFR4 = sharpe(MonthEnd24.Mom24_FR4, MomVsMarket_new.Rf24Weeks);
Sharpe24wFR5 = sharpe(MonthEnd24.Mom24_FR5, MomVsMarket_new.Rf24Weeks);

% Annualize Sharpe Ratios and display in table format
SharpeNormVsFR_OT = [{Sharpe4wNorm*sqrt(13) ...
    Sharpe4wFR1*sqrt(13) Sharpe4wFR2*sqrt(13) Sharpe4wFR3*sqrt(13) ...
    Sharpe4wFR4*sqrt(13) Sharpe4wFR5*sqrt(13)}; ...
    {Sharpe12wNorm*sqrt(13/3) Sharpe12wFR1*sqrt(13/3) ...
    Sharpe12wFR2*sqrt(13/3) Sharpe12wFR3*sqrt(13/3) ...
    Sharpe12wFR4*sqrt(13/3) Sharpe12wFR5*sqrt(13/3)}; ...
    {Sharpe24wNorm*sqrt(13/6) Sharpe24wFR1*sqrt(13/6) ...
    Sharpe24wFR2*sqrt(13/6) Sharpe24wFR3*sqrt(13/6) ...
    Sharpe24wFR4*sqrt(13/6) Sharpe24wFR5*sqrt(13/6)}];
SharpeNormVsFR_Annualized = cell2table( ...
    SharpeNormVsFR_OT);
SharpeNormVsFR_Annualized.Properties.RowNames = ...
    {'4-week Momentum', '12-week Momentum', '24-week Momentum'};
SharpeNormVsFR_Annualized.Properties.VariableNames = ...
    {'MonthEnd', 'FR_1week', 'FR_2weeks', 'FR_3weeks', 'FR_4weeks', ...
    'FR_5weeks'};
write(SharpeNormVsFR_Annualized, 'SharpeNormVsFR_Annualized.xlsx');

% Kruskal-Wallis Test is a non-parametric test and compares medians
% between groups, assuming their data have non-normal distributions and
% the shape of the distributions among the groups in question exhibit
% more or less the same shape. Since our data is non-normally
% distributed due to its negative skewness, the use of the one-way
% ANOVA method would be misleading.
% The null hypothesis of the Kruskal-Wallis test is that the mean ranks
% of the groups are the same, e.g. the underlying distributions are
% similar
KruskalWallis4w = [MonthEnd4.MomHold4Weeks*100, MonthEnd4.Mom4_FR1*100,
... MonthEnd4.Mom4_FR2*100, MonthEnd4.Mom4_FR3*100, ...
    MonthEnd4.Mom4_FR4*100, MonthEnd4.Mom4_FR5*100,];
p_KW4w = kruskalwallis(KruskalWallis4w)
ylabel('% Return')
xlabel('Base Momentum vs. Front-Running Cases')
```

```
% result: p~=1 (means more or less the same)

% Kruskal-Wallis Test 12-Week Momentum
KruskalWallis12w = [MonthEnd12.MomHold12Weeks*100,
MonthEnd12.Mom12_FR1*100, ...
    MonthEnd12.Mom12_FR2*100, MonthEnd12.Mom12_FR3*100, ...
    MonthEnd12.Mom12_FR4*100, MonthEnd12.Mom12_FR5*100,];
p_KW12w = kruskalwallis(KruskalWallis12w)
ylabel('% Return')
xlabel('Base Momentum vs. Front-Running Cases')
% result: p~=1

% Kruskal-Wallis Test compares inter-group medians alltogether,
assuming
% they have a non-normal distribution
KruskalWallis24w = [MonthEnd24.MomHold24Weeks*100,
MonthEnd24.Mom24_FR1*100, ...
    MonthEnd24.Mom24_FR2*100, MonthEnd24.Mom24_FR3*100, ...
    MonthEnd24.Mom24_FR4*100, MonthEnd24.Mom24_FR5*100,];
p_KW24w = kruskalwallis(KruskalWallis24w)
ylabel('% Return')
xlabel('Base Momentum vs. Front-Running Cases')
% result: p~=1

% Summary of p-values for Kruskal-Wallis test outcomes
JJ = table(p_KW4w, p_KW12w, p_KW24w);
KW_MomFR.Properties.VariableNames = {'FR_with4Mom_Setup'
'FR_with12Mom_Setup' ...
    'FR_with24Mom_Setup'};
KW_MomFR.Properties.RowNames = {'p_value'}
writetable(KW_MomFR, 'KW_MomFR.xlsx')



% E.5 Analysis of Intra-Month Trading Volumes
% -----------------------------------------------------------------------


% Question to be addressed: are trades crowded at month-end? We will
% test this empirically now

% Load data (column of Trading Volume in 'column vector' form)
% Note that the matching date vector and ticker vector are already
stored
% as variable "t" and "Ticker" respectively
load('data for volume analysis.xlsx');

% Create table out of 3 column vectors
TS_VolumeAnalysis = table(t,Ticker,Volume);

% Transforming daily into weekly data:
% Find the last business day in each week, by first finding the end of
% the week and then stepping back
TS_VolumeAnalysis.BusDate = busdate(EndOfWeekDate,'previous',hol);
TS_VolumeAnalysis.BusDate.Format = ['eee ' ...
    TS_VolumeAnalysis.BusDate.Format];
```

```
% Apply mean to the trading volume, grouping by ticker and week
T_weekly_VolumeAnalysis = varfun(@mean,TS_VolumeAnalysis, ...
    'GroupingVariables',{'Ticker' 'BusDate'},...
    'InputVariables','Volume');

% T_weekly_VolumeAnalysis has been saved at this stage in Excel to
% remove ‘s everywhere. The result is saved as
% "WeeklyData_VolumeAnalysis.xlsx". Next, I only import columns 1,2 and
% 3 in 'table' form (either via load function or manually)
load('WeeklyData_VolumeAnalysis.xlsx');

% Rename the table as "WeeklyDataVolumeAnalysis"; it has the dimension
% 152523 x 3

% Pivoting of table "WeeklyData"
T_VolumeAnalysis = unstack(WeeklyDataVolumeAnalysis, 'Volume',
'Ticker', ...
    'GroupingVariables', 'Date',...
    'AggregationFunction', @sum);

% Overwrite time that was previously in "array form" into readable
% Matlab time
T_VolumeAnalysis.Date = [datetime(T.Date, 'InputFormat', ...
    'dd-MMM-yyyy')];

% Sort table by descending date (first column): latest date first,
% oldest at bottom.
T_VolumeAnalysis = sortrows(T_VolumeAnalysis,1,'Descend');

% Now we have to include the content of the loser and winner portfolio
% Idea: we calculate month-end trading volume for momentum stocks only,
% not the entire market
T_adjCase = T;
T_adjCase([555:end],:) = [];

T_VolumeAnalysis_adjCase = T_VolumeAnalysis;
T_VolumeAnalysis_adjCase([555:end],:) = [];

Z_VolumeAnalysis = [T_adjCase(:,1:1) Y(:,2:3) ...
    T_VolumeAnalysis_adjCase(:,1+1:end)];

% Date Containers (we use same framework as for "week-effect")
TradingVolume1st_5th = T_VolumeAnalysis_adjCase(container1st_5th, :);
TradingVolume6th_10th = T_VolumeAnalysis_adjCase(container6th_10th, :);
TradingVolume11th_15th = T_VolumeAnalysis_adjCase(container11th_15th,
:);
TradingVolume16th_20th = T_VolumeAnalysis_adjCase(container16th_20th,
:);
TradingVolume21st_25th = T_VolumeAnalysis_adjCase(container21st_25th,
:);
TradingVolume26th_31st = T_VolumeAnalysis_adjCase(container26th_31st,
:);

% Find the mean trading volume for each stock, given its date container
P1 = nanmean(TradingVolume1st_5th{:,2:end}, 1);
```

```
P2 = nanmean(TradingVolume6th_10th{:,2:end}, 1);
P3 = nanmean(TradingVolume11th_15th{:,2:end}, 1);
P4 = nanmean(TradingVolume16th_20th{:,2:end}, 1);
P5 = nanmean(TradingVolume21st_25th{:,2:end}, 1);
P6 = nanmean(TradingVolume26th_31st{:,2:end}, 1);

% Matrix rotation in preparation for two-sided t-test
P2_adj = rot90(P2);
P6_adj = rot90(P6);

% Lastly, make vertical average calculations
AvTrVolume_1st_5th = mean(P1);
AvTrVolume_6th_10th = mean(P2);
AvTrVolume_11th_15th = mean(P3);
AvTrVolume_16th_20th = mean(P4);
AvTrVolume_21st_25th = mean(P5);
AvTrVolume_26th_31st = mean(P6);

% Summuarize
OverviewAvTrVol = table(AvTrVolume_1st_5th, AvTrVolume_6th_10th, ...
    AvTrVolume_11th_15th, AvTrVolume_16th_20th, AvTrVolume_21st_25th,
... AvTrVolume_26th_31st);
writetable(OverviewAvTrVol, 'OverviewAvTrVol.xlsx')

% Two-sample t-test between date container with highest vs. lowest
% trading volume
[h_TrVol, p_TrVol, ci_TrVol, stats_TrVol] = ttest2(P2_adj, P6_adj, ...
    'Vartype', 'unequal', 'Alpha', 0.1);
Outcomettest_TrVol = {p_TrVol; stats_TrVol.tstat; h_TrVol};

% What would Kruskal-Wallis return as result?
P1_adj = P1';
P3_adj = P3';
P4_adj = P4';
P5_adj = P5';
KWTrVol = [P1_adj, P2_adj, P3_adj, P4_adj, P5_adj, P6_adj];
p_KWTrVol = kruskalwallis(KWTrVol)
ylabel('Trading Volume')
xlabel('Intra-Month Date Containers')
% result: p~=1

% Case where only winner and loser portfolio trading volume is
% taken into account:
% Algo examines trading volume of winner and loser portfolios at any
% given times, and then calculates averages of the trading volumes.
U_VolCon = zeros(height(Z_VolumeAnalysis),1);
col_namesVolConU = Z_VolumeAnalysis.Properties.VariableNames;

for k = 1:height(Z_VolumeAnalysis)
    col_forAvU = any(cell2mat(...
        cellfun(@(x)
strcmp(col_namesVolConU,x),Z_VolumeAnalysis.U{k},...
        'UniformOutput', false).'),1);
    % logical indexing for define eligible columns for summation
    U_VolCon(k) = nansum(Z_VolumeAnalysis{k,col_forAvU})/ ...
        numel(Z_VolumeAnalysis.U{k});
end
```

```
L_VolCon = zeros(height(Z_VolumeAnalysis),1);
col_namesVolConL = Z_VolumeAnalysis.Properties.VariableNames;

for k = 1:height(Z_VolumeAnalysis)
    col_forAvL = any(cell2mat(...
        cellfun(@(x)
strcmp(col_namesVolConL,x),Z_VolumeAnalysis.L{k},...
        'UniformOutput', false).'),1);
    % logical indexing for define eligible columns for summation
    L_VolCon(k) = nansum(Z_VolumeAnalysis{k,col_forAvL})/ ...
        numel(Z_VolumeAnalysis.L{k});
end

% Concatenate Time and Volume Matrices
OverviewWLPF_TrVol = table(Y.Date, Z.L, Z.U, L_VolCon, U_VolCon);
OverviewWLPF_TrVol.Properties.VariableNames = {'Date' 'L' 'U' 'Vol_L'
...
    'Vol_U'};
OverviewWLPF_TrVol.Date = Z.Date;
OverviewWLPF_TrVol.Sum = OverviewWLPF_TrVol.Vol_L +
OverviewWLPF_TrVol.Vol_U;

% Extract data now
Vol1st_5th = OverviewWLPF_TrVol(container1st_5th, :);
Vol6th_10th = OverviewWLPF_TrVol(container6th_10th, :);
Vol11th_15th = OverviewWLPF_TrVol(container11th_15th, :);
Vol16th_20th = OverviewWLPF_TrVol(container16th_20th, :);
Vol21st_25th = OverviewWLPF_TrVol(container21st_25th, :);
Vol26th_31st = OverviewWLPF_TrVol(container26th_31st, :);

% Table overview
TradingVolOverview_WL = table(nanmean(Vol1st_5th.Sum)/2, ...
    nanmean(Vol6th_10th.Sum)/2, nanmean(Vol11th_15th.Sum)/2, ...
    nanmean(Vol16th_20th.Sum)/2, nanmean(Vol21st_25th.Sum)/2, ...
    nanmean(Vol26th_31st.Sum)/2);
writetable(TradingVolOverview_WL, 'TradingVolOverview_WL.xlsx')
```

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