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Adjusting the Momentum Strategy for Small Investors

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This is to certify that the doctoral dissertation by

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Walden University
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Abstract

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MBA, UAS Kaiserslautern, 2012

(BA) Fach.-Kfm., IHK, 2010

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Researchers recommended investing according to the long only momentum (MOM) strategy to generate excess returns for private investors. The general problem of this study was that it was unclear when to enter and when to exit declining financial markets to avoid larger losses and to improve the overall performance with the MOM strategy. Therefore, it was important to understand the influence of a timing indicator on the MOM strategy. The purpose of this study was to examine the relationship between different moving average (MA) settings, the MOM strategy, and the performance of the returns from the construction of small U.S. stock portfolios. The research question was what MA setting as a strategy adjustment could improve the MOM strategy performance for small portfolios of U.S. stocks. A quasi-experimental research design was chosen to answer this research question. For the methods and analysis, simple- and exponential-MA, 2 econometric models, and abnormal Sharpe ratios were computed on the sample basis of 30 Dow Jones Industrial Average (DJIA) stocks. The computations allowed me to determine the optimal trading frequencies for the MA MOM strategy. The key result was that the MA MOM strategy could improve the MOM strategy on average by 0.16% per month. The optimal trading frequency for the MA MOM strategy with $5,000 was tri yearly through which (0.90 - 1.85 %) net monthly return could be achieved. The MOM strategy can be adjusted by a simple moving average (SMA) indicator on a 6 versus 36-month basis as a recommendation. This study might contribute to positive social change by adjusting the MOM strategy, which specifically impacts private investors in declining stock markets to improve the overall performance when trading the MA MOM strategy.

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Dedication

I dedicate the study to my wife, who understood and listened to the challenges I faced. I would not have gotten so far without the love and the moral support that she provided. For my family who is hopefully proud of my scholarly achievement.

For the dedicated private investors, who face the difficult circumstances of investing their capital under risky market conditions.

"If you can't measure it, you can't manage it."

Robert S. Kaplan

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The subsequent study was significantly impacted by the key people who advanced my personal and academic skills. I am thankful for the great support of my committee chair, Dr. Aridaman Jain, who continued to push me and my paper forward. From his feedback and experience, I could improve in my personal and academic skills during the dissertation process. Dr. Thomas Spencer was an excellent methodologist and motivated me in his positive feedback. The dissertation has tremendously improved through the feedback, dedication, knowledge, and care of Dr. Aridaman Jain and Dr. Thomas Spencer.

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Chapter 1: Introduction of the Study

Several studies confirm the presence of a momentum effect in the capital markets (Bornholt, Dou, & Malin, 2015; Hung & Banerjee, 2014; Jegadeesh & Titman, 1993). Jegadeesh and Titman (1993) recommended benefiting from the momentum effect, by buying recent winner stocks and selling recent loser stocks. Over the years, buying recent winner stocks and selling recent loser stocks was quite successful, but small investors could not participate at momentum profits, because exceeding short selling costs counteracted the profitability of the momentum strategy for small portfolios (Foltice & Langer, 2015). It was Foltice and Langer (2015), who suggested modifying the momentum strategy. Portfolio managers with small portfolios should follow a long-only momentum (MOM) strategy, where only recent winner stocks are bought for an investment portfolio (Foltice & Langer, 2015). The MOM strategy builds upon the findings of Levy (1967). However, the modification of the momentum strategy caused a new problem for portfolio managers. In consolidating markets, the MOM strategy is not profitable which was demonstrated by Foltice and Langer. The problem occurred that the portfolio managers did not know when to enter or when to exit the market in case of consolidation of the stock market. Because of this problem, further research needed to be conducted to test for a strategy adjustment and to verify if the profitability can be raised and the losses can be reduced. By following the moving average (MA) adjusted MOM strategy, portfolio managers with small portfolios could be supported in achieving higher returns and reducing the overall draw downs in their investment performance.

Relevant for the topic were historical findings to the momentum effect, momentum and contrarian strategies, time series momentum, MA, and three main theories: (a) random walk theory; (b) efficient market hypothesis and (c) modern portfolio theory, all further discussed in Chapter 2. A short overview of the theoretical frameworks was elaborated in the framework section subsequently.

Foltice and Langer's (2015) idea of the MOM strategy was an advancement of Jegadeesh and Titman's (1993) momentum strategy and Levy's (1967) findings. Jegadeesh and Titman developed a profitable method of responding to the momentum effect. Further researchers, such as Bornholt, Dou, and Malin (2015) and, Hung and Banerjee (2014) have verified the momentum effect in various countries around the world. Later, the concepts of a contrarian momentum strategy were a relevant topic in the literature, where profitable markets seemed to decline after 1 year and a contrarian momentum strategy could be built upon this effect. It was Moskowitz, Ooi, and Pedersen (2012) who introduced the idea of time series momentum, which was more profitable than the conventional cross-sectional variation approach. However, few of these researchers connected the findings of MA to the momentum strategy. Therefore, I examined the relationship between different MA types and settings, the MOM strategy, and the performance for small US portfolios. In this study, historical stock market data of the Dow Jones Industrial Average (DJIA) were tested to fill the gap in the scholarly literature, caused by the missing research to MA and the MOM strategy.

Background of the Study

Investors should generally follow a strategy when investing in stocks. Jegadeesh and Titman (1993) introduced the momentum strategy that considers buying the top winner stocks and selling the bottom loser stocks. In regard of the momentum strategy, investors can benefit of a momentum effect that is present in the capital markets (Jegadeesh & Titman, 1993). In the recent years, researchers like Barberis, Shleifer, and Vishny (1998), Chan, Jegadeesh, and Lakonishok (1996) and, Hong and Stein (1999) focused their studies on explaining the momentum effect. Assumptions were that investors' overreaction or underreaction could be causal for the momentum effect (Barberis et al., 1998; Chan et al., 1996; Hong & Stein, 1999). Over the next decade, researchers followed all kinds of related assumptions in trying to explain the momentum effect. For example, Hong and Stein assumed that analyst coverage could be essential, and Daniel, Hirshleifer, and Subramanyam (1998) proclaimed that behavioral aspects could be a cause for the momentum effect. However, although some promising findings were made, none of these studies could provide a complete model that explained the momentum effect sufficiently. Fama and French (1996) suspected that a multifactor model could bring more insight. In conclusion, different directions were investigated to explain the cause of the momentum effect, further research should occur and especially in consideration of multifactor models.

Despite of all the conducted research, one relevant aspect (of not selling loser stocks) was not largely covered in the scholarly literature. Because of also selling loser stocks as an investment strategy, the momentum strategy was not applicable for everybody. Foltice and Langer (2015) covered this topic and stressed the issue of constrains and high costs for investors. In their study, small portfolios for investors were of interest (Foltice & Langer, 2015). To make these small portfolios affordable, Foltice and Langer adjusted the momentum strategy and tested this by only considering recent winner stocks. Foltice and Langer's study showed that it can be profitable to follow a MOM approach and reported profits of circa 20.88% per year; but, in consolidating market losses of circa -25% per year can occur. This means that for investment managers with small portfolios, momentum strategy adjustments were made but, the changes caused a new problem that has not yet been addressed. Therefore, the new problem that was caused by not selling loser stocks is a relevant aspect to further investigations.

The problem found in Foltice and Langer's (2015) study was not yet addressed in the resent literature. A solution to the problem came from the application of an indicator. Cohen and Cliffer (2014) introduced the consideration of the MA for U.S. stocks. Dolvin (2014) experimented with different MA types and setting to determine the most profitable entry and exit signals for the S&P500. A key insight was that volatility had a large impact (Dolvin, 2014). In conclusion, a study was needed to test different indicator settings of MA in connection to applying the MOM strategy. The findings are relevant to close the gap in the literature detected in Foltice and Langer's study.

Problem Statement

The momentum effect is present in most global capital markets. Garg and Varshney (2015) reported that millions of dollars can be earned all over the world by following the momentum strategy. The momentum strategy means for investors to benefit from stock markets by buying winners and selling losers (Jegadeesh & Titman, 1993). And, for the MOM strategy only recent winners are bought (Foltice & Langer, 2015). Therefore, participating at the gains, achieved through applying the momentum strategy, is most relevant for portfolio managers, investors, and other capital market spectators.

The current situation was that the MOM strategy did not always perform in the favor of the investor and exhibits a severe deficit. From 2007 to 2008 institutional (private) portfolio managers have been losing capital for their organization in negative market phases, when applying the MOM strategy. In a comparison of gross momentum returns that were not adjusted for costs during 1992–2009, the profits ranged from 1.74% until 3.08% per month in positive market phases and were negatively impacted during the negative market phase in 2007 - 2008 with a range = [-2.12%, -2.81%] on a monthly basis (Foltice & Langer, 2015). This could mean a loss of circa -25% per year or more for the manager, and especially in case of small portfolios.

The general problem of this study was that it was unclear when to enter and when to exit declining financial markets to avoid larger losses and to improve the overall performance with the MOM strategy. Until now, timing methods have not been tested sufficiently for the MOM strategy in the investment management literature. Although Foltice and Langer (2015) reported findings that the MOM strategy was successful for small investors, they failed with the results of their study to demonstrate how investors should decide when markets decline. At the moment, the portfolio managers were required to continue buying winner stocks even when the markets consolidate (Foltice &

Langer, 2015). Other researchers (Asness, Moskowitz, & Pedersen, 2013; Jegadeesh & Titman, 1993) also explored the momentum effect, but through the modification of Foltice and Langer’s long-only strategy, a new timing issue occurred.

The specific problem was to understand the influence of a timing indicator, referred to as the MA, on the MOM strategy and the performance of the returns from the construction of small U.S. portfolios. To achieve positive social change, I helped to identify if the MOM strategy could be adjusted and improved for investment managers who construct small U.S. portfolios. This research filled the gap in understanding the impact of the MA on the long-only momentum strategy for small portfolios of U.S. stocks.

In regard of the method and design of this study, I used a quasi-experimental design to test different constructed MOM and MA MOM portfolios. In order to construct the portfolios, the population of this study was U.S. stocks of the DJIA index.

Purpose of the Study

The purpose of this study was to examine the relationship between different MA settings, the MOM strategy, and the performance of the returns from the construction of small U.S. stock portfolios. I used a quantitative methodology and a quasi-experimental design to critically test different MA indicator day combinations. This was relevant, to research a methodology, as a strategy adjustment, to apply to MOM portfolio construction. For the quasi-experimental setting and the analysis, the independent variables were DJIA index returns, 30 DJIA stock returns, risk-factors, overlapping MA MOM returns, and Sharpe ratios. The dependent variables were the DJIA bull phase returns, portfolio returns, estimated overlapping MA MOM portfolio returns, risk-adjusted excess returns (alphas), and abnormal Sharpe ratios. The control variables or treatments were two different MA types, the SMA and the EMA with seven different number of day settings, BH strategy, MOM strategy, MA MOM strategy, overlapping MA MOM strategy differentiated by the six different trading frequencies and nine different investment amounts. For the analysis, I used historical DJIA data from January 01, 1992 until December 30, 2010. The geographic location of the study was focused on the U.S. stock market and on the U.S. DJIA stocks. The study contributed to positive social change by improving the trading performance of investment managers with small U.S. stock portfolios, who apply the MA MOM strategy.

Research Question and Hypotheses

In this study, I examined the adjustment and the improvement of the MOM strategy through the application of a MA. One main research question (RQ) guided the study. The research and the quasi-experiments lead to the following seven pairs of hypotheses (H) to answer the RQ, listed in detail subsequently:

RQ: What MA setting as strategy adjustment can improve the long only momentum strategy performance for small portfolios of U.S. stocks?

H1: $H_0$1: If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then no optimal MA number of day setting and no optimal MA computation type can be found to adjust the MOM strategy.

$H_1$1: If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then the optimal MA number of day setting and the optimal MA computation type can be found to adjust the MOM strategy.

H2: $H_0$2: If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are not greater than the DJIA index and the MOM strategy returns.

H_1 2: If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are greater than the DJIA index and the MOM strategy returns.

H3: $H_0$3: If the costs are factored for the MA MOM strategy, then the MA MOM strategy is not profitable.

H_1 3: If the costs are factored for the MA MOM strategy, then the MA MOM strategy is still profitable.

H4: $H_0$4: If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects do not occur for the returns of the MA MOM strategy.

$H_1$4: If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects occur for the returns of the MA MOM strategy.

H5: $H_0$5: If the CAPM and the FF3FM alphas are computed for the overlapping

MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are not positive.

H_1 5: If the CAPM and the FF3FM alphas are computed for the overlapping MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are still positive.

H6: $H_0$6: If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount cannot be determined.

$H_1$6: If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount can be determined.

H7: $H_0$7: If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the MA MOM strategy returns are not greater than the MOM strategy returns.

$H_1$7: If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the MA MOM strategy returns are greater than the MOM strategy returns.

The setup of the research design in connection to the seven hypotheses, the variables relations, and the methodologies that were relevant for the study, are explained in more detail in Chapter 3.

Theoretical Foundation

Five theoretical frameworks were relevant for this study: (a) random walk theory, (b) efficient market hypothesis, (c) modern portfolio theory, (d) momentum strategy, and (e) moving average. The random walk theory describes the phenomena of random movements which are also referred to as Brownian motions (Cootner, 1964). Mandelbort (1963) and Samuelson (1976) detected that old information does not impact asset prices and that financial markets exhibit random walk price movements. The random walk theory was relevant for the study since it describes an important aspect of how markets function. Buyers and sellers require fair market conditions for an efficient price building.

Fama (1970) contributed to the issue of the efficient market hypothesis. The main question of Fama's study was to determine how fast financial markets can process the public available information. Stock prices seem to fall and to rise to efficient price levels impacted through arbitrage capital and market movements (Akbas et al., 2016). This means that arbitrage actions of investors can equalize market anomalies, which is relevant for the efficiency of a market. Fama reported three market efficiency forms: (a) weak, (b) semi, and (c) strong. The efficiency of capital markets is important for investors, because fair market conditions incorporate all available information equally distributed to investors. Information needs to be equally available to investors for the process of fair price building and especially when allocating scarce resources.

The modern portfolio theory (MPT) is important to state when assessing investment decisions and when constructing investment portfolios. Two key figures for the MPT were risk and return (Markowitz, 1952). Markowitz (1952) explained that in investment portfolios two forms of risk need to be distinguished: (a) unsystematic risk and (b) systematic risk. Through the diversification of an investment portfolio, correlation effects can minimize the degree of unsystematic risk. The diversification of security portfolios can lead to two main objectives for an investor. An investor can either choose to minimize the risk or to maximize the possible expected return, when diversifying a for example stock portfolio (Markowitz, 1952). Investors commonly use asset pricing models for the construction of an investment portfolio. Two leading asset price models, next to others, are the capital asset pricing model (CAPM) and the Fama and French Three Factor Model (FF3FM) (Berk & DeMarzo, 2011). I applied both asset price models in this study to evaluate the risk-adjusted excess returns of the MA MOM portfolios.

Investors generally follow an investment strategy when constructing stock portfolios. In this study, the theory of momentum strategy has a special focus. It was Levy (1967) who first reported that it can be successful for investors to buy the top of winning stocks that lead to significant abnormal returns. Jensen and Bennington (1970) confirmed this 3 years later that relative strength was a crucial aspect for momentum returns. From these findings, Jegadeesh and Titman (1993) developed their theory to the momentum strategy. Jegadeesh and Titman claimed that investors can benefit from a momentum effect in the capital markets, by buying winner and selling loser of the top

10% stocks. An implication for the momentum strategy was that different return formation and different holding period combinations can form different portfolios. For example, through h = returns and k = holding periods several [h: k] combinations can be developed (Jegadeesh & Titman, 1993). Over the years, more research occurred to optimize the theory of the momentum strategy. It was Foltice and Langer (2015) who criticized a cost issue that occurs for small investments and that the momentum strategy is not applicable for investors with small portfolios. This aspect motivated Foltice and Langer to follow Levy's approach and to adjust the application of the momentum strategy. The new concept proclaimed that investors should only buy the top winner stocks, because the investors could still stay profitable with this strategy, even after factoring the transaction costs. Further improvements occurred to the momentum theory adjustment. Foltice and Langer, Tse (2015), Hung and Banerjee (2014) found that when constructing a portfolio an overlapping investment strategy should be considered, through which higher returns can be achieved for an investment portfolio. Instead of investing a single amount at the beginning of a holding period, the investment amount is divided in smaller fractions and different frequencies according to the holding period (Foltice & Langer, 2015). The momentum theory is relevant for investors that are interested in applying a profitable strategy based on the momentum effect for their investment. Since further methodology adjustments were required to improve the MOM strategy, I focused my research on adjusting and improving the MOM strategy.

A second relevant investment strategy and theory in finance is the concept of the MA. Although Yule (1909) was one of the first who computed MA in a correlation study; however, it was Taylor and Allen (1992) who reported the popularity of MA trading rules for traders. The findings were made from currency traders in the UK, were 90% of the currency traders used trading rules as an important instrument for short-term investment strategies (Taylor & Allen, 1992). Commonly three indicator types are distinguished: (a) SMA, (b) EMA, or (c) logarithmic moving average (LMA) next to others. Dolvin (2014) contributed to the MA theory by explaining how MA can be used for investment strategies. Dolvin mentioned that MA price crossover and double crossover are signals for security investors to decide when to enter or when to exit a capital market. For Dolvin's test, two indicator time periods of 50 days and 200 days were reported; however, other time periods have also been tested and were found as profitable for MA investment strategies (i.e., Dolvin, 2014; Nedeltcheva, 2015). The MA theory is relevant for investors who require a timing signal for investment decision making or apply the MA as an investment strategy. Therefore, the second theory I focused in this study, covered the concepts of MA and in specific the issues SMA and EMA.

All five theories that were previously mentioned were relevant to the study, because a capital market related issue was subsequently further assessed. The findings of Foltice and Langer (2015) were closely tested in this study, with a connection to Dolvin's (2014) considerations of MA's. The introduced theories aligned with the research question, because the theories were relevant for testing a strategy adjustment and improvement of the MOM strategy. The presented five theories were discussed more in detail in Chapter 2.

Nature of the Study

I used a quantitative methodology and a quasi-experimental design to critically test different MA indicator day combinations (i.e., performed by Dolvin, 2014). Dolvin (2014) recommended focusing on the simple moving average (SMA) and the exponential moving average (EMA) when using a MA as a timing signal for investment decisions. I have chosen a quasi-experimental design, because the sample of DJIA stocks cannot be randomly allocated to the treatment. For the quasi-experiment, I compared three types of portfolios: (a) buy and hold (BH) portfolio, (b) MOM portfolio, and (c) MA adjusted MOM portfolio (subsequently referred to as MA MOM). For the different indicator testing, a single fit solution for all stocks is approached, meaning that the findings of different MA settings (i.e., 50 or 200 days SMA) are applied to an index. According to these index-based trading signals, I made a stock portfolio selection, while following the MOM strategy (i.e., Foltice & Langer, 2015; Jegadeesh & Titman, 1993). This means by following a quantitative approach, I applied the manipulation of the control (treatment) variable MA (i.e., SMA and EMA) to the independent variable *index returns* and test the improvement of the depending variable *returns* of the portfolios. Two econometric models were selected to assess the profitability of the returns of each portfolio after factoring the transaction costs: (a) CAPM and (b) FF3FM to determine the risk-adjusted excess returns (alphas) of the portfolios (e.g., Foltice & Langer, 2015). Essentially the excess returns, the Sharp ratios, and the independent sample *t* tests were computed to contrast the results in relation to each other. The previously mentioned statistical tools can provide support in validating the results of the dissertation.

Definitions

Capital Asset Price Model (CAPM): CAPM is an econometric method to determine the expected return of a security that considers: (a) security's sensitivity to market changes; (b) excess market return; and (c) risk-free return of for example a U.S. treasury security return (Berk & DeMarzo, 2011).

Death Cross: The cross-over [double-cross over] of one [two] moving average[s] can be a trading signal for capital market investors (Dolvin, 2014). If the current market price crosses below the for example 200 day moving average, then this cross-over can be a selling signal for downwards trending stocks (Dolvin, 2014).

Fama and French Three-Factor Model (FF3FM): FF3FM is an econometric method to determine the expected return of a security, containing three factors for the equation: (a) firm's book value to market value ratio, (b) difference in the risks of small verses large firm securities, and (c) excess market return (Berk & DeMarzo, 2011).

Golden Cross: The cross-over [double-cross over] of one [two] moving average[s] can be a trading signal for capital market investors (Dolvin, 2014). If the current market price crosses above the for example 200 day moving average, then this cross-over can be a buying signal for upwards trending stocks (Dolvin, 2014).

Momentum Strategy: Momentum strategy is a trading strategy for securities. The momentum strategy refers to buying and additionally selling the top and bottom 10% of winner and loser stocks (Jegadeesh & Titman, 1993). Portfolios are constructed through (h = return period) and (k = holding period) combinations of [h:k]; for example [3:3], [6:6], [9:9] or [12:12] combinations (Jegadeesh & Titman, 1993).

Sharpe Ratio: Sharpe ratio is a ratio to measure the excess return of an asset per unit of risk (Berk & DeMarzo, 2011). The ratio is inversely proportional to the standard deviation of the expected return (Berk & DeMarzo, 2011). Values above 1 represent a higher probability for excess returns, where values below 1 represent a higher probability for risk (Berk & DeMarzo, 2011). The ratio is ideal to conduct a risk and return comparison between different investments (Berk & DeMarzo, 2011, Vogt & Johnson, 2011).

Technical Analysis: Technical analysis is a financial market technique that considers price movements of markets primarily where turning points of price action have a special focus (Gurrib, 2015; Nedeltcheva, 2015). The technique follows traditionally short-term patterns such as (a) gaps, (b) volatility patterns, (c) wide-range bars, and (d) intraday patterns; however, also indicators are relevant such as (a) MA, (b) stochastic, (c) oscillators et cetera (Nedeltcheva, 2015). Studying charts from past market data, ratios, and market statistics is essential for the technical analysis (Nedeltcheva, 2015).

Assumptions

The first assumption was that stock market investors seek to minimize their risks and seek to maximize their returns by following a momentum strategy. This risk and return assumption was partly consistent with Markowitz's (1952) proclamations. Investors can follow various reasons to invest in financial markets. However, the investor risk- and return-seeking assumption was relevant because it referred to why investors follow a momentum strategy and why an improvement of the MOM strategy was important.

The second assumption was that the research and the results of Foltice and Langer's (2015) study were valid and correct. Therefore, I relied on Foltice and Langer's findings and I considered their data for my further analysis (i.e., transaction costs: average spreads and fee values). Since stock data were publicly available information and Foltice and Langer's article was peer reviewed, this aspect mitigated any validity and authenticity questions when considering the Foltice and Langer's results.

Scope and Delimitations

For the study, I used historical data from the DJIA index between 1992-2010. The historical stock market data allowed me to remodel parts of Foltice and Langer's (2015) findings, using a MA to adjust the MOM strategy. The DJIA data considered dividend adjusted daily closing prices of the DJIA index and of the 30 DJIA stocks. Individuals were not included for the analysis of my study, since my population only comprised U.S. corporations and a stock market index. This means that no living subjects were used for the research which would require ethical considerations.

The research question was answered through the quasi-experimental testing of the MOM strategy, to overcome methodological deficits that were detected in Foltice and Langer's (2015) study. I tested whether market timing signals, obtained from applying a MA in different types and number of day settings, created higher positive returns, when applied and compared to a MOM strategy. I also tested if the adjusted MOM strategy was still profitable after controlling for the transaction costs, for small portfolios. A comparison between the MOM strategy findings and the MA MOM strategy results validated if a strategy adjustment was more beneficial for small investors. The findings of the comparison that was conducted in this study is relevant for other researchers to investigate if the MA MOM strategy is also profitable in similar markets.

Limitations

The research in this study was limited to stock market data of the DJIA. Bond, commodities, funds, currencies, or other securities are not considered for the analysis of the MA MOM strategy. Even though the DJIA represents the 30 most relevant industrial U.S. stocks, the findings of this study were not applied to all other indices or industrialized nations. For example, other countries with a low individualistic culture did not exhibit a strong moment effect in their stock markets (Bornholt, Dou, & Malin, 2015). Therefore, further studies and further research was required to make inference conclusion to how this study results could be applicable for other, global stock markets.

Next, I discussed the limitations for the investigated strategy of this study. The findings of this study were limited to the MA MOM strategy and the findings were not applicable for the primer momentum strategy. For example, testing the impact of a MA on the momentum strategy with this studies approach would require a different research design and a different methodology. The reason for this is that the methodological issue of the MOM strategy only occurred for the MOM strategy. This means that the limitation of the generalization of the MA MOM strategy results affected a relevant aspect of the external validity. Therefore, the results of this study were limited for the generalization to the MA MOM strategy.

Further, I made limitations to the design and to the methodology that was considered for this study. The design and methodology of this study was limited to the nature and parts of Cohen and Cliffer's (2014), Dolvin's (2014), and Foltice and Langer's (2015) design and testing methods. Other research designs or other methodology variations were not applicable to answer this studies research question. Since the design of this study was a quasi-experimental design and the stocks of the DJIA were a finite, non equivalent group, the stocks of the DJIA could not be allocated randomly to the experiment (e.g., Cook, 2015). This quasi-experimental aspect limited the internal validity, because preexisting conditions influenced the causality of the MA MOM strategy performance. However, through a pre- and post test, between a BH strategy compared to the MOM strategy and the MA MOM strategy, the quasi-experimental aspect of missing randomly allocation of the stocks to the sample was mitigated.

Significance of the Study

In this section I commented on the significance of the study. Three aspects were of interested: (a) how does the performed research in the study contributes to the theory, (b) how do the findings of the study can impact practice, and (c) how do the findings of the study can achieve social change.

Significance to Theory

The study that I conducted was generally important because the existing scholarly literature barely considered the issues that small investors have, when trying to replicate the momentum strategy (i.e., the issue of constrains and of high transaction costs). Although, Foltice and Langer (2015) and other researchers have started to address private investors with small portfolios in their studies, more research is needed to fill the gap in the scholarly literature. It was relevant for answering the research question to test if the MOM strategy methodology could be improved and advanced. My study was one of the first to connect the issue of MA and the momentum effect in the scholarly literature for small security portfolios. This means introducing a new methodology combination that connected MA with the MOM strategy impacted the present, scholarly literature significantly, because the MA MOM strategy solved an existing methodology deficit of the MOM strategy and provided a potential issue for further research by other scholars. Therefore, the study that I developed was generally important for investors with small portfolios and other scholarly researchers.

Significance to Practice

Investors seek to follow investment strategies to maximize their profits in capital markets. The study was relevant for institutional investors, portfolio managers, traders et cetera, because an investment strategy with a new combination of a verified methodology of MA timing signals was investigated. The study was especially interesting for private investors that manage small portfolios to learn about an alternative method of trading the stock markets. Through an evaluation of adjusting the MOM strategy with a MA, the relevant audience could learn if the MA MOM strategy was profitable, and if the momentum effect could be capitalized with small portfolios more effectively, when compared to the results of the MOM Strategy.

The insights through the study were useful for an investment manager’s decision making of applying the MOM strategy. The investment manager could decide if replicating the MA MOM strategy was more profitable than Foltice and Langer's (2015) approach. In the study I commented on, what MA indicator type and what MA parameter setting are required for a performance improvement of the MOM strategy. Investment managers could learn from the study what optimal setting of the MA should be considered for the MA MOM strategy and what risks and returns could be expected. In consequence, investment manager's decision-making of applying the MOM strategy was supported by the research insights of this study.

The short-term benefit of this study was to validate if Foltice and Langer's (2015) findings could be improved through a strategy adjustment or not. The long-term benefit of the study was that the study opened a new topic for other researchers to conduct further testing to the MA MOM approach, and if the findings of the MA MOM strategy held for different markets, different asset classes, and so forth. Therefore, the benefits of conducting the study had long-term and short-term advantages for capital market investors and economical researchers.

Significance to Social Change

Positive social change was achieved through this study by developing a simple strategy adjustment for the MOM strategy. Through a simple MOM strategy adjustment losses decreased and returns increased for investors who applied the MA MOM strategy (Foltice & Langer, 2015). The MA MOM strategy allowed private investors with small portfolios to capitalize more effectively from the momentum effect. The novelty of this study was that private investors could respond more adequately to consolidating stock markets with their momentum investment decisions by applying the MA MOM strategy.

Through my research, I evaluated if the MOM strategy could be adjusted by a timing indicator and improved in its strategy performance.

Summary and Transition

Trading in the capital markets often requires for investors to follow an investment strategy. Jegadeesh and Titman (1993) detected that in financial markets a momentum effect is present and introduced the momentum strategy. The momentum strategy can be quite profitable for institutional investors. However, investors who manage smaller portfolios face constraint for short selling small- valued stocks and cost issues when applying the momentum strategy. Foltice and Langer (2015) have analyzed the issue that investors with small portfolios have and made recommendations and adjustments for the momentum strategy. Investors with small portfolios should follow a MOM strategy and should only buy the top 10% of the winner stocks in a stock market (Foltice & Langer, 2015). This strategy change brought up a new issue for the investor. In consolidating markets, the MOM strategy was not profitable with circa -25% losses per year (Foltice & Langer, 2015). Therefore, the main issue was to find a methodology adjustment to improve the MOM strategy.

In this chapter, I provided an overview to the momentum strategy, as well as a problem statement, a theoretical framework to the research topic, definitions of relevant terms that were used in the study, a background to relevant current studies, assumptions, delimitations, limitations, a purpose statement of the study, and comments to the significance of the research. In Chapter 2, I performed an in-depth literature review to the momentum strategy, theoretical foundations, and methodologies that were relevant for the study. In Chapter 3, I covered the research design and the methodology applied, while referring to the population, sample procedure, and data collection that were crucial for the analysis and were relevant for the testing results. For this research, numerous academic databases, Google Scholar, and other relevant sources were investigated.

Chapter 2: Literature Review

The general problem of the study was that it was unclear when to enter and when to exit declining financial markets, to avoid larger losses and to improve the overall performance with the MA MOM strategy. The specific problem was to understand the influence of a timing indicator, referred to as the MA, on the MOM strategy and the performance of the returns from the construction of small U.S. portfolios. While the purpose of this study was to examine the relationship between different MA settings, the MOM strategy, and the performance of the returns from the construction of small U.S. stock portfolios. In Chapter 2, I conducted a literature review to summarize, critically compare, analyze, and synthesize the relevant literature on the theories; the key variables and concepts; and the methodologies that were crucial for the momentum strategy and for the MA. In the literature review, I commented on three relevant theories in the theoretical framework section: (a) random walk theory, (b) efficient market hypothesis, and (c) modern portfolio theory. Five main concepts were discussed in the key variable and concepts section: (a) momentum strategy, (b) momentum effect, (c) momentum effect in countries, (d) time series momentum, and (e) MA. Four important methodology issues were explained in the methodology section: (a) CAPM, (b) FF3F, (c) Gibbon Ross Shanken (GRS) test, and (d) quasi-experiment. A special focus occurred in the chapter by examining both the strengths and the limitations of the reviewed literature issues.

Each subsection of Chapter 2 required an individual way of proceeding. In the subsection *literature search*, I first discussed the literature review strategy, and I commented on the investigated literature databases. In the subsection *theoretical* *framework*, I then presented the background of three main theories, an analytical review, and a synthesis to assess the relevance of theories for the research question of this study. For the subsection *key variables* and for the subsection *methodologies*, the findings of the literature sources were synthesized and a reflection of the strength and the weaknesses were provided. I provided a conclusion at the end of the literature review and of Chapter 2, by identifying the literature gap and by stressing the potential for further research.

Literature Search Strategy

To conduct a literature review, 14 library data bases and one search engine were accessed and searched. The selected 14 library data bases were: (a) Academic Search Complete | EBSCO host, (b) Accounting & Tax, (c) EBSCO / Business source complete, (d) Emerald Management | Emerald Insight, (e) Dissertation & Theses Q Walden University, (f) Hoover's Company Records / ProQuest, (g) Market Share Reporter, (h) National Bureau of Economic Research, (i) ProQuest / ABI/ INFORM Collection, (j) ProQuest Central, (k) SAGE Premier / Journals, (l) SAGE Stats, (m) Thorough / EBSCO, and (n) World Bank Open Knowledge Repository. The accessed search engine was Google Scholar.

For the literature review section, I conducted a literature search to current peer-reviewed journals and to seminal literature. I set the search options to peer-reviewed sources and I selected the years 2014 until 2018 to obtain current peer-reviewed journals. I individually searched for relevant seminal journals, for example to theories and to the origin publication of a topic for the years 1905 until 2013. From a time frame of 114 years, I covered approximately 40 different years of relevant finance literature through my literature search.

The circa eight used search-terms were (a) *finance,* (b) *investment,* (c) *MA,* (d) *market efficiency,* (e) *market timing strategy,* (f) *modern portfolio theory,* (g) *momentum,* and (h) *volume* and combinations of the search-terms. The literature search resulted in 380,190 literature sources that were connected to the key search terms. From these literature findings, I identified as relevant 217 peer-reviewed journals, from which I considered 103 peer-reviewed journal articles, as well as five books for the literature review.

Using the term *momentum* led to 219,916 results in all data bases. Using the term *momentum investment* led to 99 results in the database EBSCO / Business source complete. Using the term *momentum* AND *finance* led to 21,148 results in seven databases including Google scholar. Using the term *market timing strategy* led to 27,647 results in the database ABI/ INFORM Complete and led in five databases to 51,866 results including Google scholar.

Theoretical Foundation

In this section, I performed a literature review to the most relevant theories for the study. The following three theories and hypothesis subsequently were further elaborated: (a) random walk theory, (b) efficient market hypothesis, and (3) modern portfolio theory.

Random Walk Theory

The random walk theory refers to random movements that were closer specified over the years by several researchers. According to Cootner (1964), the issue of random walk was first observed by Brown in 1827. Brown observed the motion of small leaves on the surface of water and recognized that the movements of the leaf's occurred randomly (Cootner, 1964). Today, such random movements are also referred to as *Brownian motion*. Cootner postulated that small particles react in liquids. In 1905, Karl Pearson reported the problem of the random walk in an essay and brought the term to the discussion (Pearson, 1905). Mandelbort (1963) and Samuelson (1976) connected the issues Brownian motion and random walk to observations of financial markets. Mandelbort and Samuelson stated that future price changes can follow the order of a random walk, where older information did not seem to impact the asset prices. This means that over the years random movements were closer specified and quantified in a theory. The random walk theory was connected to different science areas and was connected to the field of financial markets.

The random walk theory was relevant to mention in this study because it describes one important aspect of how finical markets function. Buyers and sellers can benefit from a market that is based upon random price building because the conditions of such a market are fairer for investors (Fama, 1965). For example, fair market conditions are relevant for investors to decide if participating in a market is beneficial to gain abnormal returns. I selected the theory because the random walk theory is groundwork in financial research. This theoretical groundwork led Fama (1965) to further insights on the function of markets and the theory of efficient markets.

Efficient Market Hypothesis

The efficient market hypothesis (EMH) indicates that it seems impossible for investors to beat an efficient capital market. Fama (1970) concluded that if imperfections in capital markets occur (i.e., abnormal returns), then investors would immediately exploit such imperfections. Akbas, Armstrong, Sorescu, and Subrahmanyam (2016) suggested that arbitrage trading actions support the efficiency of prices. The argument was that if a lot of arbitrage capital is available in the markets, then stock prices will rise [fall] fast to efficient price levels. Jiang (2017) felt that inquiring on how well asset prices can adjust to market information was important for an efficient market. This means that efficient share prices incorporate all relevant market information and that efficient securities trade at a fair price level (Fama, 1970). Efficient markets seem irrational and hard to predict for investors (Fama, 1970). Investors can only obtain higher returns from an efficient market, by accepting to take over a higher risk. Efficient markets can be seen as perfectly allocated markets, where the security prices reflect all available public information (Fama, 1970).

Fama (1970) was the first who quantified the issue of efficient markets by developing a model to determine a market's efficiency. The model distinguished three markets efficiency forms of: (a) weak, (b) semi, and (c) strong (Fama, 1970). In Scenario A, the market prices were independent to past prices (Fama, 1970). In Scenario B, price-changes occurred dynamically to all publicly available market information (Fama, 1970). And in Scenario C, the prices included all available information, both publicly and privately available, which occurs rather rare in reality and is more of a theoretical conception (Fama, 1970). The question of what efficient market state is most desired could be answered through the econometric model that Fama introduced. As a result, the semi efficiency form is a widely most desired form, where prices reflect all publicly available market information (Fama, 1970). The benefit of an efficient market is that the prices ensure all types of investors having equal information for their investment decisions. Fama was one of the first who provided a quantified model that validated how efficient a market was to the research field.

Various studies in finance have discussed the issue of EMH and the issue of efficient market variation meanwhile. Oprean, Tănăsescu, and Brătian (2014) tried to differentiate if current capital markets follow an evolutionary pattern or simply follow a random walk. From an analysis, the Brazilian markets were found to be the closest markets that fit the assumptions of the EMH (Oprean et al., 2014). The Estonian, Chinese, and Romanian markets were found to be the furthest away from the proclamations of the EMH, when observing the fractal Brownian motions (Oprean et al., 2014). Jiang (2017) disagreed here and brought the issue of time horizons to the discussion for the EMH. For long time horizons the markets seemed efficient and for short time horizons the markets could exhibit some inefficiency (Jiang, 2017). In comparison Jiang provided a different explanation to Oprean et al.'s approach in explaining market efficiency variation. Akbas et al. (2016) confirmed that the level of cross-sectional stock market efficiency can vary over time and indicated that market efficiency variation could also depend on the availability of arbitrage capital. Since Akbas et al. (2016) saw enough capital flow as relevant to equalize arbitrage anomalies in efficient markets, an insight was that when the capital flows were high, then quantitative funds could realize arbitrage strategies effectively. The findings of Akbas et al. strengthened the argument for time horizon and enough capital flow as potential indicators that impact the variation of market efficiency. However, high capital flows lead to lower performance of future market anomalies and vice versa (Akbas et al., 2016). In other words, investors in future markets could achieve a better performance if more anomalies would occur. Akbas et al.'s findings seemed contradicting, because investors seek efficient markets to benefit from fair market conditions, but, on the other hand require inefficiencies to achieve a better performance outcome for their investing in securities. Jiang found that market efficiency can vary greatly across individual asset classes. The prices were close to random walk movements for stocks with good liquidity, frequent trading, high return volatility, high prices, larger market capitalization, and a small trade size (Jiang, 2017). But, depending on the information environment of a market, the market efficiency can exhibit variation (Jiang, 2017). Oprean et al. (2014) criticized that some EMH studies seemed to be conflicting with inconclusive outcomes. I can conclude that some findings of the researchers for the EMH supported the argument of conflicting outcomes. Oprean et al. found evidence in their studies for random walk price movements and efficiency in markets. The markets varied in their efficiency, depending on the markets time horizons; across markets and across assets classes; depending on enough capital flow and depending on the information environment.

The EMH was important to mention because it determines a relevant condition and a relevant explanation for the efficiency variation of a market. For example, when an investor selects a market to apply an investment strategy, then the selected market should align with the proclamations of the EMH for optimal market conditions. When determining optimal market conditions, criteria to consider can be that information availability, enough capital, and frequent trading which should be present. I selected the EMH because the EMH is relevant to know for stock market decisions and investment decisions.

Modern Portfolio Theory

For the modern portfolio theory (MPT), two key figures are risk and return (Biswas, 2015; Markowitz, 1952). Biswas (2015), Markowitz (1952), and Otuteye and Siddiquee (2014) all agreed that the relation between risk and return is fundamentally important for MPT. Markowitz (1952) distinguished portfolio risk in two kinds of forms, as: (a) systematic risk and (b) unsystematic risk. Biswas and Markowitz explained that systematic risk exists inherently for security investments, depending on the deviation of economic, political, and social conditions. Systematic risk is therefore not diversifiable in a portfolio. Unsystematic risk is diversifiable, which can be achieved by increasing the amount of securities in a portfolio (Biswas, 2015; Markowitz, 1952). This means that investors can benefit from correlation effects. Overall, not all risks can be diversified in a portfolio. Investors can avoid unsystematic risk through diversification. A certain minimum amount of systematic risk is relevant for a portfolio to receive a higher reward. Therefore, the two key figures relevant in MPT are risk and return (Biswas, 2015).

However, there are effects on the construction of portfolios from risk and return. Markowitz (1952) explained that investors can follow two approaches for portfolio construction. For the first approach, the portfolio manager can seek to maximize the possible expected return through diversification (Markowitz, 1952). For the second approach, the portfolio manager can seek to maintain a minimal level of risk through diversification (Markowitz, 1952). Rutterford and Sotiropoulos (2016) confirmed Markowitz 's finding that different investments cancel the risk out in diversified portfolios. Rutterford and Sotiropoulos argued that geographical (or international) diversification seemed superior to reduce risk, rather than sectoral diversification. Rutterford and Sotiropoulos validated their findings through observations for UK investors. This means that the risk and return of an individual investment is not too important in MPT, rather how an investment impacts the overall portfolios risk and return relation. The effects of risk and return lead to two approaches for portfolio construction, a minimal risk and a maximal return approach, impacted through the effects of diversification.

For the construction of an optimal portfolio, the CAPM is commonly used. It was Sharpe (1964) who first presented findings to the CAPM. In the next years, Lintner (1965) and Mossin (1966) advanced the CAPM by elaborating the issue of risky asset valuation on the basis of an econometric model in connection to a general equilibrium of capital markets. Next to Sharpe, also Blume, King, and Rosenberg (as cited in Markowitz, 1991) helped to clarify the issue of estimating covariances for the analysis of securities. Mazzola and Gerace (2015) demonstrated how the CAPM is used today, and how to compute the expected returns of stocks for the portfolio selection. Otuteye and Siddiquee (2014) agreed that the consideration of asset pricing models is today a commonly used method. However, both Mazzola and Gerace and Otuteye and Siddiquee (2014) saw large limitations for the pricing models of choice. For example, Markowitz (1952) assumed that investors prefer less risk and only accept more risk for a higher reward. Markowitz's assumption is important to know when applying the MPT. On the other side, Otuteye and Siddiquee countered that investors do not act rational when participating at the financial markets. Investors are quite different with heterogeneous goals to invest their capital (Otuteye & Siddiquee, 2014). Further, not all capital market participants are investors and essentially the decisions made are often not rational choices (Otuteye & Siddiquee, 2014). Otuteye and Siddiquee and Mazzola and Gerace were skeptical how optimal portfolios perform. And, Mazzola and Gerace were especially critical for multi period timeframes. After testing an optimal portfolio that was rebalanced each week with an adjusted beta, Mazzola and Gerace concluded that in multi-period timeframes, a higher performance could be achieved with the CAPM approach, even when subtracting the transaction costs. I can conclude that econometric models, like the CAPM, are a substantial part of MPT and support the construction of security portfolios. The critique of irrational investors' decisions choices can be addressed by rebalancing a portfolio, especially for multi period timeframes.

The MPT was a critical theory, for this study because the implications of diversification are the basis for modern portfolio management. According to the theory, portfolio managers focus risk and return as two key figures that are relevant for financial decision making (Markowitz, 1952). Diversification decisions can be made from an assessment of the risk and the return of a portfolio. While diversification is not only relevant for security and stock portfolios, diversification is also applicable for all kinds of investment objects (i.e., real estate portfolios; organizational project portfolios etc.; Markowitz, 1952). I regarded the MPT as important for the study because portfolios need to be constructed to answer the research question.

Literature Review

In the section literature review, I exhaustively reviewed the current literature considering the following information. The methodologies and methods were reviewed that considered the scope of the study, by stressing the strength and the weaknesses inherent of each approach. I reviewed the key variables and the key concepts, by synthesizing the relevant studies in regard of the independent, dependent, and covariate variables. Finally, I commented on what remains to be studied at the end of this section.

Methodologies

In this part, I performed a literature review to the methodologies that were relevant for the study. Four methodology topics were identified and further discussed subsequently: (a) CAPM, (b) FF3FM, (c) Gibbon Ross Shanken (GRS) test, and (d) quasi-experiments.

Capital Asset Price Model (CAPM). The CAPM can display the relation between systematic risk and expected return of assets. The model is commonly applied for stock valuation and widely spread in finance. Berk and DeMarzo (2011) reported that the model is appropriate to price risky securities, because the model considers the risk of the analyzed assts. The CAPM is relevant, because the costs of capital of an investment can be determined by computing the expected return. Lintner (1965) stressed that risk is generally measured through the standard deviation of dollar / rate of return. However, in Lintner's analyses the assumptions referred to the sum of the variance of the analysis own aggregate dollar returns and their total covariance of risk averter portfolios. This means that researchers commonly either measure risk through the beta or through the volatility (while volatility is a part of a regression function to determine the beta). The formula of the CAPM is:

$$r_i = R_F + \beta_i \ (R_m - R_F) \qquad [1]$$

Where, r_i = excess return of portfolio i = 1,… , k; R_F = the risk free rate; β_i = the beta value or sensitivity of the risk factor i = 1,… , k; k = the number of variables; R_m = the expected market return or (R_m - R_F) is the equity risk premium (Berk & DeMarzo, 2011). Through equation 5, two main issues for an investor are considered: (1) The time value (i.e., through the risk free rate) and (2) the risk (i.e., through the beta) of an investment. Dempsey (2013) argued that the pricing of assets comes at a trade-off between undiversifiable risk and expected return. Mossin (1966) explained that the price of risk reduction is connected to the rate between expected yield and risk next to others. In other words, the expected yield will be reduced by the amount of risk reduction in case of a low risk investment decision, also referred as the price of risk. Therefore, the CAPM takes systematic risk into account which is mostly left out by regular return models.

On the other side, the CAPM exhibits also some limitations. Bornholt (2007) reported that the CAPM raised doubt about its validity. Most empirical issues of the CAPM invalidate the current application of the model (Bornholt, 2007). The critique was that the constructed factor of the CAPM was empirically driven. This means that the model is backwards looking and future market reactions are not considered in the CAPM (Berk & DeMarzo, 2011). Bornholt continued and found that the CAPM required a better method to estimate expected returns. Instead of considering the mean risk beta of the assets risk premium, as the bearing risk that an investor has to take for the reward, Bornholt followed a reward beta approach. Bornholt found that the reward beta approach was an effective method based on the asset pricing theory and empirical held against the CAPM. Dempsey (2013) added that the CAPM assumed that markets are rational, and this is not always the case. A critique point was that the CAPM is too simplistic and more sophisticated models exist on the basis of the CAPM (Dempsey, 2013). Dempsey detected that alternative models lacked to formulate a robust risk-return relation and that the risk-return relation can vary across asset classes. Berk and DeMarzo (2011) saw further limitations of the CAPM that the formula is highly sensitive to the referring variables. Despite from that, volatility can occur in the CAPM through changes of the risk free rate. This means that if the return on the market changes, a large effect on the expected return can occur. Berk and DeMarzo stressed that in some cases the market return can even be negative, for example during the finical crises in 2008. If the market return considers a long time period, this could smoothen the results of the expected returns. Dempsey and further authors argued that the assumptions that were made for the CAPM are an unrealistic view of the world. In reality, investors cannot borrow capital at a risk free rate (Dempsey, 2013). The CAPM does not consider taxes or transaction costs (Berk & DeMarzo, 2011). Li, Livdan, and Zhang (2009) added that the CAPM could not explain long-term stock-price drifts. And, some projects require a proxy to compute the CAPM through the consideration of a representative beta, which can be difficult to find. Essentially, the critique occurred for unrealistic assumptions; sensitivity to the referring factors; issues from negative market returns; missing taxes; and issues for finding suitable beta proxies.

The CAPM can be seen as a simple valuation model, because of the CAPM limitations. Researchers have advanced the CAPM over time. More advanced asset price models are for example the global or the international CAPM or the FF3FM which I discussed in the next section.

Fama and French Three Factor Model (FF3FM). The FF3FM is an econometric model, which is similar and based on the CAPM; but, the model considers more risk factors for the asset valuation. The FF3FM considers two additional factors compared to the CAPM, by adding the factor *size* (Small Minus Big; SMB) and the factor *value* (High Minus Low; HML) to the market risk factor (Akhtar, 2017; Diegnau & Masten, 2014). The FF3FM takes into account that small-stocks can outperform the market or can outperform value stocks, because a higher risk and return ratio is incorporated (Akhtar, 2017). Akhtar (2017) investigated the two risk factors more closely and found that the factors *size* and *average return* were negatively correlated (the smaller the firm, the larger the returns). And, *value* and *average returns* were positively correlated (the higher the value, the larger the returns). This means that the FF3FM extends the CAPM by two factors: (1) *size* and (2) *value*; while the aspect that small-stocks can outperform value stocks is taken into account; and both additional factors of the FF3FM exhibit correlation effects with average returns. By considering more factors in a valuation model, the outperforming tendencies can be adjusted, and more accuracy can be achieved for asset valuation or performance management.

The equation of the FF3FM is:

$$r_i = R_F + \beta_i^{mkt} RMRF + \beta_i^{size} SMB + \beta_i^{value} HML \qquad [2]$$

Where, r_i = excess return of portfolio i = 1,… , k; R_F = risk free rate; β_i = beta or the sensitivity of the risk factor i = 1,… , k; k = the number of variables; *RMRF* = excess market return; *SMB* = the return of small stocks minus the return to large stocks; *HML* = the return of value stocks minus the return to growth stocks (Berk & DeMarzo, 2011).

The three factors of the FF3FM are not the only way to approach the valuation of assets. For pricing models, Balakrishnan (2016) saw the factors *size*, *value*, and *momentum* as interesting. Balakrishnan added that *accruals* and *asset growth* for stock returns can also be of relevance. Racicot and Rentz (2016) agree to the relevance of the factors *size* and *value*. However, Racicot and Rentz saw the factors *profitability* and *investment* as important to extend a model (i.e., FF5F model), while comparing their results to the *liquidity* factor presented in Pástor-Stambaugh's (2013) study. In consequence, the three factors of the FF3FM have been extended over time and are not the only way to approach the valuation of assets.

The FF3FM was also criticized, next to the efforts of finding more accuracy for the model. Akhtar (2017) reported that in his analysis of the FF3FM, a firm's size and firm's value effect was observed which indicated that the model did not capture a certain risk premium. The results of the FF3F's seemed not properly priced, through which abnormal returns can occur for a portfolio. Balakrishnan (2016) explained that the factors *size* and *value* of the FF3FM only explained average returns partly. This supported the argumentation that the FF3FM does not capture all average expected returns for asset valuation and that a part of the risk premium could be missed. Therefore, the FF3FM is an advancement of the CAPM; but, the FF3FM can also have the tendency of mispricing and of inaccuracies.

I discussed the FF3FM in this section, because the model helped to answer the research question by quantifying the expected performance in connection to the given risk of a portfolio. In comparison to the CAPM, the FF3FM is more sophisticated and therefore provides a robust comparison to the results of a simpler model. This brought up the question; what model is best to choose, when computing and comparing the CAPM and the FF3FM, which I investigated in the next section.

Gibbon Ross Shanken (GRS) test. When computing and comparing the CAPM and the FF3FM, the question arises what model is the best to choose? Gibbon, Ross, and Shanken (1998) introduced here the GRS test. Through the GRS test, an evaluation for asset pricing models is possible, according to the asset pricing model's performance measures. The GRS test can help to quantify the decision which model to prefer, the CAPM or the FF3FM (see Rehman & Baloch, 2016).

But how can the GRS test be summarized? Researchers such as Lintner (1965) and others have tried to validate the CAPM. But during this attempt problems occurred, and unobservable risk was detected for the market portfolios (Dempsey, 2013). Validating the CAPM was seen as important, because validating the CAPM could prove that the market portfolios of the model were efficient. This observation inspired Gibbon, Ross, and Shanken (1998) to develop the GRS test. Gibbon et al. were interested in the mean-variance-efficiency of any given ex ante portfolio. From proclamations and assumptions for the Shapre-Linder CAPM, Gibbon et al. used a multivariate procedure (with two steps) to conduct a time series regression analysis and a cross-sectional regression analysis (CSRA) to test a given portfolio for its mean-variance-efficiency. This means that through the multivariate procedure, all coefficients were analyzed combined.

Inspired from Sharpe-Lintner-CAPM the following equation was relevant:

$$\tilde{r}_{it} = \alpha_{ip} + \beta_{ip}\tilde{r}_{pt} + \tilde{e}_{it} \qquad [3]$$

Where, i = 1,2, …N, and t = 1, 2, …, T; $\tilde{r}_{it}$ = the excess return on asset i in period t; $\tilde{r}_{pt}$ = the excess return on portfolio p, which efficiency is being tested; N = the number of assets being tested; α_{ip} refers to the coefficient of a multivariate linear regression model for asset i; also known as the y-axis intercept or constant coefficient; and $\tilde{e}_{it}$ = the disturbance term for asset i in period t (Lintner, 1965).

Through this, it was possible to develop an exact multivariate test for the CAPM by considering the CSRA. This F-test is constructed from a likelihood-ratio test from Ross (1983) and later advanced by Gibbon et al. (1998) in the GRS test. The GRS test was derived from a univariate T-Test connected to the T^2-Hotelling test. Where the F-test value underlay a not centralized F-distribution and the not centralized parameter λ (a valid term for analyzing the quality of tests) should be under the null hypothesis equal to zero. In this case a F(N,T-N-1)- distribution is present.

In regard of the formulas, Gibbon et al. (1998) proved in their study the relationship of:

$$\hat{\alpha}_p^{'} \hat{\Sigma}^{-1} \hat{\alpha}_p = \theta^{*2} - \theta_p^2 \qquad [4]$$

Where $\hat{\alpha}_p^{'} = (\hat{\alpha}_{1p}, \hat{\alpha}_{2p}, ..., \hat{\alpha}_{Np})$; Σ = the N x N disturbance covariance matrix; $\hat{\theta}_p$ is the ex post maximum Sharpe ratio of a K factor portfolios; θ^* is the slope of the ex ante efficient frontier based on all assets; and θ_p is the ex ante maximum Sharpe ratio of the K factor portfolios (Gibbon et al., 1998). The non centrality parameter given by λ is computed through:

$$\lambda = \left[T/(1+\hat{\theta}_p^2)\right] \alpha_p^{'} \Sigma^{-1} \alpha_p = \left[T/(1+\hat{\theta}_p^2)\right] \theta^{*2} - \theta_p^2 \qquad [5]$$

For the GRS test, the null hypothesis is equivalent to testing a particular portfolio's mean-variance efficiency, as followed:

$$H_0 : \alpha_{iP} = 0, \qquad i = 1, 2, \ldots, N.$$

To conduct the F-Test, the F-value can be derived from W as the equation shows subsequently:

$$W = \left[\frac{T(T-N-K)}{N(T-K-1)} \times \frac{\hat{\alpha}_p^{'} \Sigma^{-1} \hat{\alpha}_p}{1 + \overline{\mu} \hat{\Omega}^{-1} \overline{\mu}} \right] = F \qquad [6]$$

Where, T is the sample size, N is the number of securities or portfolios, and K is the number of risk factors (risk factors e.g., Fama & French, 1993); $\overline{\mu}$ is a $K \times 1$ vector of the sample means of asset pricing factors; and $\hat{\Omega}$ is a $K \times K$ factor covariance matrix (Gibbon et al., 1998). Gibbon et al. (1998) saw θ_p / θ^* as the proportion of the potential efficiency. If H_0 holds and all α_i are equal to zero, then $\theta_p / \theta^* < 1$ and the F value follows a non-central distribution indexed by $\lambda > 0$.

Although the GRS test is widely used in asset pricing, some critical arguments occurred. Harvey and Liu (2015) criticized that the GRS test mostly rejects the tested models. The models cannot totally explain the cross-section of the expected returns (Harvey & Liu, 2015). And, MacKinlay (1987) added that the GRS-test has the tendency to exhibit a low power when the sample size is too small. Researchers commonly use the GRS test as a heuristic method to evaluate the model's performance and to make a preference selection (Harvey & Liu, 2015). For example, if the FF3FM generates a smaller GRS test value, compared to the CAPM model, then the FF3FM would be selected. According to the example, the FF3FM would seem to be the better model, although neither of the models met the assumption that the intercepts are at zero (Harvey & Liu, 2015). This means that the GRS test statistic should meet the null hypothesis that the intercept is equal to zero. Valuation Models that are closer to zero are commonly preferred. The critique was that the GRS test cannot sufficiently answer the question what model to prefer, since the null hypothesis is often not met. Rather a heuristic methodology is used to determine the best performance of a model comparison. Therefore, the application of the GRS-test was also criticized.

Quasi-Experiment (QE). In this section, I discussed the main findings for the research design of a quasi-experiment. A key question was; how does a QE differ from an experimental design? In a QE, similarly to an experiment, the objective is to measure or to test for an effect that is caused by a treatment and applied to a target population (Thyer, 2012). This means that through a treatment, a causal impact is tested, while the design follows a traditional experimental setting (Thyer, 2012). However, the allocation of the population is not randomized (DiNardo, 2008; Thyer, 2012). Therefore, the difference between an experiment and a QE is the not randomized assignment of the population to the testing sample.

What needs to be considered for a QE design? For a QE design, it is relevant to identify the quasi-independent *(x)*, dependent (*y*), and treatment (*T*) variables (Gribbons & Herman, 1997). Where, mostly the *x*-variables are continuous variables (i.e., age) or categorical variables (i.e., gender) to use in an experiment. The *x*-variables are generally manipulated through the *T* variables to affect the *y*-variables in a QE (Gribbons et al., 1997). Schnell, Hill, and Esser (2008) stated that hypothesis need to be tested through a controlled application of a treatment, while the experimental conditions need to be maintained as constant, for example through techniques of elimination (and randomization). Through the selection of different test groups, different *x*-variable manipulations can be tested, for example according to the Solomin four group experimental plan (Schnell, Hill, & Esser, 2008), also shown in Figure 1. The predicted outcome of a QE is observed in the *y*-variable. This makes a QE design similar to an experimental design. For a QE design, the variables need to be identified, the conditions need to be constant, and the application of the treatment needs to be controlled.

SOLOMON Four Group Experimental Plan

R:	*O*	X	*O*	Experimental Group1
R:	*O*		*O*	Control Group 1
R:		X	*O*	Experimental Group 2
R:			*O*	Control Group 2
	t_1	t_2	t_3	

Figure 1. Solomon four group experimental plan. Where, O = observed or assessment of clients in time *t*; X = (new) treatment in time *t*; and R = random assignment of the group (Schnell, Hill, & Esser, 2008). Thyer (2012) added that usually *Y* is the treatment and *Z* refers to the placebo treatment. Adapted from “Methoden der empirischen Sozialforschung [Methods of the empirical social science]” by R., Schnell, P. B., Hill, & E., Esser, 2008, Germany, Munich: Oldenbourg Verlag, p 225. Copyright 2018 by Ulrich R. Deinwallner.

Why are QE designs effective? A QE design is effective, because pre- and post-testing is used (Morgan, 2000). For pre-tests, the tests are done before the treatment is applied and the data is collected, without knowledge if the population is confounding (Morgan, 2000). The post-tests occur after the experiment is conducted (Morgan, 2000). After realizing the experiment, the pre- and post- tested results can be compared (Morgan, 2000). This test setup is seen as effective, because pre- and post- effects can be analyzed in a QE. This means that QE's are effective for testing the causal impact of an effect.

What are the QE design strengths? A QE design can have several advantages in comparison to an experimental design. Randomized controlled trials are often very expensive, the external validity of trials can be very poor, while exhibiting larger deviations (Kontopantelis, Doran, Springate, Buchan, & Reeves, 2015). QE's have advantages in controlling confounding variables (Kontopantelis et al., 2015). This means that the researcher can assign the population to the treatment or can assign the control through a criterion-based selection, cutoff marks, or a controlled assignment (DiNardo, 2008). This allows the researcher to make individual selections, which can be easier to setup when for example the randomization is impractical, unethical, or for a longitudinal study with changing environments over time (DiNardo, 2008). This means that QE's provide some more flexibility than experiments. Therefore, the not randomized assignment of the population to the experimental group can have disadvantages and advantages on both sides.

What are the QE design weaknesses? For QE design, issues can occur for the internal validity, which is commonly reported (DiNardo, 2008). The treatment group and the control group may not be comparable without some bias (DiNardo, 2008). In specific, the participants do not have the same chance to be in the treatment group or in the control group, without a randomized assignment (DiNardo, 2008). The critique is that the detected differences in a comparison between two test groups could be caused through the selection probabilities, and could not be caused through the systematic factors that are connected to the treatment (DiNardo, 2008). Essentially, proving a causal connection between the treatment condition and the observed results can be an issue for QE. The issue of proving a causal relation increases especially, in case of further confounding variables that cannot be controlled for in a QE (DiNardo, 2008). The strength of a QE design, by allocating the population individually, comes with a payoff and a thread to internal validity.

How can the QE design weaknesses be addressed? As mentioned, the weakness of a QE design can be possible confounding biases, which can impact the internal validity (DiNardo, 2008; Kontopantelis et al., 2015). For example, possible confounding biases can affect the causation mean of observational studies (Kontopantelis et al., 2015). However, these biases can be controlled by using statistical methods of multiple regression, if the confounding variables can be determined (Armstrong & Patnaik, 2009). Through a regression model the confounding effect can be cancel out, by estimating causal effects, through which the accuracy of the outcome can be increased (Armstrong & Patnaik, 2009; Kontopantelis et al., 2015). Kontopantelis et al. (2015) reported about the method of interrupted time series analysis, segment regression, or discontinuity analysis to evaluate longitudinal effects of interventions and by modeling the results with a regression model. Also, the development of a propensity score matching, to match participants on variables that are relevant to the treatment selection plan, can increase the accuracy of a QE's outcome (Armstrong & Patnaik, 2009). This means that through the introduced controlling methods QE data can closely match the outcome of experiment data. In conclusion, the weaknesses of QE designs can be addressed and can provide similar results to experimental data.

What seems to be relevant for the internal validity of a QE? In a QE the internal validity refers to the assumed truth of the predicted causal effect (DeRue, 2012). Internal validity is important when all variables are controlled, and when the treatments affect the results (DeRue, 2012). The computation method, the experiment history, and the population can all affect internal validity of a QE (DeRue, 2012). It is the task of the researcher to keep the validity as high as possible in a QE. Minimizing validity threats in a QE is important to maintain the truth of assumed causal effects.

What can be mentioned to external validity of a QE? In a QE the external validity refers to the degree that the data of a study can be generalized to a target population (Calder, 1982). A high external validity represents how accurate the experiment results are generalizable for the real world (Calder, 1982). This means that the depiction of a population plays an important role in a QE. A low external validity can jeopardize the credibility of a study (Calder, 1982). In case of low external validity of a QE, the threats need to be reduced and this can occur through a representative selection of a population.

Key Variables and Concepts

In this part, I performed a literature review on the key variables of the study. Five main topics emerged from the key variables and were further discussed subsequently: (a) Momentum strategy, (b) momentum effect, (c) momentum effect in countries, (d) time series momentum, and (e) MA.

Momentum strategy. For the background of the momentum strategy two main findings were essential. Levy (1967) first reported the success of buying winner stocks, with higher average prices of the last 27 weeks that lead to significant abnormal returns. Three years later, Jensen and Bennington (1970) contributed an analysis of 68 trading strategies in connection to Levy's trading rules and confirmed that the relative strength was a crucial aspect. With these findings, Jegadeesh and Titman (1993) developed and reported the momentum strategy. Jegadeesh and Titman explained how investors can benefit from a momentum effects in the capital markets, by buying and additionally selling the top and bottom 10% of winner and loser stocks. From these proclamations two directions of investing emerged, either following the momentum strategy or to follow the MOM strategy. Therefore, two main findings are essential to know for the background of the momentum strategy.

Jegadeesh and Titman (1993) were very specific in explaining the momentum strategy. Jegadeesh and Titman stated that there are different strategies of how a security portfolio can be formed. For example, a portfolio can be differently constructed through (h = return period) and (k= holding period) combination of [h:k] or [3:3], [6:6], [9:9], or [12:12] trading strategies (Jegadeesh & Titman, 1993). In case of a [3:3] combination, the returns of the past 3 months are considered for the selection of the top and bottom 10% winner and loser stocks, and then these stocks are held for the next 3 months and so forth. The momentum strategy is easy to remodel for investors.

Criticism of the momentum strategy came from Foltice and Langer (2015). Foltice and Langer criticized that the momentum strategy might only be applicable for institutional investors. Buying and selling of the top and bottom 10% winner and loser stocks from a U.S. stock market with on average 2,102 tradable stocks (i.e., $n_{10\%} = 210$ stocks), could lead to several constrains and to very high transaction costs (Foltice & Langer, 2015). Foltice and Langer confirmed Levy's (1967) approach and found that individual investors should rather follow a strategy were only the top winner stocks are bought. With a MOM strategy, investors could still stay profitable even after factoring the transaction costs. Individual investors can apply this MOM strategy with small portfolios with a minimum of $5,000, a minimal selection of 5-8 stocks, and a trading frequency period of at least 2-months or viewer (see Foltice & Langer, 2015). Essentially, the application of the MOM strategy was introduced and recommended as alternative strategy to the momentum strategy.

The momentum strategy can be improved by following the overlapping trading strategy. The application of the overlapping trading strategy is very profitable according to Foltice and Langer's (2015), Tse's (2015), Hung and Banerjee's (2014) findings. The strategy proclaims that portfolios are formed in an overlapping way. For example, for a holding period of 12 months, stocks are bought on a quarterly level. This means that each quarter ¼ of the total portfolio is bought and held for 12months. An investor who buys five stocks each quarter would hold 20 stocks in his portfolio over a period of 1 year (Foltice & Langer, 2015). The overlapping method is easy to apply and highly profitable for momentum portfolio.

The momentum effect is not present in all financial markets. Hung and Banerjee (2014) agreed with Jegadeesh and Titman (1993) that a momentum effect can be found in the U.S. stock markets. However, Hung and Banerjee could not find evidence or only insignificant results in Taiwan, Hong Kong, and Korean stock markets. A reason for this could be the degree of cultural individualism in these countries (Bornholt, Dou, & Malin, 2015). Bornholt et al. (2015) argued that the higher an individualistic cultural score is, the stronger a momentum effect occurs in the considered countries stock market. This is relevant to know, because conducting momentum research might not lead to significant results in some parts of Asian stock markets.

In conclusion, the here discussed momentum strategy of Jegadeesh and Titman (1993) and the MOM strategy of Foltice and Langer (2015) create statistically significant profits in markets with a high cultural individualistic degree (Bornholt et al., 2015). Private investors should follow the MOM approach, since constrains and transaction costs might not matter much too institutional investors (Foltice & Langer, 2015). The overlapping trading strategy was highly recommended for the application of the momentum strategy.

Momentum effect. In this part and in Figure 2, I presented an overview of the factors that were assumed and tested in the literature to explain the momentum effect.

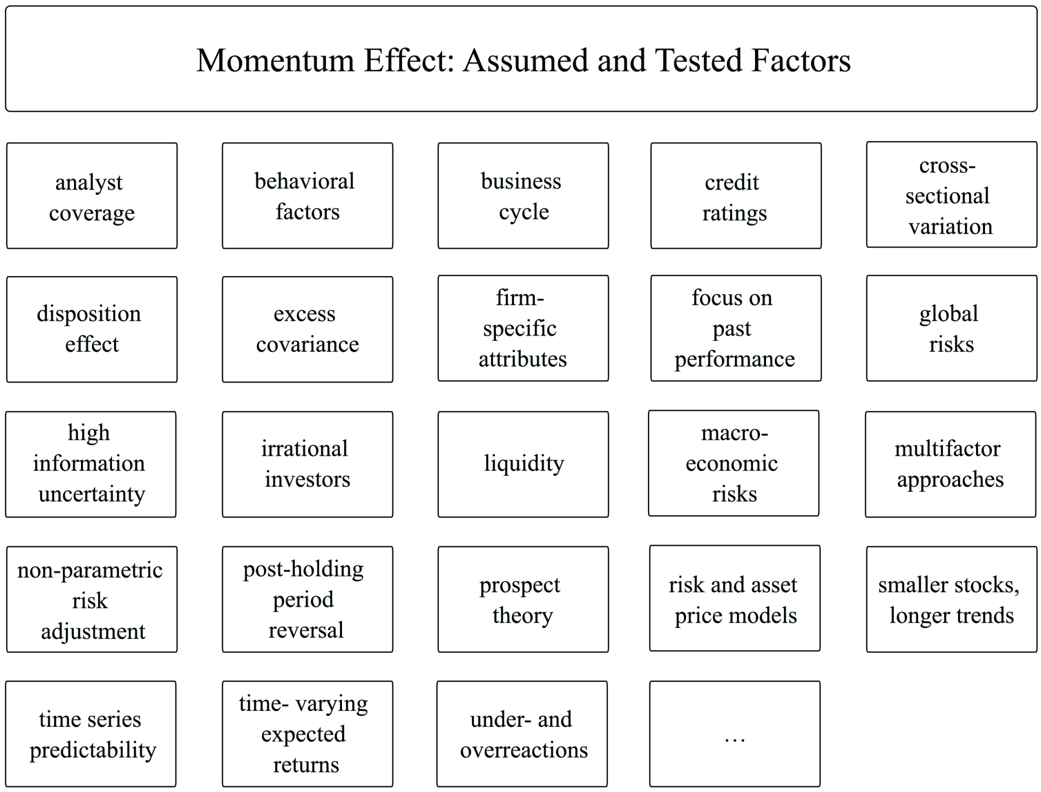

Figure 2. Momentum effect, displaying 23 different factor-assumptions tested by researchers.

The momentum effect has not been explained sufficiently yet in the scholarly literature, although researchers could significantly find momentum across the world in various capital markets. In the past 30 years, several relevant contributions have been made in the literature in explaining the momentum effect. For example, one of the first assumptions that a majority of researchers agreed on was that investors under- or overreactions to corporate news information could be causal for a momentum effect in the stock markets (Barberis et al., 1998; Chan et al., 1996; Hong & Stein, 1999). Barberis et al. (1998) presented a model, based on the findings of Tversky and Kahneman (1974), in which representativeness heuristics (like *under- and overreactions*) were responsible for momentum in stock markets. According to the model, the earnings of a corporation can follow a random walk behavior (Barberis et al., 1998). However, investors that heard about positive (negative) earning-news and then heard subsequently about negative (positive) earning-news, assumed a reversal (positive trend) for the stock price development of the news related corporation (Barberis et al., 1998). This reaction of investors, connected to random walk events, supported the assumption that under- and overreactions could cause the occurrence of momentum. Amir and Ganzach (1998) and Easterwood and Nutt (1999) confirmed these proclamations and found a connection to under- and overreactions in heuristics that referred to representativeness, leniency, anchoring, corporate adjustment; and on good or bad corporate news.

Hong and Stein (1999) brought an interesting thought to the momentum discussion. According to Hong and Stein, momentum investors do not follow news information to much; the momentum investors rather follow the indicator of *past performance* and consider the size of a corporation for their investment decisions. Hong et al. (2000) tested Hong and Stein's study results, by taking the corporation size and the *analyst coverage* into account and assessed the speed of information diffusion in a stock market. Hong et al. found from this analysis that *smaller stocks* with low analyst coverage influence the momentum performance in a stock market, especially for past loser stocks. Considering small stocks is relevant for investors, since the smaller a corporation is, the longer a momentum trend lasts and vice versa. Therefore, the three indicators were introduced and closer assessed in explaining the momentum effect of past performance, corporate size, and analyst coverage.

A further approach of explaining the momentum effect occurred through the analysis of post holding period reversals. Jegadeesh and Titman (2001) conducted a data mining study, in which Jegadeesh and Titman's study from 1993 of conflicting behavioral theories was replicated. Jegadeesh and Titman found that medium momentum trends are followed by trend reversals or *post-holding period reversals*. This information is interesting, because momentum strategies are only for a medium time period of 12-months successful and then reversals occur, either in a very short or in a very long time period of 3 to 5 years (e.g., De Bondt & Thaler, 1985; Lehmann, 1990). I can conclude that momentum portfolios should not exceed the holding period of 1 year for a profitable momentum strategy investing. Essentially, post holding period reversals of medium momentum trends could explain one critical observation in connection to the momentum effect.

Conrad and Kaul (1998) continued the discussion of explaining the momentum effect. Conrad and Kaul analyzed 120 trading strategies, of which 50% were profitable. Conrad and Kaul found that *cross-sectional variation* in the mean return of stocks were relevant for the profits of the momentum strategy. This observation lead Conrad and Kaul to the assumption that cross-sectional variation can explain parts of the momentum strategies. In connection to this, Daniel et al. (1998) and Chan et al. (1996) tried to explain momentum from a *behavioral point of view*. Bornholt et al. (2015), Chan et al., and Daniel et al. detected that an individualistic culture could cause momentum in stock markets, which was linked to the overconfidence of stock market investors. This means that investors seem to be overconfident about their abilities, which influences the stock prices to rise or to decline. To behavioral aspects, Frazzini (2006) and Grinblatt and Han (2005) mentioned the *disposition effect* and the *prospect theory*. Shefrin and Statman (1985) and Grinblatt and Han explained that investors are averse in realizing losses, which could lead to market anomalies. This means that investors tend to sell winner stocks early and hold on to losing stocks too long. Essentially, the disposition effect and the prospect theory are two important concepts to know in regard of investor behavior.

Up till then, the issues of information uncertainty, irrationalities, and negative shocks were not yet sufficiently addressed in the momentum literature. Daniel et al. (2001a, b) and Zhang (2006) argued that *high information uncertainty* could cause stock prices to drift towards the proclamation of new information. This means that stocks with a high uncertainty level and for which new information is expected, are of interest for an investor to increase the profitability of a portfolio's momentum performance. Back et al. (1999) brought the issue of *time-varying expected return* to the momentum discussion. Chordia and Shivakumar (2002) explained that time-series patterns in profitable portfolios can be caused by irrationalities of investors. Irrational behavior can create abnormal security returns. Bloomfield et al. (2009), Hong and Stein (1999), and Kaniel et al. (2008) confirmed the assumptions for abnormal security returns and explained that *irrational investors* are important for long-term momentum reversals. Slezak's (2003) assessed the inter-temporal predictability in regard of irrational investors and found significant results. However, Vayanos and Woolley (2013) reported that negative shocks can lead to mispricing and can lead to fund outflows which were seen as causal for reversals respective negative momentum to occur. These insights indicated that uncertainty, irrational investors, shocks, and funds outflows could serve as explanations for parts of momentum reversals.

Another direction of explaining momentum occurred through a combination of quantitative factors and behavioral factors. Avramov and Chordia (2006) proclaimed that the role of the *business cycle* and *macroeconomic risks* could be relevant to explain momentum in stock markets. Antoniou et al. (2007) developed a model to explain momentum by considering two factors: (a) risk-based and (b) behavioral-based variables. Antoniou et al. (2007) found that behavioral variables seemed not to matter much, which Chordia and Shivakumar (2002) already reported in their study. However, the risk-based factors that were attributed to business cycles could explain parts of momentum profits for the European stock markets. Liu and Zhang (2008) confirmed these findings and proclaimed that momentum returns could be caused by macroeconomic risk, which was measured through the growth rate of the industrial production. Asness et al. (2013) and Fama and French (2012) agreed on the issue of risk and added that international risk seemed to be more relevant than national risk might be. Essentially, these quantitative and behavioral considerations are interesting, because business cycles and macroeconomic risk (which are a kind of international risk) seem to explain a small part of momentum returns.

Further explanations to momentum were assumed for time series, excess covariance, and non parametric risk adjustment. Chan et al. (2000) assessed the *time series predictability* in stock markets, through the testing of indices from global equity markets. Lewellen (2002) found evidence for *excess covariance*, which could be responsible for momentum returns. Lewellen argued with his findings against the assumptions of market underreactions. Ahn et al (2003) detected that *non-parametric adjustment of risk* or stochastic discount factors could be allocated with 50% to the tested momentum returns. These are all valid findings that show that relevant parts of momentum have been detected and can be explained. However, more evidence needs to be found to explain momentum in financial markets with a verified model.

Several econometric models have been developed to explain the momentum effect. Fama and French (1996) provided a generally accepted momentum model that appeared to offer sufficient explanations. However, Antoniou et al. (2005, 2006, 2013) argued against the presented momentum models that *risk and asset price models* failed to explain momentum in financial markets sufficiently. Even though *multifactor approaches* seemed to work well, multifactor models still do not fully capture momentum in financial markets. Asness et al. (2013) and other researchers recommend testing momentum models with further factors, such as liquidity (i.e., liquidity measurement) and global risks; credit ratings; behavioral factors; or firm-specific attributes (Avramov et al., 2007, 2013; Sagi & Seasholes, 2007) and so forth. This discussion showed that for momentum some promising factors have been found and that maybe a multi factor model could provide a sufficient solution. A model that can sufficiently explain momentum has not been found for 30 years, and the discussion to the cause of momentum will continue to go on.

Momentum Effect in Countries. The momentum strategy is a profitable investment method to apply; but the question is, in which markets or in which countries are the momentum effects present? Since Jegadeesh and Titman (1993) first stressed the presence of momentum in U.S. capital markets, several researchers have provided evidence to the momentum effect worldwide. Interestingly, the momentum effect seemed to depend on the individualistic culture degree of each county (Bornholt et al., 2015). This means that in the United States the momentum effect was detected as highly significant, because the U.S. society exhibits a high individuality score. However, in Asian countries that exhibited a lower individualistic culture score, the momentum effect was not so strong or even reported as missing, for example in Japan (see Bornholt et al., 2015). Garg and Varshney (2015) conducted a literature review to the issue of momentum occurrence in different countries. Garg and Varshney found that in 1965-1993 the U.S. markets exhibited significant momentum. In 1994 short-run momentum effects were detected in Canadian markets (Garg & Varshney, 2015). In 1998, significant momentum effects were found in 12 European markets (Garg & Varshney, 2015). In 2000, momentum effects were reported in eight Asian countries (Garg & Varshney, 2015). And in 2002, the momentum effect was claimed as missing in Swedish and in Australian markets (Garg & Varshney, 2015). However, in 2003 until 2010 the momentum effect was found again in Australian and New Zealand's markets (Garg & Varshney, 2015). In 2007, the momentum effect was validated in the Baltic States, Poland, Slovenia, Hungary and Croatia (Garg & Varshney, 2015). In 2010, the Taiwan stock market was assessed and for short-term momentum a significant effect could be determined (Garg & Varshney, 2015). Finally, in 2011-2012, the Colombo Stock Exchange and the Egyptian market were tested for momentum effects and empirical evidence was presented (Garg & Varshney, 2015). This overview of momentum occurrence in counties shows that the momentum effect is present worldwide, but can partly be missing, vanishing, and reappearing for example in Australia or Japan.

Some researchers speculate that the momentum effect could start to become weaker and could start to vanish in the capital markets. Tse (2015) reported difficulties in finding momentum for U.S. exchange traded funds (ETF's). Tse argued that in the last years the momentum effect could have declined in the global markets. Since the capital markets have become more efficient in the past years, Tse's argument could hold some truth. However, I can speculate that the financial crises in 2008 could have impacted Tse's proclamations, since Tse's analysis occurred on the basis of post-crises results.

Time Series Momentum. In this section, I discussed literature findings to time series momentum. Moskowitz, Ooi, and Pedersen (2012) were one of the first who introduced the method of time series momentum (TSM). Moskowitz at al. reported that for each day of the selected TSM securities, the daily excess return is computed. For each security *s* and month *t*, the excess return over *k* months is either positive or negative (Moskowitz at al., 2012). If the cumulated excess return of *s* was positive (negative), then an investor should go long (short). An overlapping strategy was not applied to the TSM strategy by Moskowitz at al.. However, the excess returns were regressed, while the returns were scaled by an ex ante volatility of 40% (Moskowitz at al., 2012). This means that through a regression, the positions for the portfolios were sized according to the ex-ante annualized volatility. The procedure of considering the ex ante volatility made the results comparable to other asset classes, such as commodities, equities, currencies, or bonds (Moskowitz at al., 2012). The advantage of the TSM method is that for each security the historical time series is considered compared to a cross sectional momentum strategy.

A cut-off method is commonly applied for the construction of TSM portfolios. Bird et al. (2016) argued that for the formation of TSM portfolios, a threshold of 5% for the winner stocks and -3% for the loser stocks should be considered to allocate the different winner stocks and loser stocks to the portfolios. This means that through Bird et al.'s approach, a different amount of stocks is allocated to each TSM portfolio, compared to a cross sectional method (CSM). It is this effect of different stock amounts in each TSM Portfolio, which makes the difference in the significance of the TSM portfolio returns.

Four main factors are relevant for the TSM strategy. Bird et al. (2016) reported that besides from the cut-off method, four factors are relevant for the implementation of momentum strategies: (a) the formation period; (b) the holding period; (c) the rebalancing regime (rebalanced every month independent from the holding period (CAR), or buy-and-hold strategy rebalanced at the end of each holding period (BHAR)); and (d) the weighting scheme (equal weights (EW); market weights (MW); inverted volatility (IVOL) weights). Bird et al. found that 9 or 12 months formation period, 3 months holding period, CAR or BHAR depending on the stock cycle; and MW or IVOL weights were most successful for TSM strategies. In conclusion, Bird et al. structured and tested the factors that impact the TSM strategy. Depending on the setting, the four factors made a significant difference in the outcomes of the TSM strategy.

The TSM strategy is more profitable compared to the CSM strategy. Moskowitz at al. (2012) stressed that the TSM strategy exhibited higher significant returns, than the CSM strategy, even though both concepts are related. Moskowitz at al. saw a reason for the effect that TSM strategies are more profitable in markets under-reaction and delayed over-reaction. Chevallier and Ielpo (2014) reported that for commodity markets different investor reactions must be expected. Chevallier and Ielpo found contradicting results for commodity markets of no significant momentum returns. Commodity trading advisors only trust on trend-following strategies in commodity markets (Chevallier & Ielpo, 2014). The commodity markets are rapidly growing into an investment alternative for pension, hedge, and mutual fund investors (Chevallier & Ielpo, 2014). Therefore, I can speculate that because different investors reactions are expected in commodity markets, compared to stock markets, under reactions and delayed overreactions might not be as present in commodity markets as required for the momentum effect to occur strongly. TSM strategies are more profitable than CSM strategies; however, commodity markets seemed to lead to controversial results.

Two studies were interesting that analyze the issue of MA, as a timing indicator, in connection to the TSM strategy. Hong and Satchell (2015) and Zakamulin (2014) presented findings to the use of MA trading strategies and to TSM. Hong and Satchell assumed various stationary influences for the pricing of stocks. Hong and Satchell hypothesized that because autocorrelation works as an amplifier, a MA timing strategy could be well adopted for TSM strategies. The reason for this is that through a MA rule, price momentum can be identified in a financial market. Hong and Satchell stressed that a MA rule provides an easy form to assess and detect a price-autocorrelation-structure, while a more in-depth knowledge of the securities price structure is not relevant. Essentially, Hong, and Satchell (2015) presented empirical proof that autocorrelation has an amplification effect. Zakamulin (2014) questioned the performance of MA, applied as a market timing rule. Zakamulin conducted an out-of-sample test, which considered realistic transaction costs for a MA decision-based portfolio. Zakamulin found that MA market timing strategies were highly overrated. MA market timing strategies were found at large as non-uniform in a longer time period (Zakamulin 2014). This means that the MA performance was effective in short time-frames and underperformed in long time-periods. Both research contributions were interesting, because they use a MA as a timing instrument to identify TSM.

Moving Average. Two main methods can be used to analyze securities: (a) fundamental analysis and (b) technical analysis. Nedeltcheva (2015) saw four methods for security analysis as relevant to differentiate and added two more methods: (c) traditional time series forecasting and (d) machine learning methods. The fundamental analysis considers mainly corporate values for a security analysis. The technical analysis focuses primarily market price movements to determine investment decisions. Gurrib (2015) agreed that turning points of price action are important for the technical analysis. For Nedeltcheva, technical analysis was on the one hand the identification of traditional short-term patterns, such as: (a) gaps, (b) volatility patterns, (c) wide range bars, and (d) intraday patterns. And on the other hand, MA's were important, such as: (a) SMA, (b) EMA, and (c) LMA to determine turning points of security price movements (Nedeltcheva, 2015). Nedeltcheva regarded indicators as relevant prediction tools for market signals, for example: (a) MA convergence divergence (MACD), (b) stochastics, (c) oscillators, (d) volatility as sentiment measures (i.e., VIX index) and so forth. In comparison, both Gurrib and Nedeltcheva saw price movements of markets as essential, while MA strategy rules served as a forecast method to determine turning points. Therefore, MA's can be allocated to the main domain of the technical analysis.

Next, I discuss two equations of the MA's: (a) SMA and (b) EMA. The SMA is the unweighted mean of an asset in a period of n data:

$$SMA = \frac{P_M + P_{M-1} + \ldots + P_{M-(n-1)}}{n} \qquad [7]$$

Where, P_M = the price of the asset M; and n = the number of days considered of the closing prices, i.e., commonly 10, 20, 50, 100, or 200 days (Nedeltcheva, 2015). While the successive SMA values can be computed through a shorter equation of:

$$SMA_{today} = SMA_{yesterday} - \frac{P_{M-(n+1)}}{n} + \frac{P_{M+1}}{n} \qquad [8]$$

The EMA is also named exponentially weighted moving average (EWMA) and considers weight factors which decrease exponentially (Nedeltcheva, 2015). This means that recent observations have a high focus and through the weighting each older value decreases exponentially (Nedeltcheva, 2015). The advantage of the EMA is that both recent and older observations are considered proportionately. In a technical analysis term, the equation can be expressed as followed:

$$EMA_{today} = EMA_{yesterday} + \alpha(price_{today} - EMA_{yesterday}) \qquad [9]$$

And,

$$EMA_{today} = \frac{p_1 + (1-\alpha)p_2 + (1-\alpha)^2 + ... + p_n + (1-\alpha)^n}{1 + (1-\alpha) + (1-\alpha)^2 + ... + (1-\alpha)^n} \qquad [10]$$

Where, p is the asst price; n = 1, …, k; k = the number of days; α is the degree of weighting decrease of a constant smoothing factor between 0 and 1 (Nedeltcheva, 2015). This means that a higher α increasingly discounts older observations (Nedeltcheva, 2015). Both equations, the SMA and the EMA, are commonly used as a timing indicator for technical analysis.

This raises the question; what general signals or rules can be found for MA's? Two main concepts can be reported as general signals for MA's. Nedeltcheva (2015) introduced the concept of *price crossovers* and Gurrib (2015) mentioned the concept of *double crossovers* to determine turning points in security markets. This means that for price crossovers, the security price has to move above the MA for a bullish signal and vice versa (Nedeltcheva, 2015). And for double crossovers, the short-term MA has to move above a long-term MA for a bullish signal and vice versa (Nedeltcheva, 2015). Glabadanidis (2015) added that these kinds of crossovers are also named the *golden cross* and *dead cross*. Essentially, if researchers refer to MA as a timing signal or method of predicting turning points, then the researchers refer commonly to price crossover or double crossover MA signals as the basis for an investment decision.

At this point the question arises; what is the optimal number of day setting for a MA that can be found in the MA literature? Dolvin (2014) recommended a 50 day setting for EMA as most profitable strategy for price crossovers signals. For double crossover strategies (except for higher volatility market phases), Dolvin recommended a 50 day and 200 day setting for EMA strategies that worked best. Nedeltcheva (2015) distinguished MA strategies in short-term and long-term investment time periods. Nedeltcheva saw for double crossover systems a 5 day and 35 day EMA setting as profitable for a short-term perspective. A 50 day and 200 day setting were seen as optimal for SMA, for a medium and a long-term investment dimension (Nedeltcheva, 2015). Pätäri and Vilska (2014) and Zoicaş-Ienciu (2014) were here stricter for the short-term periods and proposed a 1 day and 20 day combination as optimal for MA double crossover strategies. Glabadanidis (2015) and Pätäri and Vilska agreed on the general use of 50 day and 200 day setting for MA's long-term time period. Zoicaş-Ienciu disagreed here and saw a range of [10, 100] as relevant period for a long-term investment dimension. While Glabadanidis contributed values on a monthly basis and recommended 24 months for SMA's, while checking for robustness of the SMA time periods of [6, 12, 36, 48, and 60 months]. Zakamulin (2014) disagreed here and saw 10 months to 200 days as relevant for long-term SMA trading rules. New to the discussion were the statements of Zoicaş-Ienciu, who argued that MA settings can be fixed or can vary. Zoicaş-Ienciu agreed with all of the other findings, but added that common MA day combinations can vary between [1, 50], [1, 150], and [1, 200] days. Essentially, Zoicaş-Ienciu found that most profitable MA combinations varied for short-term period between a range of [1, 5] and for long-term period in a range of [10, 100]. In conclusion, the findings of the researchers mostly differed in their results. MA's were differentiated for three time periods: (a) short-term, (b) medium-term, and (c) long-term. For cross over rules 50 days SMA was seen as optimal setting, while most researchers contributed to double crossover MA strategies (Dolvin, 2014). Double crossover strategies were recommended for short-time periods 1 day and 20 day MA or 5 day and 35 day EMA (Nedeltcheva; 2015; Pätäri & Vilska, 2014; Zoicaş-Ienciu, 2014). For long-term horizons, the researchers mostly agreed on 50 day and 200 day combinations as optimal setting for SMA or EMA strategies (Dolvin, 2014; Nedeltcheva; 2015). I can speculate that four factors impacted the researchers results, which caused the difference in the optimal number of day combinations and the optimal MA types: (a) the selected markets; (b) the tested time frames; (c) the volatility occurred; and (d) the securities observed.

Three aspects can be mentioned to make a MA strategy more profitable. The first aspect is to distinguish between SMA and EMA. Nedeltcheva (2015) explained that each MA is not better than the other. However, EMA's seemed to have less lag, are more sensitive to price changes, and the EMA will turn sooner before a SMA turns (Nedeltcheva, 2015). SMA seemed to be better to determine resistance levels or benchmarks (Nedeltcheva, 2015). The investors should differentiate what MA to prefer, depending if sensitivity is required or if the determination of resistance levels is relevant.

The second aspect to make a MA strategy more profitable considers the issue of volatility (see Dolvin, 2014). Dolvin (2014) stressed that volatility has a large impact on the profitability of applying a MA strategy. Dolvin proclaimed that to apply a MA strategy successfully, it is important to consider low volatility for the selected security returns, which produced a better risk-adjusted performance. This was confirmed by Glabadanidis (2015), who also mentioned the impact of volatility of MA strategies and agreed on the issue of risk-adjusted returns. Essentially, considering the volatility is crucial for the application of MA strategies.

The third aspect to make a MA strategy more profitable was the consideration of filter value. Zakamulin (2014) mentioned the issue of using a filter value for MA strategies. According to Zakamulin, a filter value (f) can reduce error signals (i.e., $f \geq 0$) with a common choice between 0% and 1%. This means for example that after a crossover signal occurred, 1% gain has to be reached in order to take buying (selling) actions. Zakamulin found that results with a filter of 1% produced higher average excess returns, compared to returns with a filter of 0%. All findings seemed relevant for applying an MA strategy. Therefore, differentiating between EMA and SMA; considering low volatility; and using a filter value of 1% were important to improve the profitability of MA strategies.

Several authors have confirmed that following a MA strategy is more profitable than following a BH strategy. Glabadanidis (2015) reported that advantages exist for applying a MA strategy, which lead to high returns, skewness, and lower variance compared to BH strategies. Gurrib (2015) tested if optimized MA can outperform BH strategies. A contradiction was that higher absolute returns occurred during correction waves for the BH strategy (Gurrib, 2015). This indicated that BH strategies could be more profitable than MA strategies at some point or in correction phases. However, during the financial crises in 2008 the optimized double crossover MA strategy exhibited lower risk and low returns (Gurrib, 2015). Zoicaş-Ienciu (2014) pointed out that a basic trading rule for MA can already generate higher excess returns compared to a BH strategy. I can conclude that applying a MA as a timing strategy, even if the MA rules are simple, can lead to higher returns than following a BH strategy. Because of the simplicity, the MA strategy is easy to use for private investors, and applying a MA strategy can be relevant to avoid possible availability and representativeness biases (Gurrib, 2015).

Not only confirming literature exists to MA strategies. Zakamulin (2014) was very skeptical about the performance of MA strategies and assumed that data-mining biases and market frictions could impact the trading results negatively. To analyze this assumption, an out-of-sample test was conducted with two timing models connected to strict transaction costs. Zakamulin saw one-way transaction costs with $0.50 per cent as realistic and defined (Lambda = .005) for stocks and (Lambda =.001) for bonds, because bonds exhibit higher liquidity. Glabadanidis (2015) disagreed with this method of applying transaction costs. Glabadanidis explained that the assets of a MA strategy could be switched, by considering the payoffs of protective put options on the underlying asset. This means that a more aggressive implementation of a MA strategy could involve selling the underlying asset short in case of a signal to switch, instead of shifting the funds into cash. This method could reduce the transaction costs for a MA strategy.

However, Zakamulin applied very high transaction costs and constrains, because it appeared that he assumed that market timing strategies were overrated, to be polite.

Nedeltcheva (2015) intervened here and specified that to benefit from capital markets: future developments need to be projected into the current equities prices. The technical analysis and the consideration of expert opinions can support the task of future projections. Nedeltcheva continued that to some degree emotions will be a part of MA trading decisions. I can speculate that considering emotions and experience in the mathematical analysis of asset price movements might have been one of the issues Zakamulin (2014) was facing. Nedeltcheva concluded that technical analysis and fundamental analysis might work over time. In conclusion, I could find that some critique exists to MA. For example, the findings only refer to historical data and optimal MA strategies might not fit as good for future market movements as reported. However, the majority of researchers are convinced of the profitability of MA strategies, even after factoring realistic transaction costs.

Summary and Conclusions

Although I reviewed various articles in Chapter 2, the main topics to momentum and MA did not largely cover the issue of MA and MOM strategies. Researchers tried to explain in their recent, scholarly research the momentum effect and commented in detail on the momentum strategy application; however, I detected a gap in the momentum literature to the issue of the MA MOM strategy. Especially since Foltice and Langer (2015) reported to adjust the momentum strategy, the question was raised how to decide in declining market phases, but further insights were not provided. Another gap that occurred from the momentum literature considered the momentum effect. Since up till circa 23 factors have been tested in the momentum literature and have failed to explain the momentum effect sufficiently; researchers like Fama and French (1996) speculated that a multifactor model could be a future area of research.

The scholarly literature did cover the momentum strategy; in regard of how the strategy is applied and what method is the best to use (see Jegadeesh & Titman, 1993). Different variations have been tested in the momentum literature; how to improve or how to adjust the momentum strategy? For example, adjustments for the momentum strategy were made for the needs of investors with small portfolios by Foltice and Langer (2015). Other researchers like Barberis et al. (1998), Chan et al. (1996), and Hong and Stein (1999) tried to explain the momentum effect in their studies. Over time the hypothesis of investors under- and overreactions as casual for the momentum effect seemed to hold, but could not sufficiently be verified by researchers (Barberis et al., 1998). The momentum effect was detected all over the world, with some exceptions in Asian regions. Findings indicated that the individualistic level of a culture correlated with the appearance of the momentum effect (Chan et al., 1996; Daniel et al., 1998).

In Chapter 3, I described the design, methodologies, and data that were used in this study, to examine the effect of considering a MA for the MOM strategy. This study followed a quantitative, QE design, in which I presented seven hypotheses. Through the first hypothesis, I planned to assess the optimal MA number of day setting from the DJIA index returns. And, I planned to determine, with the optimal MA settings, the MA signals from the DJIA index to select the winner stocks for the tested MOM portfolios.

In the next hypotheses, I saw a relevance to construct MOM and MA MOM portfolios and to compare the portfolio's performance. I assumed that the results of a comparison between the MOM strategy and the MA MOM strategy could allow me to answer the research question, if the MOM strategy can be adjusted and improved by an MA.

Chapter 3: Research Method

In Chapter 3, I provided nine sections that are focused on the design, the methodology, and the data of the study. In the research design section, the setup of the QE's was described in detail. In the section, I elaborated the justification of using an U.S. index and its stocks as the population for this study. Further, I commented on the time frame and the sample size considered in this study. In the data collection section, I gave an outline of how the data was gathered for the study and from what source was the data obtained. In the methodology section, six main methodologies were introduced that were relevant for the analysis. For example, equations and discussions were presented how to apply the considered MA's, the econometric models et cetera. In the validity section, I reported three validity issues that occurred for the study. In the data analysis plan section, three relevant analysis methods were mentioned. In the ethical section, I addressed ethical concerns of the data that could occur for the study. I concluded the Chapter 3 with a summary section.

Research Design and Rationale

In this study, I used a quantitative methodology and a quasi-experimental design to critically test different MA indicator day combinations. Currently, there was a methodology deficit for investors with small portfolios applying the MOM strategy, which created a gap in the momentum literature (Foltice & Langer, 2015). The questions arose; can the application of a MA as timing indicator improve the MOM strategy for small portfolios of U.S. stocks? What indicator settings are required? Can the application of a MA indicator help to adjust the MOM strategy? Findings to these questions could support portfolio managers in decision making and could help to improve profits, in case of declining markets.

To answer the research question, I constructed the following QE's and tests to investigate seven directional and nondirectional hypotheses (*H*). First, I tested for *H1*: If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then the optimal MA number of day setting, and the optimal MA computation type can be found to adjust the MOM strategy. I decided to test two differently computation types of the MA: (a) SMA and (b) EMA. The independent variables (*x*) were DJIA index returns. The control variables (*m* and *n*) were two different MA types, the SMA and the EMA with seven different number of day settings to test two variations of MA strategy signals: price crossover signals and double-crossover signals. I planned, through a heuristic test, to determine the number of day settings for (6, 12, 36, 48, 60, 80, and 100 months; see Glabadanidis, 2015). The dependent variables (*y*) were the returns of the DJIA bull phases. For the test of Hypothesis 1, I planned to consider return data of the DJIA index. For this test and the subsequent tests, I planned to consider the total returns or the adjusted closing prices of the DJIA index and stocks to fully reflect the dividends. The test setting could allow testing for two kind of trading signals: (a) crossover single and (b) double-crossover signal. For example, crossover signals can occur for SMA 60 or EMA 100, where the DJIA index price crosses the MA; double-crossover signals can occur for 60v100 SMA or 60v100 EMA, where the MA crosses the MA. In total I decided testing 18 MA combinations (see Dolvin, 2014). The time period that I selected for the test ranged from [1992 until 2010].

The results of the first QE could provide an optimal MA method with the optimal MA day settings. From this, I could determine the Bull market phases for the DJIA and the Bear market phases of the DJIA (see Cohen & Cliffer, 2014). This could allow me to determine the dates of trading the MOM strategy, respective when to stop trading the MOM strategy.

Next, I tested *H2*: If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are greater than the DJIA index and the MOM strategy returns. To test for this hypothesis, the following limitations needed to be made. I decided to only test for one MOM strategy variation, with the formation period of 6 months (-5 to 0 months) and the holding period of 12 months. After defining the winner stocks, I planned to rank the stocks from best to worst and test for 30% of the stocks. This means that I planned to construct portfolios for one until nine stocks for the test of the MA MOM strategy. The test of the MOM strategy should be limited to a nine stock portfolio. The independent variables (x) were 30 DJIA stocks for which three treatments (m, n, and o) should be applied: (m) the BH strategy; (n) the MOM strategy; and (o) MA MOM strategy. The dependent variables (y) were the portfolio returns. This test could be relevant to answer the research question through a comparison and a parametric significance t test of whether the application of a MA with optimal settings could improve the MOM strategy.

Since the results were unadjusted for costs, I next tested *H3*: If the costs are factored for the MA MOM strategy, then the MA MOM strategy is still profitable. I decided to factor the transaction costs for each trade. I applied a cost function of the Equation 19, further described in the method section. The factoring of the costs could require considering different investment amounts. I decided to limit the different investment amount to [$5,000, $10,000, $15,000, $30,000, $50,000, $100,000, $250,000, 500,000, $1,000,000]. The analysis was planned to result in two kinds of tables. The first Table 4 could show the real turnovers of the real trades that occurred for the MA MOM stock portfolios. For example, if the same stock is held for more than 1 year in a portfolio, then the amount of trades is reduced by one trading amount. In the second Table A1, I planned to display the full turnovers if all stocks have to be changed each year over the full investment period.

Since the holding periods could vary for the momentum strategy, I tested *H4*: If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects occur for the returns of the MA MOM strategy. This means, according to the previous limitations made for the MOM strategy, I now tested different trading frequencies (and trading amounts). I made the following limitations: (a) the trading frequencies should be [monthly, bi-monthly, quarterly, tri-yearly, bi-yearly, and yearly]; and (b) the investment amounts should be [$5,000, $10,000, $15,000, $30,000, $50,000, $100,000, $250,000, $500,000, $1,000,000]. The independent variables (x) were the 30 DJIA stock returns. The control variable (m) was the overlapping MA MOM strategy differentiated by the trading frequencies and the investment amount. The dependent variables (y) were the portfolio returns. Hypothesis 4 allowed testing for each investment amount and different trading frequencies, which could provide the net monthly returns.

Through the application of different trading frequencies to the MOM strategy, I assumed that the observed volatility could reduce and that the transaction costs could increase for the portfolios, because more stocks are bought and sold (see Foltice & Langer, 2015). The next hypothesis tested was *H5*: If the CAPM and the FF3FM alphas are computed for the overlapping MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are still positive. Through Hypothesis 5, I investigated the profitability, which was connected to the variation of volatility effects and transaction costs effects. Similarly, I investigated if the MA MOM strategy was still profitable after varying the trading frequencies and the investment amounts. The hypothesis was tested through the application of the valuation model (CAPM and FF3FM) and the computation of a linear- and a multiple regression analysis (i.e., Equation 14 and 15). The independent variables (x) were overlapping MA MOM portfolio returns and the risk factors of the valuation models and the dependent variable (y) were the estimated overlapping MA MOM strategy portfolio returns (e.g., risk factors; see Fama & French, 1993). Through the regression models, I could compute the risk-adjusted excess returns (alphas), from which I could learn how the volatility (systematic risk) and the transaction costs impacted the net monthly returns. For the profitability of the MA MOM strategy, the alphas needed to stay positive.

This led to the testing of *H6*: If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount can be determined.

Through the Equation 18, I computed the Sharpe ratio for the different portfolios, trading frequencies, and investment amounts. The independent variable (x) was the MA MOM strategy portfolio returns; the dependent variables (y) were the Sharpe ratios; the control variables (m and o) were the trading frequencies and the investment amount. From a result table, I could determine the optimal trading frequencies, controlled for volatility and cost effects, for each investment amount of the MA MOM strategy.

The final question tested was *H7*: If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the overlapping MA MOM strategy returns are greater than the MOM strategy returns. Through the test of (H7: $x_{\text{MA MOM}} > x_{\text{MOM}}$), I compared the results in an overview for the MOM strategy and the overlapping MA MOM strategy. The independent variables (x) were the MOM strategy and overlapping MA MOM strategy Sharpe ratios. The dependent variables (y) were the MOM strategy and overlapping MA MOM strategy portfolio returns. The control variables (m and o) were the optimal trading frequencies and the investment amount for the MA MOM strategy. I sought to determine the optimal trading frequencies for the overlapping MA MOM strategy and to determine if the overlapping MA MOM strategy could significantly improve the MOM strategy under the most successful overlapping conditions. The CAPM alphas, FF3FM alphas, GRS values, and maximum traded stocks for the MA MOM strategy could be displayed in connection to the optimal trading frequency. My goal was also to determine if the MA MOM strategy is practical, even with the costs factored, to answer how to adjust the MOM strategy and if the MA MOM strategy improves the MOM strategy.

Methodology

In this section, I commented on seven main methodologies that were relevant for the study: (a) MA, (b) multiple regression models, (c) econometric models CAPM and FF3FM, (d) Sharpe ration, (e) transaction costs, (f) overlapping MOM strategy, and (g) MA MOM strategy.

Moving Averages

The MA is used in the technical analysis as an indicator to smoothen stock prices (Gurrib, 2015; Nedeltcheva, 2015). The MA is an n-lagged indicator that is based on past asset prices. From the indicator and for financial decision making, two main trading signals can be gained: (a) price crossover signals and (b) double cross over signals (Gurrib, 2015; Nedeltcheva, 2015). For example, if the stock price crosses the indicator from below and moves above, a buying signal occurs. If the 50-day MA crosses the 200-day MA from below to above, a buying signal occurs and vice versa. Cohen and Cliffer (2014) recommended considering a threshold of two until three time units but not more than five time units occurred when determining the trading signals.

I decided to compute two different types of MA methods: (a) SMA and (b) EMA.

SMA.

$$SMA = \frac{P_M + P_{M-1} + ... + P_{M-(n-1)}}{n} \quad [11]$$

Where, P_M = the price of the asset *M*; and *n* = the number of days considered for the closing prices (Nedeltcheva, 2015).

EMA.

$$EMA = p - (EMA_{-1})(\frac{2}{1+n}) + EMA_{-1} \quad [12]$$

Where, *p* is the asset price; number of *n* = 1, …, *k*; *k* = the number of days; EMA_{-1} = the EMA from the prior trading day (Dolvin, 2014). Computing both MA's is relevant in this study, because I test for the optimal type and optimal day setting of the MA to adjust the MOM strategy.

Multiple Regression Models

For the study, the computation of a multiple regression model is relevant to compute two econometric models. The general equation for the multiple regression is presented subsequently.

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon \quad [13]$$

And for the econometric model the equations are:

$$Y_1 = \beta_0 + \beta_{mkt}(R_m - R_F) + \varepsilon \quad [14]$$

$$Y_2 = \beta_0 + \beta_{mkt} RMRF + \beta_{size} SMB + \beta_{value} HML + \varepsilon \quad [15]$$

Where, x_i = independent variables or the risk factor values of the CAPM and the FF3FM *i* = 1, …, *k; k* = the number of variables; ε = error term; β_0 = y-axis intercept or the risk-adjusted excess return (alpha value); β_i = slope or beta coefficients *i* = 1, …, *k*;

β_{mkt} = beta coefficient for the excess market risk factor (market factor return minus risk free rate return; R_m-R_F or *RMRF*) or the sensitivity of the security relevant for the econometric model; β_{size} = beta coefficient for the size risk factor (small minus big; SMB); β_{value} = beta coefficient for the value risk factor (high market capitalization minus low market capitalization; HML); Y = dependent variable or the estimated security (portfolio) return; Y_1 = the estimated portfolio returns computed by the CAPM metrics; Y_2 = the estimated portfolio returns computed by the FF3FM metrics. Equation 14 (CAPM) and Equation 15 (FF3FM) are relevant for the study to obtain the alpha value (β_0). Further definitions of the variables can be found subsequently in the CAPM and the FF3FM section in three forms: (a) independent (IV) and dependent (DV) variable form; (b) standard form for the (x_1, x_2, etc.) and beta values, relevant for the multiple regression model; and (c) the factor, variable, or coefficient terms. I discuss both econometric models more in detail in the econometric model section subsequently.

Regression Hypothesis.

The hypothesis for the multiple regression models were

H_o: $\beta_1 = \beta_2 = ... = \beta_k = 0$, and

H_1: At least one β_i <> 0, for i = 1, …, k, where k is the number of IV's of the multiple regression model.

Econometric Models

CAPM.

The CAPM is an econometric model that can help to explain the relation between systematic risk and expected returns (Berk & DeMarzo; 2011). The model is commonly applied for stocks valuation and widely spread in finance (Berk & DeMarzo; 2011). Through the CAPM, the pricing of risky securities is possible. The model generates the expected return of stocks connected to the given risk (Berk & DeMarzo; 2011). This is relevant, to determine the costs of capital for an investment (Berk & DeMarzo; 2011). The CAPM can help to answer the research question, because it quantifies the expected performance in connection to the given risk of a portfolio. The equation for the CAPM is

$$r_i = R_F + \beta_i \,(R_m - R_F) \qquad [16]$$

Where, the independent variables (IV) and the dependent variables (DV) are:

$IV_{CAPM1} = x_{CAPM1}$ = Excess market return (R_M-R_F)

$IV_{CAPM2} = x_{CAPM2}$ =Risk free rate (R_F)

DV_{CAPM} = Excess return of portfolio (r_i) and $i = 1,\dots, k$

β_i = the sensitivity of the security $i = 1,\dots, k$; k = the number of variables;

FF3FM.

The FF3FM is also an econometric model that is similar and based on the CAPM (Berk & DeMarzo; 2011). The model considers two additional factors, by adding size and value to market risk (Berk & DeMarzo; 2011). The FF3FM considers that small-stocks can outperform the market, because of a higher risk and return ratio (Berk & DeMarzo; 2011). This means that the model adjusts outperforming tendencies to establish more accuracy for asset valuation or performance management. The FF3FM can help to answer the research question, because it also quantifies the expected performance in connection to the given risk of a portfolio. However, the model is more sophisticated and is therefore suitable for a robust comparison to a simpler model result. The equation is

$$r_i = R_F + \beta_i^{mkt} RMRF + \beta_i^{size} SMB + \beta_i^{value} HML \quad [17]$$

Where, the independent variables (IV) and the dependent variables (DV) are:

$IV_{FF3F1} = x_{FF3F1}$ = Excess market return (*RMRF*)

$IV_{FF3F2} = x_{FF3F2}$ = Risk free rate (R_F)

$IV_{FF3F3} = x_{FF3F3}$ = Size risk premium (*SMB*)

$IV_{FF3F4} = x_{FF3F4}$ = Value risk premium (*HML*)

DV_{FF3F} = Excess return of portfolio (r_i) and $i = 1,\dots, k$

β_i = the sensitivity of the security $i = 1,\dots, k$; k = the number of variables;

Sharpe Ratio

The Sharpe ratio represents an average excess return value per unit of the underlying systematic risk (Bailey & López de Prado, 2012). The ratio allows commenting on an asset's or a portfolio's performance associated to the risk taking (Bailey & López de Prado, 2012). For example, for a riskless portfolio with U.S. treasury bills, the Sharpe ratio would be equal to zero. The larger the Sharpe ratio value is, the more attractive the risk-adjusted return is assumed.

$$SR_i = \frac{(Nr_i - R_f)}{\sigma_i} \quad [18]$$

Where, Nr = net monthly turnover return, R_f = the risk free rate, σ = standard deviation, of the portfolio $i = 1,\dots, k$; k = the number of variables; *SR* = Sharpe Ratio.

Computing and comparing the Sharpe ratio is relevant in this study, to evaluate the optimal trading frequencies for the overlapping MA MOM strategy.

Further, I decided to add the following equation. To determine the significance levels when comparing the Sharpe ratios to the BH strategy, the standard deviation is relevant. The equation for the estimated Sharpe ratio standard deviation is:

$$\hat{\sigma}_{SR} = \sqrt{\frac{1 - \hat{\gamma}_3 SR + \frac{\hat{\gamma}_4 - 1}{4} SR^2}{n-1}} \quad [19]$$

Where, $\hat{\sigma}_{SR}$ = estimated Sharpe Ratio (SR) standard deviation, $\hat{\gamma}_3 = \frac{(\mu - Rf)^3}{\sigma^3}$, $\hat{\gamma}_4 = \frac{(\mu - Rf)^4}{\sigma^4}$, Rf = risk free rate; and μ = mean of the index returns (see Bailey & López de Prado, 2012).

Transaction Costs

Three kinds of transaction costs occur for a trade:

- Commission per trade, where Foltice and Langer (2015) saw $10 as realistic.
- Bid/ask spread, computed by an average and differentiated according to the market capitalization. Foltice and Langer used the time frame from April 2006 until December 2010: (market capitalization < $215.6 m = 0.750 % spread); ($215.7 m < market capitalization > $11,365.8 m = 0.497 % spread); (market capitalization > $11,365.8 m = 0.212 % spread).

- Securities and Exchange Commission (SEC) fee, which was reported by Foltice and Langer (2015) for a time period prior to December 29, 2001, with 0.003333% for every sale of stock.

The equation to compute the transaction costs is:

$$o = (2 * c) + (2 * 0.5s) + f \qquad [20]$$

Where, c = sales commission of $10 per trade; s = the spread; f = the SEC sales fee; and o = the total costs implied for the MOM strategy trading (Foltice & Langer, 2015). Applying the transaction cost was relevant to obtain the net monthly returns and was relevant for a more precise analysis of the profitability of the MOM strategy trading.

Overlapping Momentum Strategy

Jegadeesh and Titman (1993) reported that for constructing the momentum strategy a formation period needs to be defined, which can be for example [3, 6, 9, 12 months]. Foltice and Langer (2015) explained that the stocks are formed according to the formation period (i.e., returns from the last 6 months) and are ranked from best to worst and the top 10% of the winning stocks are bought. After the stocks are bought, the stocks are held according to a holding period for example bi-monthly, quarterly et cetera. For a 12 month holding period, the stock is bought at the closing price on August 1 and held until the closing price of July 31.

For the overlapping MOM strategy, the investment amount needs to be equally divided. The equation for the buying power (BP) is:

$$BP = (A / t) / k \qquad [21]$$

Where, A = initial investment amount, t = the trading frequency per year, k = the number of stocks in the portfolio (Foltice & Langer, 2015). The overlapping MOM strategy requires the trading frequencies and holding periods to overlap, which can be explained best at an example. If $100,000 is invested in buying four stocks with a quarterly overlapping frequency, then for each of the four stocks $6,250 can be invested, and for the first portfolio $25,000 can be invested in total. The holding period could be 12 months. After 3 months, the next portfolio would be bought with $25,000 and also held for 12 months et cetera. If the overlapping MOM strategy is fully established, the investor will hold up to 16 stocks. Applying the overlapping MOM strategy was relevant for the study, because the overlapping MOM strategy can generate significantly higher profits (i.e., monthly return = 2.95%) compared to a simple MOM strategy (i.e., monthly return = 1.33%; Foltice & Langer, 2015).

MA MOM Strategy

The MA MOM strategy requires determining, with the application of an MA indicator, the Bull and the Bear market phases of a stock market index, from which the stocks for the portfolios are considered. The determination of the Bull and the Bear market phases, on a monthly basis, allows the investor to decide when to follow the MOM strategy or when to stop investing respectively when to sell the MOM portfolios. For the MA trading rules a threshold of two until three-time units, but not more than five time units could be considered; but, were not considered in this study. The optimal settings of the MA were the main focus of this study and were further tested and analyzed in the QE's.

Population

The main population of this study is recognized as the U.S. stocks of the DJIA index. The DJIA comprises the most prominent U.S. market values, with the 30 largest industry stocks (since October 1, 1928) and circa 25% of the total market value of the New York Stock Exchange (NYSE; Brock, Lakonishok & LeBaron, 1992; Gartley, 1935). The DJIA represents a historically approved market barometer for the U.S. stock market, similar to London's FTSE 100, Germany's DAX 30, or the Japans Nikkei 225. This means that most of the stock price development participated in significant historical events. This makes the DJIA potential to drive empirical insights from this population. Over time, the composition of the DJIA has changed. The changes skewed the index performance upwards. If a DJIA stock starts to develop poorly, the stock is replaced after a few years with a company that has a higher earning potential. Since the United States is a culture, with a high individualistic degree and the DJIA reflects high earning expected stocks, I could assume that the momentum effect could be observed at this population, which Bornholt, Dou, and Malin (2015) and Garg and Varshney (2015) indicated in their studies. Therefore, the target population in this study considered the stocks of the DJIA index.

Sampling and Sampling Procedure

The sampling frame considered 30 companies that were represented in the DJIA index (NYSE stocks); the DJIA index returns; and the risk factors that Kenneth French provides. Since the proclamations of the MOM strategy recommend selecting 10% until 30% of the winning stocks, the portfolio sample size should consist of one until nine stocks (see Foltice & Langer, 2015; Jegadeesh & Titman, 1993). The sampling time frame ranged from January 01, 1992 until December 30, 2010. This time frame captured a high progression phase from 1992 until circa 2000 and an on average declining market phase from 2000 until 2010 (also see Cohen & Cliffer, 2014). The year of the financial crises in 2008 was also considered in the sample time period. This means that 19 years of stock price data could be utilized. With circa 250 trading days per year x 19 years, (n_{19} = 4,750 days) of sample data emerged for the analysis.

Data Collection

For the data collection of this study, three authors mentioned the following sources. Data of the risk factors for the econometric models is provided by Kenneth French, published on the website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datajibrary.html (Bird, Gao, & Yeung, 2016). Foltice and Langer (2015) reported that Thomson Reuters offered stock data from the NYSE. Moskowitz, Ooi, and Pedersen (2012) mentioned that Bloomberg could also be a valid source for U.S. stock market data.

However, I decided to use tailor made collected data from Yahoo!Finance, which is free of charge, and I decided considering the data that Kenneth French provides. The sampling frame required data of daily adjusted returns; dates; market capitalization of 30 DJIA - NYSE stocks; from the period of January 01, 1992, until December 30, 2010.

Data Analysis Plan

I provided a data analysis plan in this section. I identified the software that I used for the subsequent data analysis. I explained how the data was cleaned and screened as relevant for the study. Further, I restated the research question and the hypothesis again as mentioned in Chapter 1. And, I addressed four main aspects: (a) statistical tests; (b) procedures for multiple statistical tests; (c) a rational to the potential covariates or confounding variables; and (d) how the results could be concluded (i.e., key parameter, estimates, confidence intervals, and probability values). Subsequently, I elaborated the formerly defined objectives.

The analysis and computation of the data occurred with the following software. I used the software Microsoft Excel 2007 for general computations, specific computation of matrixes, regression models, econometric models, and construction of tables, graphs, charts, and outputs. Excel is a software product of the Microsoft Office product group. Through Excel, table-based computations were possible as well as several data analysis options (i.e., regression analysis). I used the software R Studio to compute the GRS values. The software R is an open coding language for statistical computation and the plotting of diagrams and charts. The software R Studio is an add-on software that makes R more accessible to use through a desktop-software. The Fama risk factors were essential for my analysis together with the net monthly portfolio returns to compute the GRS values. And, I used International Business Machines Corporation (IBM) Statistical Package for the Social Science (SPSS) Statistics 23 to compute significance tests, confidence intervals, and effect sizes. SPSS is a modular statistic-software for the analysis of data and to plot diagrams to the results. The three software packages that I considered for my analysis allowed the specification and the customization of the results, to obtain the required data and conduct the described tests for this study.

Next, I provided an explanation how the data was cleaned and screened. The data that I collected for the study was stock market data, in specific 30 DJIA stock data and the DJIA index data. I computed return values in percent from the stock prices for the data cleaning procedure. I used the return data to plot charts of each stock (index). Via a heuristic analysis of each chart, I screened the data to find out if outliers existed. If outliers existed, then I applied the method of creating a mean to exchange the outlier value. This means for example, if the data exhibits the monthly values [r = 1%, 50%, 3%] and 50% would be identified as the outlier then I would delete 50%, and I would insert the mean of 2%. I planned to report all changes applied to the data in an outlier protocol.

The research question and the hypotheses as written in Chapter 1 were restated here.

RQ: What Moving Average (MA) setting as strategy adjustment can improve the long only momentum strategy performance for small portfolios of U.S. stocks?

H1: H_1 1: If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then the optimal MA number of day setting and the optimal MA computation type can be found to adjust the MOM strategy.

H2: H_1 2: If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are greater than the DJIA index and the MOM strategy returns.

H3: H_1 3: If the costs are factored for the MA MOM strategy, then the MA

MOM strategy is still profitable.

H4: H_1 4: If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects occur for the returns of the MA MOM strategy.

H5: H_1 5: If the CAPM and the FF3FM alphas are computed for the overlapping MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are still positive.

H6: H_1 6: If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount can be determined.

H7: H_1 7: If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the MA MOM strategy returns are greater than the MOM strategy returns.

Finally, I addressed the four main aspects as mentioned in the first paragraph above. In Chapter 4, I planned to use two tests, metrics and matrix computations, and regression models for the data analysis: (a) simple parametric significance *t*-tests, (b) GRS tests, (c) SMA and EMA indicator metrics, (d) factoring with a cost function, (e) Sharpe ratios, and (f) multiple regression models. After determining the results through the QE's and the determination of the optimal MA, I planned to compare the benchmark, the MOM strategy, and the MA MOM strategies returns; and I planned to test for significant differences. This could allow me to identify, if the returns of the MA MOM, MOM portfolios, and benchmark differed significantly, where the *z*-value needed to exceed the critical $z_{95\%}$ value for example.

I planned to compute the GRS value in connection to the risk-adjusted excess returns from the valuation models. The GRS test could allow assessing the efficiency of the two valuation models, in this study the CAPM and the FF3FM. Depending on which valuation model is more efficient, the GRS value could be smaller and the average alphas could be near zero (Gibbon, Ross, & Shanken, 1998). I planned to perform a multiple regression analysis to compute the risk-adjusted excess returns, which were relevant for the GRS tests. I also planned to consider the alpha values from a multiple regression analysis to answer volatility, cost, and model efficiency questions.

I planned to compute the Share ratios, in order to gain insights to the risk and return relation of the portfolios and to determine the optimal trading frequencies for the MA MOM strategy. To obtain the standard deviation to compute the Sharpe ratios and to avoid discrete return effects, I planned to compute the returns as continuous returns, by dividing the future time period stock price by the previous time period stock price and applying the natural logarithm. From these continuous returns, the excess returns could be computed, by considering the geometric mean of the MA MOM portfolios. Then, the covariance-variance matrix could be computed and multiplied to the portfolio weights vectors, to receive the portfolio variance, or by applying the square root the standard deviation could be obtained. High significant Sharpe ratios could be an indication for the optimal trading frequency of the MA MOM portfolios.

Threats to Validity

In this section, I referred to three main validity threats and commented on how these issues were addressed.

External Validity

The external validity refers to the extent to which the results of a study can be generalized to a population. In other words, the validity of the inferences made from this study's research was in this section of interest. An issue that could occur for external validity can come from the DJIA data. The DJIA only represents U.S. stocks of large industries. This means that stocks with a smaller market capitalization, technology stocks, or start-up industries were underrepresented in the population of this study. The underrepresentation of a larger horizontal and vertical stock variety could have an effect on making inference conclusions for U.S. stocks. I referred to this issue in the result section by making limitations for the generalizations.

Further threats to validity can come from testing reactivity. Testing reactivity can for example occur through correlation effects in the DJIA stock portfolios. The stocks that were considered in this study were not selected randomly from a wide range of U.S. stock markets. The stocks for this research were the most dominant U.S. stocks in regard to their earning expectation. This means, if a general, strong economic growth is expected in a year for the United States, then stocks with high earning expectation could benefit collectively from economic growth. This described behavior for DJIA stocks and the issue of testing reactivity could be expected for the narrow collection of the U.S. stocks in this study. For example, if I make inferences in this study, to positive portfolio returns of stocks with high earnings expectations, then the results might differ for stocks with weaker earnings expectations. This reactivity effect could impact the generalizability of the study's results. I considered this described issue in the result section for the generalization of the conclusions as well.

Internal Validity

For the portfolio constructions in the result section, stocks were virtually traded. If stocks were traded, then the spreads of stock prices became relevant for the application of the transaction costs. The first inaccuracy that could occur came from the average computed spreads for the transaction costs. Average spread values could deviate from real values and could be higher or in some phases lower than assumed for the stocks. To react on this internal validity thread, I assumed three different average spread values dependent on the market capitalization.

A second possible issue could occur for data snooping. If data is used more than once for inference analysis, then data snooping can occur. For example, the satisfactory results could be caused by chance, rather than caused by the method (White, 2000). Data snooping occurs especially for time series data and financial asset pricing models and can threaten the internal validity (White, 2000). Dimson and Marsh (1990) reported that sophisticated valuation models could perform worse without data snooping. Bootstrapping the data or applying a Monte Carlo simulation could reduce the issue (Lo & Mac Kinlay, 1990). However, I addressed the issue of data snooping for valuation models by computing a simple model (CAPM) and a more sophisticated valuation model (FF3FM) for a comparison.

Construct Validity

In this section, the validity of a study's construct or the threats to a construct were of interest. The study I conducted did not hold any construct that needed to be further assessed through a literature review in Chapter 2 or needed to be assessed for its validity in this section. An operationalization for measuring a construct was also not required in this study.

However, the question if the statistical conclusions were valid could also be discussed in this section. In this study, I considered parametric significance *t*-tests and regression models as a methodology to obtain statistical conclusions. In regard of the significance tests, it was relevant to minimize an alpha error or a beta error. Therefore, I chose significance levels with an alpha level of 10%, 5%, and 1 % in comparison for the analysis in Chapter 4. The comparison of the different significance levels could allow me to differentiate, with what risk of validity, statistical conclusions for detected differences that could be made. Second, from the regression model coefficients I could report statistical values for a conclusion; however, the same issue of conducting an alpha error or a beta error could occur. I planned to test if the variables for the coefficients of the regression models differed significantly, by considering a significance test level of 5% alpha level, and I planned to test with an *F*-test if the variables distribute independently. Essentially, I planned to consider the effect size for all tests to see if the differences were meaningful for the tested variables.

Ethical Procedures

The ethical issues that could occur when conducting a research study needed to be ruled out. Main ethical concerns could relate to the data collection process; how the data was treated; which means for example, was personal data anonymized; who had access to the collected data; and when would the data be destroyed? For the data that I analyzed in this study, no human participants were considered. The data that I considered was publicly available stock market data from U.S. corporations. This means that no concerns occurred for participants that refuse or might withdrawal from the study; the data did not need to be anonymized, and no personal data needed to be deleted. Therefore, no specific ways to address such data handling considerations were required. The data was obtained from free of charge accessible domains for third party and real time audits. In other words, the data was not confidential. A historical concern did not occur about the validity and authenticity for the data collection from the published sources. The data was assessed in a qualified and careful handling, documented, and available by Thomson Reuters, Bloomberg, Yahoo!-finance et cetera (Foltice & Langer, 2015; Moskowitz, Ooi, & Pedersen, 2012).

Summary

In the research design section, I determined how to measure and how to answer the research question. Seven hypothesizes were introduced in connection to the research design and I made comments on how the QE’s and tests were planned to be constructed in this study.

The data for the research in this study was stock market data from the NYSE and the DJIA. The considered time period was from 1992 until 2010 and the time period reflected the most relevant progression and declining market phases. Internal validity threats could occur for assessing the spreads and could occur for data snooping issues in this study. I responded to the internal validity thread, by distinguishing three average spread values and by computing a simple and complex asset price model.

In the study, the CAPM and the FF3FM were planned to be computed, connected to a multiple regression model to determine the alphas and to evaluate volatility and costs effects for the MA MOM strategy. Further, simple parametric significance *t*-tests and a GRS test were planned to be applied to determine differences among the portfolio returns and the efficiency of the valuation model.

Overall, I discussed in Chapter 3 the main issues of research design, methodology, and a population that was relevant for the further investigation of the MA MOM strategy. How the MOM strategy was best adjusted by an MA, and what results could be expected for the MA MOM strategy were further discussed in Chapter 4.

Chapter 4: Research Results

In this study, the purpose of the research was to examine the relationship between different MA settings, the MOM strategy, and the performance of the MA MOM returns from the construction of small U.S. stock portfolios. To provide an answer to the research question and to provide an answer to seven hypotheses, I conducted four quasi-experiments and three analyses. I was required to determine the optimal MA setting to adjust the MOM strategy in this section. The yearly MA MOM strategy was compared to the yearly MOM strategy. I needed to apply the transaction costs to the MA MOM strategy to evaluate if the MA MOM strategy was still profitable. I considered six different trading frequencies and nine different investment amounts for the MA MOM strategy returns to analyze how volatility effects impacted the transaction costs. I computed alpha values, GRS values, and Sharpe ratios to establish a final overview that displayed the optimal trading frequencies for the MA MOM strategy and to answer the research question. The research question was: *What MA setting as strategy adjustment can improve the MOM strategy performance for small portfolios of U.S. stocks?* Therefore, I first comment in this chapter on the data collection that I conducted. I present the research results to address the seven hypotheses, structured according to seven hypotheses sections in the format: (a) null hypothesis, (b) design, (c) analysis, and (d) discussion. Finally, I answer to the research question at the end of this chapter.

Data Collection

In this data collection section, I list the data that I required for my analysis and I comment on where I obtained the data from. For the research of this study, I considered

30 DJIA stocks and the DJIA index, which represented U.S. companies with the highest earnings expectations and the highest market capitalizations compared to other U.S. stocks. I obtained the stock data from Yahoo!Finance for my research. I required obtaining the alpha values for each constructed MA MOM portfolio in my analysis to test the fifth hypothesis of this study. To compute the positive alpha values, I required market risk factor-data for a multiple regression analysis that was connected to the CAPM and the FF3FM. I obtained the risk factor-data from Kenneth French's published data library (see Chapter 3 data collection) for my research. The time period of the collected data ranged from 1992 until 2010. The selected time period led to (228 months) of data from which I determined the net monthly portfolio returns through my further assessments. The sample is representative for the population with a 95% probability and a population error deviation of 0.045%, if ($n_{MA\ MOM}$ = 4,736 days) are processed, which was the case during the given time period. Finally, no relevant discrepancies occurred between the presented data collection plan in Chapter 3 and the actual data collection.

Study Results

The research question of this study is: *What MA setting as strategy adjustment can improve the long only momentum strategy performance for small portfolios of U.S. stocks?* In this section, I present the results to each of seven hypotheses to the research question. I then provide an answer to the research question at the end of this section.

Hypothesis 1

Null Hypothesis 1. If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then no optimal MA number of day setting and no optimal MA computation type can be found to adjust the MOM strategy.

Alternative Hypothesis 1. If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then the optimal MA number of day setting and the optimal MA computation type can be found to adjust the MOM strategy

QE Design. The QE design allowed me evaluating the optimal MA number of days setting and optimal MA type. I could evaluate the number of Bull phases and the monthly average returns, while gaining an understanding to the potential transaction costs. First, I tested the MA variables heuristically in a chart that I plotted to the MA data, and then I compared the MA data in a QE design. The sample consisted of monthly adjusted closing prices for the DJIA index. The allocation of the MA's to the QE did not occur randomly, the allocation occurred through a qualified selection that was oriented at the reported findings of the source Glabadanidis (2015).

Analysis. I plotted the DJIA index on a monthly basis in a chart in Figure 3, to determine which MA number of day combinations I should select for the QE. I applied seven different SMA's to the chart [6, 12, 36, 48, 60, 80, and 100 months] according to Glabadanidis (2015) findings, to heuristically determine the effect of different MA signal occurrence. For my assessment of the chart, I saw two criteria as relevant in regard of what SMA's can capture the DJIA Bull and Bear phases best: (a) crossover and double-crossover SMA signals and (b) SMA turning point speed.

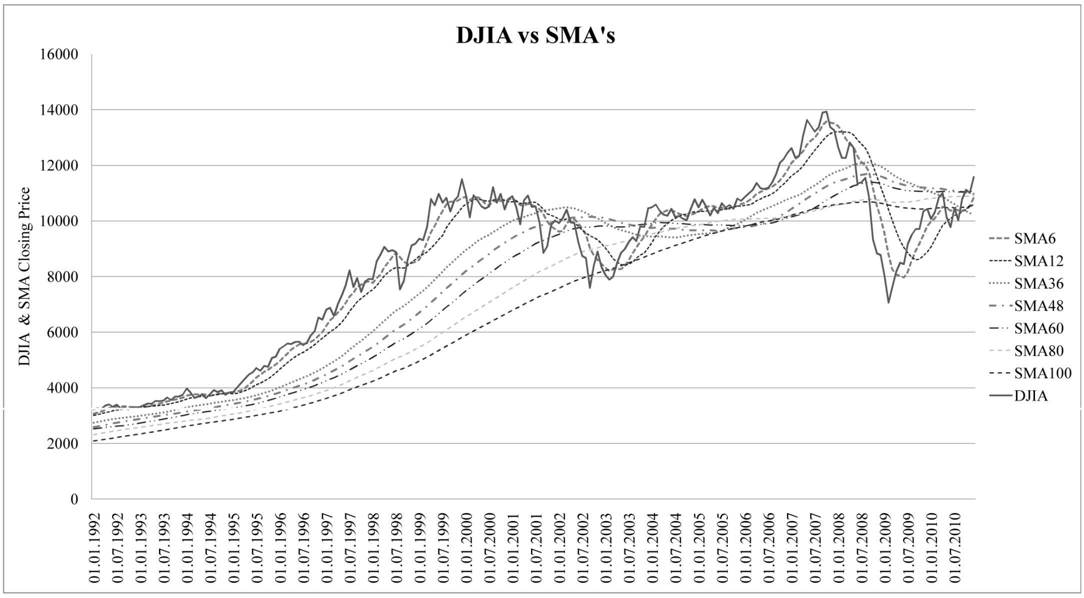

Figure 3. DJIA versus SMA's. Monthly adjusted closing prices n = 228, from 1992 until 2010 of the DJIA and SMA's (6, 12, 36, 48, 60, 80, and 100 months). Copyright 2018 by Ulrich R. Deinwallner.

Form the chart in Figure 3, I could learn that SMA's above 80 months did not capture the Bull and Bear phases sufficiently. SMA's around and below 12 months caused a high frequency of Bull and Bear phases. The 6 SMA seemed to turn between Bull and Bear phases very rapidly, while the 36 SMA turned at a moderate rate. The second moderate turning rate for the MA with average Bull and Bear phases seemed to occur for a 48 SMA. In combination, double-crossover signals for the 6 versus 36 SMA seemed most promising, because a high sensitivity (6 months) was combined with a high moderate price movement (36 months). To quantify the observations through a QE, I selected the 3 months combinations (6, 36, and 48 months) and I computed the SMA's and the EMA's for these 3 months, in Table 1.

Table 1

Performance Results Across MA Strategies

Strategy	r_{BH}	r_{BUP}	BUPAD	BUP	BUP Ratio
Pv6 SMA	0.56	2.20***	7	26	0.08
Pv6 EMA	0.56	2.11***	9	25	0.08
Pv36 SMA	0.56	0.99***	44	5	0.19
Pv36 EMA	0.56	0.54	44	10	0.05
Pv48 SMA	0.56	0.93***	47	5	0.18
Pv48 EMA	0.56	0.99***	46	6	0.16
6v36 SMA	0.56	0.78***	48	3	0.26
6v36 EMA	0.56	0.78***	46	5	0.15
6v48 SMA	0.56	0.62***	50	2	0.31
6v48 EMA	0.56	0.73***	52	3	0.24
36v48SMA	0.56	0.49	54	2	0.24
36v48EMA	0.56	0.45	103	1	0.45

Aggregated Performance Results

Strategy	r_{BH}	r_{BUP}	BUPAD	BUP	BUP Ratio
Average by Strategy					
Pv6	0.56	2.16***	8	26	0.08
Pv36	0.56	0.75***	44	8	0.10
Pv48	0.56	0.96***	47	6	0.17
6v36	0.56	0.78***	47	4	0.19
6v48	0.56	0.67***	51	3	0.27
36v48	0.56	0.47	79	2	0.31
Average by Method					
SMA	0.56	1.94***	42	7	0.27
EMA	0.56	1.87***	50	8	0.22

Note. Adapted from "The efficacy of trading based on moving average indicators: An extension" by S. D. Dovlin, 2014, *Journal of Wealth Management, 17*(1), p. 55. Copyright 2018 by Ulrich R. Deinwallner. *r* is the monthly average return (GEO mean's) in percent and computed from DJIA adjusted closing prices. Pv is price verses. BH is the buy and hold strategy. BUPAD are the Bull phase average days. BUP are the total number of Bull phases. The MA time period computation ranged from 1988 February until 2010 December. The monthly average returns time period returns ranged from 1992 until 2010. BUP ratio is the return of the Bull phase divided by the Bull phases. DJIA monthly standard deviation = 0.043%; n = 228. Significant level at: *p < 10%, **p < 5%, ***p < 1%.

Discussion

From the results in Table 1, I could find that for the *average by method* results the SMA was superior to the EMA returns (r_{BUP} = 1.94% SMA > 1.87% EMA). The *average by strategy* results reviled that the Pv6 MA's (r_{BUP} = 2.16%) exhibited the highest significant returns compared to the other MA returns, but the Pv6 MA's had also the highest amount of Bull phases (BUP = 26) compared to the other MA Bull phases. The results of the 36v48 MA's had the highest (BUP ratio = 0.31) compared to the other BUP ratios, meaning that the highest returns occurred in connection to the lowest amount of Bull phases for the 36v48 MA's. The second largest BUP ratio value occurred for the 6v48 MA's, which could be observed in the result Table 1.

I could reject the Null Hypothesis 1 from the findings in Table 1. I will select the 6v36 SMA combination further in this study with significant returns at 1% alpha level, as the optimal MA number of day combination to adjust the MOM strategy, and as the optimal MA method type to adjust the MOM strategy. The 36v48 MA's did not cover efficiently the samples Bull and Bear phases, with one until two Bull and Bear phases and very late turning points for the trading signals. In the chart, the 6v48 MA's seemed secondly as superior; however, a third Bull and Bear phase was about to occur, which was not covered in the 6v48 MA's sample period. If a third Bull phase would have occurred, which the chart in Figure 3 indicated, then the BUP ratios would have been (BUP $\text{ratio}_{6v36\ SMA}$ = 0.26, which is greater than BUP ratio $_{6v48\ SMA}$ = 0.21and BUP $\text{ratio}_{6v48\ EMA}$ = 0.24) in comparison to the other most relevant MA strategies. According to this, I will consider the MA combination 6v36 SMA for my future investigation in this study.

The 6v36 SMA combination exhibited the highest returns in connection to the lowest Bull market phases in a closer assessment (r_{BUP} *6&36 SMA*= 0.78%; BUP = 3). I saw a low number of Bull market phases as important for the further analysis, because a low number of Bull market phases would lead in consequence to a low amount of transaction costs. The cumulated amount of transaction costs needs to be subtracted from the MA MOM portfolio returns and can impact especially small investments largely. The identified Bull market phases of the 6v36 SMA seemed reliable and profitable to cover the main DJIA Bull and Bear market phases from a heuristic and from a quantitative assessment perspective. The 6v36 SMA strategy returns exceeded the returns of a BH strategy (r_{BH} = 0.56%) significantly at a 1% alpha level in the QE.

Hypothesis 2

Null Hypothesis 2. If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are not greater than the DJIA index and the MOM strategy returns.

Alternative Hypothesis 2. If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are greater than the DJIA index and the MOM strategy returns.

QE Design. The selected QE design allowed me answering a main part of the research question, if the MA MOM strategy can significantly improve the MOM strategy and if the MA MOM strategy is more profitable than a BH strategy, where the BH strategy is represented through the return performance of the DJIA. The independent variables were 30 DJIA stocks, for which the treatments of three strategies (MA MOM, MOM, and BH) were applied to assess the dependent variables (portfolio returns). The sample considered (n = 228 monthly adjusted closing prices) in a time period of 19 years, from 1992 until 2010. All DJIA stocks prices started from the starting date of January 02, 1992, except for two stocks. The stock prices of the GS stock started from May 04, 1999, and the stock prices from the V stock started from March 19, 2008.

Analysis. The stocks that I considered are listed in the subsequent table.

Table 2

Selected 30 DJIA stocks and their market capitalizations

Stock	Market Cap	Stock	Market Cap
AAPL	$1,085 B	KO	$195 B
AXP	$93 B	MCD	$130 B
BA	$214 B	MMM	$123 B
CAT	$91 B	MRK	$188 B
CSCO	$228 B	MSFT	$877 B
CVX	$236 B	NKE	$109 B
DD	$73 B	PFE	$257 B
DIS	$174 B	PG	$206 B
GE	$98 B	TRV	$34 B
GS	$86 B	UNH	$256 B
HD	$237 B	UTX	$112 B
IBM	$138 B	V	$266 B
INTC	$220 B	VZ	$221 B
JNJ	$372 B	WMT	$276 B
JPM	$384 B	XOM	$364 B

Note. B is billion and Market Cap is market capitalization. The market capitalization was obtained from Markets Insider (2018). Copyright 2018 by Ulrich R. Deinwallner.

I applied the treatment *MA MOM strategy* and *MOM strategy* to 30 DJIA stocks for the analysis. From the stock price staring date January 04, 1993, I computed the geometric mean of the formation period of 6 months. After the 6 months, I ranked the stocks from the best returns until the worst returns, and then I constructed the stock portfolios of the top 30% of 30 DJIA stocks. This means that for each strategy, I could construct one until nine portfolios that contained equally weighted amounts of stocks. I theoretically bought the stocks for the portfolios on the first trading day of January for each year and held the stocks for 12 months, respective until an exit signal occurred by the 6vs36 SMA indicator for the MA MOM strategy. For the MA MOM strategy ($n_{MA\ MOM}$ = 14 trades) occurred and for the MOM strategy (n_{MOM} = 18 trades) occurred. This means that I could identify through the 6v36 SMA indicator four signals, which considered two exit signals and two entry signals to avoid two main stock price declining periods during September 28, 2001 until December 31, 2003 and during August 29, 2008 until October 29, 2010. The results of the portfolio returns allowed me a comparison between the MA MOM strategy-, MOM strategy- and BH strategy returns and further values presented in Table 3.

Table 3

MA MOM strategy returns, unadjusted for costs (% per month)

Portfolio size	r_{DJIA}	1	2	3	4
Values of r_{MOM}					
Jan 199 - Dec 2010	0.56	1.39	1.17	1.37	1.24
Monthly Std	4.30	18.22	12.06	10.57	8.53
Values of $r_{MA\ MOM}$					
Jan 1992 - Dec 2010	.56	1.74***	1.19**	1.46***	1.31***
Max	10.61	11.36	7.34	8.78	6.39
Min	-15.13	-6.12	-4.28	-3.68	-3.18
Median	1.05	1.47	2.09	2.90	2.53
Monthly Std	4.30	18.45	12.28	10.96	9.02
Correlation	NA	.45	.40	.51	.50
Outperform DJIA	NA	50%	57%	71%	71%
Sub-periods					
1992 - 2000	0.53	0.94	0.77	1.10	0.94
2001 - 2010	0.03	0.72	0.39	0.31	0.34

Portfolio size | r_{MOM}	5	6	7	8	9
Jan 1992 - Dec 2010	1.27	1.24	1.26	1.17	1.13

Portfolio size	5	6	7	8	9
Values of r_{MOM}					
Jan 1992 - Dec 2010	1.27	1.24	1.26	1.17	1.13
Monthly Std	8.08	7.54	7.66	8.09	7.70
Values of $r_{MA\ MOM}$					
Jan 1992 - Dec 2010	1.31***	1.23**	1.28**	1.21**	1.17**
Max	6.75	6.62	6.46	5.88	5.43
Min	-3.05	-2.59	-1.96	-2.37	-2.05
Median	2.23	2.20	2.09	1.92	1.66
Monthly Std	8.60	7.86	7.68	8.05	7.62
Correlation	.53	.56	.57	.59	.61
Outperform DJIA	79%	71%	79%	71%	71%
Sub-periods					
1992 - 2000	1.03	1.00	1.07	1.02	1.01
2001 - 2010	0.25	0.20	0.18	0.17	0.14

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 90. Copyright 2018 by Ulrich R. Deinwallner. *r* is the monthly average return (Geo mean) in percent and computed from DJIA adjusted closing prices. The *r* MOM consists of 1 until 9 stock portfolios. The monthly average returns time period ranged from 1992 until 2010. For the MA MOM strategy and MOM strategy, the formation period was 6 months, where each stock was ranked from the best returns to the worst returns. Equally weighted portfolios were formed for (1 until 9 stocks). A 12 months holding period was assumed. The annual geometric mean and standard deviation was computed over the multiple time periods for the portfolios, to obtain monthly values. The correlation was computed between the DJIA trading returns and the portfolios trading returns. The *Outperform DJIA* referred to the percentage when the portfolio returns (n = 14 trades) outperformed the DJIA returns. The DJIA returns provided (n = 228 values) on a monthly basis over the given time period. Significance levels were assessed for the monthly MA MOM returns compared to the monthly DJIA returns at: *p < 10%, **p < 5%, ***p < 1%.

Discussion

From the results in Table 3, I could find that the MA MOM strategy is significant at a 1% alpha level more profitable compared to the BH strategy, for one, three, four, and five stock portfolios. For example, one stock portfolio has a return of ($r_{1\ MA\ MOM}$ = 1.74 % per month) and is significant at a 1% alpha level $t(226)$ = 4.144, p < .001, where DJIA $CI_{99\%}$ [-0.17, 1.29] for the given time period. However, the volatility was very high for a one stock portfolio observed from Table 3 with ($s_{MA\ MOM\ 1\ Stock}$ = 18.45% per month). This means that depending on the date when the buying of the stock of the MA MOM portfolio started, for example January or June, large deviations could be observed for the monthly MA MOM returns. I will assess this observation further in the subsequent experiments and analysis of this study.

Interestingly, the MA MOM strategy is in this comparison not significantly more profitable than the MOM strategy at a 1% alpha level, but significant at a 10% alpha level with $t(8)$ = 2.043, p = .075; partial η^2 = .732 displaying a strong effect. Therefore, I could not reject the Null Hypothesis 2 at a 1% alpha level in this analysis for the results of Table 3. The aspect that the equity capital for trading the MA MOM strategy was not reinvested in bonds during the MA initiated trading stops impacted the MA MOM results. Also, I can speculate that diversification effects, connected to a holding period of 1 year, seemed to cancel out the main losses during the downwards trending time periods for the yearly MOM strategy portfolio stocks. If the MOM strategy had been applied with a higher trading frequency, more drastic losses might have cumulated. However, the large observed volatility and the only yearly result comparison could be an indication that a more differentiated analysis could bring positive results for the effectiveness of the MA MOM strategy.

The draw downs, expressed through the minimum values of the MA MOM strategy in Table 3, were during all time periods less compared to the BH strategy ($MA\ MOM_{Min} \geq$ -6.12% per month; BH_{Min} = -15.13% per month). The sub periods in Table 3 were all positive for the MA MOM portfolios with a range = [0.03% until 1.10 % per month]. The benchmark in Table 3 was outperformed in at least ≥ 50% of the cases through the MA MOM strategy. The correlation between the MA MOM portfolios and the BH portfolio was high for a nine stock portfolio with (R = .61) in Table 3. I could find that the application of a MA could adjust the MOM strategy; the MA MOM strategy was on average ($r_{difference}$ = 0.07% per month) more profitable than the yearly MOM strategy; and the application of the MA MOM strategy could reduce the overall risk of the traded portfolios. Also interesting was that a cut off level of 30% did not much differ from a cut of level of 10% of the winner stocks, while the returns were still significant at a 10% alpha level for a nine stock portfolio. Both strategies, the MA MOM strategy and the MOM strategy, clearly benefited from a momentum effect in the tested finical market, compared to the BH strategy returns. Investor's under-reactions and delayed over-reactions could be causal for the observed abnormal returns in the MA MOM portfolios. Therefore, I can summarize that the MA MOM strategy is significantly more profitable compared to a BH strategy, where the BH strategy is represented through the return performance of the DJIA. However, in this analysis the MA MOM strategy could only significantly outperform the MOM strategy at a significance alpha level of 10%. This means that in conclusion the Null Hypothesis 2 could not be rejected at a 1% alpha level.

Hypothesis 3

Null Hypothesis 3. If the costs are factored for the MA MOM strategy, then the MA MOM strategy is not profitable.

Alternative Hypothesis 3. If the costs are factored for the MA MOM strategy, then the MA MOM strategy is still profitable.

Design. The research design allowed me comparing the MA MOM strategy net monthly returns to the BH strategy monthly return. It was important to compute the transaction costs and to apply the costs to the MA MOM strategy returns. The analysis required to assess the impact of the transaction costs on the returns of nine different MA MOM portfolios and differentiated by nine different investment amounts. During the time period from 1992 until 2010, 14 trading opportunities occurred in connection to the sample, which meant for example, for a nine stock MA MOM portfolio (n_{9x14}= 126 traded stocks). I could obtain (n_{9x9} = 81 result values) for nine different investment amounts and nine different stock amount MA MOM portfolios. To determine the significant differences between the compared portfolios, I compared the MA MOM strategy net monthly returns with a parametric *t*-test to the BH strategy monthly return.

Analysis. It was the main task for Hypothesis 3 to assess the net monthly returns of the MA MOM strategy. I selected the MA MOM strategy portfolio data from experiment 2 for the analysis of Hypothesis 3. I counted the number of trades for the MA MOM portfolio data that occurred for each stock portfolio to determine the transaction costs and to compute the real turnovers. The real turnover considered the aspect that one stock could be held in a MA MOM portfolio over multiple trades, which could decrease the amount of factored transaction costs. A trade referred to one buying action and one selling action of the selected MA MOM stocks. The transaction costs for buying and selling the stocks of the MA MOM portfolios were computed according to Equation 20. The average spread size that I considered for the transaction cost equation was (0.212% spread), since the market capitalization of all stocks in the MA MOM portfolios were greater than $11 billion. After obtaining the MA MOM net monthly returns, I applied a parametric *t*-test to compare the portfolio return differences between the MA Momentum strategy and the BH strategy.

Table 4

Cost adjusted MA MOM returns by subtracting transaction costs (%) form real turnovers, yearly trading frequency, DJIA return: 0.56

Initial $ amount / stocks	1	2	3	4	5	6	7	8	9
Unadjusted MA MOM returns	1.74	1.19	1.46	1.31	1.31	1.23	1.28	1.21	1.17
$ 5,000	1.70***	1.10**	1.34***	1.16**	1.13**	1.01	1.03	0.94	0.86
$ 10,000	1.71***	1.13**	1.38***	1.21**	1.19**	1.08*	1.11*	1.03	0.96
$ 15,000	1.72***	1.14**	1.39***	1.23**	1.21**	1.11*	1.14**	1.06*	0.99
$ 30,000	1.72***	1.15**	1.41***	1.24**	1.23**	1.13**	1.16**	1.09*	1.03
$ 50,000	1.72***	1.15**	1.41***	1.25**	1.24**	1.14**	1.18**	1.10*	1.04*
$ 100,000	1.72***	1.15**	1.42***	1.25**	1.24**	1.15**	1.18**	1.11*	1.05*
$ 250,000	1.73***	1.16**	1.42***	1.26**	1.25**	1.15**	1.19**	1.11*	1.06*
$ 500,000	1.73***	1.16**	1.42***	1.26**	1.25**	1.15**	1.19**	1.11*	1.06*
$ 1,000,000	1.73***	1.16**	1.42***	1.26**	1.25**	1.15**	1.19**	1.12*	1.06*
Real trade amount	11	25	32	40	48	59	69	73	85

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management*, *29*(2), p. 93. Copyright 2018 by Ulrich R. Deinwallner. The trading amount represents a full trade, meaning one buying action and one selling action. For the real turnover, the costs were only applied to new stocks and not to the stocks that could be held over several time periods. The costs were computed according to a low spread average of 0.212%, since the market capitalizations of the stocks were all greater than $11 billion. The equation was ((2 * $10 commission) + (2 * 0.5 * 0.212% spread) + 0.003333% SEC fee). The DJIA standard deviation = 4.30%; statistical significance was given by a parametric *t*-test that compared the portfolio monthly average returns with the DJIA monthly average return. Significant alpha levels at: *p < 10%, **p < 5%, ***p < 1%.

Discussion

I could find from the results of the transaction cost analysis that most MA MOM net monthly returns, differentiated by nine portfolios and differentiated by nine investment amounts, remained significantly greater at a 10% alpha level compared to the BH return with (r_{BH} = 0.56% return per month). In Tables 4, I could find that the application of the transaction costs, in connection to different investment amounts, had a decreasing effect on the MA MOM portfolio returns. The returns in the MA MOM portfolios declined, if the trading frequency of the traded stocks in the MA MOM portfolios was increased. This means that the smaller the investment amount was and the more stocks were considered for a MA MOM portfolio, through which more trades occurred, the larger the decreasing effect was, when applying the transaction costs. For example, a three stocks MA MOM portfolio for a full turnover trading period, for $1 million required 42 trades ($r_{3stocks_\$1million}$ = 1.41***% net return per month) and had a lower transaction cost impact compared to a nine stock portfolio for $5,000 with 126 trades ($r_{9stocks_\$5,000}$ = 0.71% net return per month), as shown in the full turnover table in the appendix. Overall, the MA MOM net returns per month ranged from [0.86% until 1.73%] according to the real turnover Table 4.

I provided a full turnover Table A1 in the Appendix section, since the real turnover table does not cover the case in which the MA MOM investor is required to exchange all of the stocks each year over the full investment period. I could find from the results of the full turnover table that most MA MOM returns were significantly larger than the BH strategy at a 10% alpha level, while the net monthly MA MOM returns ranged from [0.71% until 1.72%]. The MA MOM returns were largely impacted by a transaction cost effect, caused through a higher trading volume of the traded MA MOM stocks compared to the real turnover table. Essentially, I could conclude that the Null Hypothesis 3 could not be rejected at a 1% alpha level according to the findings and the results that I could obtain from the transaction cost analysis.

Hypothesis 4

Null Hypothesis 4. If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects do not occur for the returns of the MA MOM strategy.

Alternative Hypothesis 4. If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects occur for the returns of the MA MOM strategy.

QE Design. A QE design for the analysis of Hypothesis 4 allowed me analyzing the results for six different trading frequencies and to nine different investment amounts, when applying the overlapping MA MOM strategy to 30 DJIA stocks. The net monthly returns of the traded stocks were relevant for the results of the QE. The overlapping MA MOM strategy, differentiated by the trading frequencies and differentiated by the investment amounts as treatments, was of interested for this QE, because both control variables of the QE impacted the transaction costs directly. The sample for the analysis of Hypothesis 4 considered 30 DJIA stocks, from which I constructed nine portfolios for the QE.

Analysis. For the QE of Hypothesis 4, I applied the overlapping MA MOM strategy to 30 DJIA stocks, differentiated by six different trading frequencies and nine different investment amounts. This meant for the analysis that I first selected the formation period of 6 months for all 30 DJIA stocks. Then, I computed the (1 until 9) highest geometric mean returns for all 30 DJIA stocks to determine the winner stocks. From this determination of the winner stocks, I constructed the (1 until 9) overlapping MA MOM portfolios for the QE. I held the selected stocks in the overlapping MA MOM portfolio for 1 year. After 1 year holding period, the overlapping MA MOM portfolio stocks were rebalanced. Rebalancing meant that I repeated the cycle of *formation* and *determination of winner stocks* for the overlapping MA MOM portfolio construction again.

I applied the overlapping strategy according to six different trading frequencies and for nine different investment amounts for the MA MOM portfolios. For example, if I invested $5,000 in a one stock overlapping MA MOM portfolio for a bi-yearly trading frequency, then I divided $5,000 by two and received $2,500 to invest in January in one stock that I held for 1 year, and I had $2,500 to invest in one stock in July that I held for 1 year (respective according to the MA rules). After 1 year holding period, I rebalanced the stocks of the overlapping MA MOM portfolios to continuously hold the markets winner stocks in the portfolios over the given time period (also see equation 21 to buying power for the overlapping strategy).

I received (6 frequencies x 9 portfolios = 54 return results) through the application of six different trading frequencies for the overlapping MA MOM portfolios. I considered the overlapping MA MOM portfolio returns and factored the transaction costs (also see equation 20) according to nine different investment amounts. I received through the application of the transaction costs the net monthly overlapping MA MOM returns, displayed in Figure 4.

I required the real trading frequencies for the computation of the transaction costs because some stocks needed to be held over multiple time periods. This meant that I counted the stocks that were held over multiple time periods and subtracted the resulting amount from the total number of trades that occurred per overlapping MA MOM portfolio. The real trading frequencies for six different variations over the tested time period were (n_{yearly} = 14 trades; $n_{bi\text{-}yearly}$ = 29 trades; $n_{tri\text{-}yearly}$ = 42 trades; $n_{quarterly}$ = 56 trades; $n_{bi\text{-}monthly}$ = 85 trades; $n_{monthly}$ = 169 trades). For example, a nine stock overlapping MA MOM portfolio on a monthly basis led to (9 portfolios x 169 real trading frequency = 1,521 traded stocks) from 1992 until 2010. During the given time period, the net monthly MA MOM returns varied for the different trading frequencies and for the different investment amounts in a range from [-1.36 % until 1.94 %] according to Figure 4.

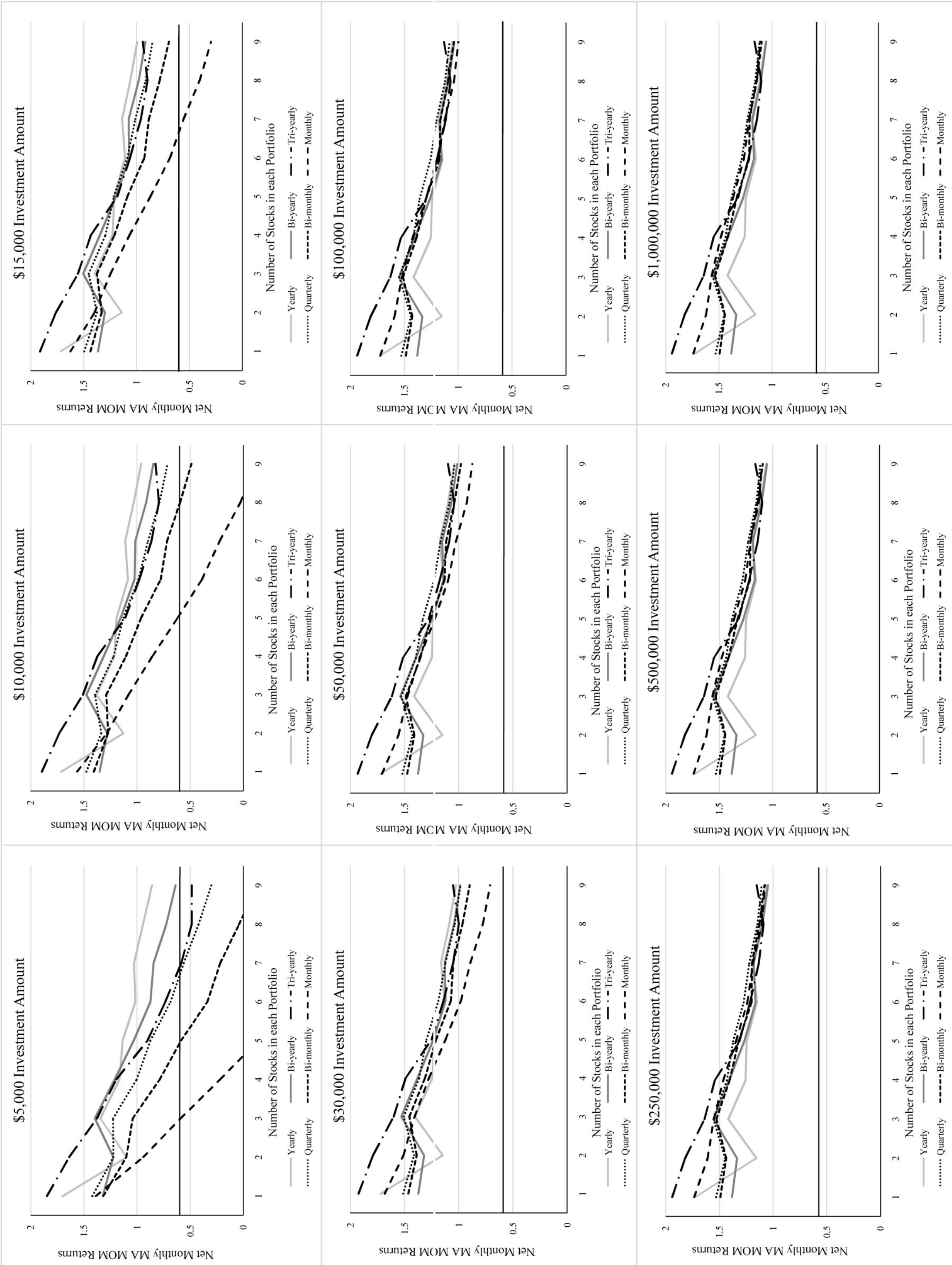

Figure 4. Displaying the net monthly overlapping MA MOM strategy differentiated by nine different investment amounts and by six different trading frequencies. Adapted

from “Profitable momentum trading strategies for individual investors” by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 112. Copyright 2018 by Ulrich R. Deinwallner.

Discussion

From the results of Figure 4, I could find that overlapping MA MOM portfolio returns with a small investment amount of $5,000 were not in all cases profitable, except for the yearly and bi-yearly strategies. The yearly overlapping MA MOM strategy was profitable for small investment amounts, because only one trade occurred per year and the transaction costs could not impact the overlapping MA MOM returns largely. The trading frequency in connection to the transaction costs had a significant negative effect at a 1% alpha level for the returns, especially on the monthly and the bi-monthly returns of the overlapping MA MOM portfolios, below $30,000 investment amount. For example, the return of a nine stock portfolio with a monthly trading frequency and $5,000 investment amount reduced the overlapping MA MOM portfolio by ($r_{9Stock_\$5,000}$ = -1.36% per month) over the entire trading time period. Overlapping MA MOM portfolios with an investment amount of $30,000 and above, exhibited positive returns for all different trading frequencies. From the diagrams, I could observe that the transaction costs had a lower impact on the overlapping MA MOM portfolio returns, the higher the trading amounts were. The observed effect showed in the diagrams through a decreasing deviation of the different trading frequency diagram trend-lines. For example, a lower impact of the transaction costs on the overlapping MA MOM portfolio returns was valid for investment amounts of $100,000 and above. Where, all trading frequencies performed similarly and ranged from [1.00% until 1.94% per month]. The analysis of the QE showed that volatility effects and transaction cost effects did have a significant impact on the results of the overlapping MA MOM strategy, especially for small investment amounts, through which I could reject the Null Hypothesis 4 at a 1% alpha level.

Hypothesis 5

Null Hypothesis 5. If the CAPM and the FF3FM alphas are computed for the overlapping MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are not positive.

Alternative Hypothesis 5. If the CAPM and the FF3FM alphas are computed for the overlapping MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are still positive.

Design. The multiple regression analysis design of the Hypothesis 5 analysis allowed me evaluating the net monthly alphas for the overlapping MA MOM strategy, by obtaining the alphas from the CAPM and the FF3FM. The independent variables for the linear and the multiple regression analysis were the risk factors obtained from Fama and French (1993). The dependent variables were the overlapping MA MOM portfolio returns and the DJIA index returns (BH strategy returns). I differentiated the results by six different trading frequencies for one until nine stock portfolios, while I factored the transaction costs for nine different investment amounts.

Analysis. I formed six different data sets, according to the six different trading frequencies, that I obtained from the experiment 4 for the analysis of the net monthly alphas. I collected the portfolio returns from experiment 4, I collected the risk factors from the Kenneth French webpage, and I adjusted the required time period for the collected data. With this collected data, I computed a linear regression model / analysis (equation 14) for the CAPM alphas and I computed a multiple regression model / analysis (equation 15) to obtain the FF3FM alphas. The alphas needed to be positive and significantly larger than the BH alpha for the overlapping MA MOM strategy to be interpreted as profitable. Then, I subtracted the transaction costs from the overlapping MA MOM monthly alphas to obtain the overlapping MA MOM net monthly alphas. For most portfolios with different trading frequencies, positive alphas could be observed in Table 5. For example, the largest positive alpha could be observed in Table 5 with ($alpha_{1stock\_\$50,000}$ = 3.70%) from the FF3FM, for a one stock portfolio, over $50,000, and for a yearly trading frequency. After I obtained the alphas, I computed the average GRS value for each trading frequency and for each valuation model. As a result, the CAPM GRS-test values tended all to be smaller compared to the FF3FM value in a heuristic econometric model comparison, which I further elaborate in the subsequent discussion section.

Table 5

CAPM – net monthly alphas (in %)

	1	2	3	4	5	6	7	8	9
1 x year									
$ 5,000	2.17***	1.05*	1.08***	0.87**	0.81**	0.71	0.72	0.61	0.56
$ 10,000	2.17***	1.06**	1.09***	0.89**	0.84**	0.74*	0.75*	0.66	0.61
$ 15,000	2.17***	1.06**	1.10***	0.90**	0.85**	0.75*	0.77**	0.67*	0.62
$ 30,000	2.17***	1.06**	1.10**	0.90**	0.86**	0.76**	0.78**	0.69*	0.64
$ 50,000	2.17***	1.06**	1.10***	0.91**	0.86**	0.76**	0.78**	0.69*	0.65*
$ 100,000	2.18***	1.06**	1.10***	0.91**	0.86**	0.77**	0.79**	0.70*	0.65*
$ 250,000	2.18***	1.06**	1.10***	0.91**	0.86**	0.77**	0.79**	0.70*	0.65*
$ 500,000	2.18***	1.06**	1.10***	0.91**	0.87**	0.77**	0.79**	0.70*	0.66*
$ 1,000,000	2.18***	1.06**	1.10***	0.91**	0.87**	0.77**	0.79**	0.70*	0.66*
GRS Average									0.55
2 x year									
$ 5,000	1.55***	0.96**	0.95**	0.76**	0.55*	0.39	0.36	0.23	0.15
$ 10,000	1.58***	1.02**	1.03***	0.86**	0.67**	0.54	0.53	0.43	0.36
$ 15,000	1.59***	1.04***	1.06***	0.89**	0.71**	0.59*	0.59*	0.49	0.43
$ 30,000	1.60***	1.06***	1.08***	0.93**	0.76**	0.64**	0.64**	0.55*	0.50
$ 50,000	1.61***	1.06***	1.09***	0.94**	0.77**	0.66**	0.67**	0.58*	0.53
$ 100,000	1.61***	1.07***	1.10***	0.95**	0.78**	0.67**	0.68**	0.60*	0.55*
$ 250,000	1.61***	1.07***	1.11***	0.96***	0.79**	0.68**	0.69**	0.61*	0.56*
$ 500,000	1.61***	1.07***	1.11***	0.96***	0.79**	0.68**	0.70**	0.61*	0.57*
$ 1,000,000	1.61***	1.08***	1.11***	0.96***	0.79**	0.69**	0.70**	0.62*	0.57*
GRS Average									2.27

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management*, 29(2), p. 96. Copyright 2018 by Ulrich R. Deinwallner. The CAPM regression equation 14 was used to compute the monthly alphas. The variables for the equation 14 were the risk factor (IV) and the net monthly portfolios returns (DV). The risk free rate and risk factor were obtained from French's data webpage. The GRS Average represents the average value of the GRS-test. The MA MOM net monthly returns were compared to the DJIA monthly return of 0.56% and were significant at an alpha level of: *p < 10%, **p < 5%, ***p < 1%.

Table 6

FF3FM net monthly alphas (in %)

	1	2	3	4	5	6	7	8	9
1 x year									
$ 5,000	3.69***	1.84*	2.05***	1.68**	1.59**	1.40	1.39	1.28	1.18
$ 10,000	3.69***	1.84**	2.06***	1.70**	1.61**	1.43*	1.43*	1.33	1.23
$ 15,000	3.69***	1.84**	2.06***	1.71**	1.62**	1.44*	1.44**	1.34*	1.25
$ 30,000	3.69***	1.84**	2.07**	1.71**	1.63**	1.45**	1.45**	1.36*	1.27
$ 50,000	3.70***	1.84**	2.07***	1.72**	1.63**	1.45**	1.46**	1.36*	1.27*
$ 100,000	3.70***	1.84**	2.07***	1.72**	1.63**	1.45**	1.46**	1.37*	1.28*
$ 250,000	3.70***	1.84**	2.07***	1.72**	1.64**	1.46**	1.46**	1.37*	1.28*
$ 500,000	3.70***	1.84**	2.07***	1.72**	1.64**	1.46**	1.46**	1.37*	1.28*
$ 1,000,000	3.70***	1.84**	2.07***	1.72**	1.64**	1.46**	1.46**	1.37*	1.28*
GRS Average									3.95
2 x year									
$ 5,000	2.34***	1.29**	1.34***	1.14**	0.96*	0.71	0.65	0.49	0.36
$ 10,000	2.37***	1.34**	1.42***	1.25***	1.09**	0.86	0.82	0.68	0.57
$ 15,000	2.38***	1.36***	1.45***	1.28***	1.13**	0.91*	0.88*	0.75	0.64
$ 30,000	2.39***	1.38***	1.48***	1.31***	1.17**	0.96**	0.93**	0.81*	0.71
$ 50,000	2.40***	1.39***	1.49***	1.33***	1.18**	0.98**	0.96**	0.84*	0.73
$ 100,000	2.40***	1.40***	1.50***	1.34***	1.19**	0.99**	0.97**	0.86*	0.76*
$ 250,000	2.40***	1.40***	1.50***	1.34***	1.20**	1.00**	0.98**	0.87*	0.77*
$ 500,000	2.40***	1.40***	1.50***	1.35***	1.20**	1.01**	0.99**	0.87*	0.77*
$ 1,000,000	2.40***	1.40***	1.50***	1.35***	1.21**	1.01**	0.99**	0.87*	0.77*
GRS Average									4.71

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management*, 29(2), p. 97. Copyright 2018 by Ulrich R. Deinwallner. The FF3FM regression equation 15 was used to compute the monthly alphas. The variables for the equation 15 were the risk factors (IV's) and the net monthly portfolios returns (DV). The risk free rate and risk factors were obtained from French's data webpage. The GRS Average represents the average value of the GRS-test. The MA MOM net monthly returns were compared to the DJIA monthly return of 0.56% and were significant at an alpha level of: *p < 10%, **p < 5%, ***p < 1%.

Discussion

The results in Tables 5 and 6 display the net monthly alphas for the tested overlapping MA MOM strategy, while the alphas were obtained from the CAPM and the FF3FM. The overlapping MA MOM alphas for the yearly trading frequency were all positive for each investment amount, due to the low transaction costs that occurred through the selection of a low trading frequency. The overlapping MA MOM alphas for the yearly trading frequency were not all significant at a 10% alpha level for the CAPM and the FF3FM, epically for six and more than six stock portfolios. In regard to all trading frequencies, not all reported overlapping MA MOM alphas indicated statistically significant abnormal returns, after the costs were subtracted.

The overlapping MA MOM alphas for the monthly trading frequency started to be profitable from one until three stock portfolios for the CAPM; from one until four stock portfolios for the FF3FM; or at an investment amount of $30,000 or higher for both econometric models. The highest overlapping MA MOM alphas, that were obtained from the CAPM, could be observed for a yearly trading frequency with an investment amount of $100,000 and higher, for a one stock portfolio with ($alpha_{1xyear,CAPM}$ = 2.18%); and for a tri-yearly trading frequency with an investment amount of $250,000 and higher, for a one stock portfolio with ($alpha_{3xyear,CAPM}$ = 2.19%). The high MA MOM positive alpha results for the yearly trading frequency were similar to Foltice and Langer's (2015) findings, who also reported high positive alphas for the yearly MOM strategy, which supported the plausibility for the results of this study.

The GRS-test was computed with an average value for all portfolios, differentiated by the econometric models, and differentiated by the trading frequencies. For example, the yearly CAPM GRS value was smaller ($GRS_{1xyarly,CAPM}$ = 0.55) compared to the yearly FF3FM value ($GRS_{1xyearly,FF3FM}$ = 3.95), which indicated that the yearly CAPM model had heuristically a higher efficiency in estimating the risk-adjusted net monthly MA MOM returns. The alphas tended mostly towards the value zero for the CAPM values compared to the FF3FM values, except for the tri-yearly trading frequency. The heuristic assumptions, that the CAPM exhibits a higher efficiency compared to the FF3FM, could be assumed for almost all results, since all average GRS values were smaller for the CAPM compared to the FF3FM. However, in general I could conclude that not all alphas were significantly positive at a 1% alpha level, through which I could not reject the Null Hypothesis 5.

Hypothesis 6

Null Hypothesis 6. If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount cannot be determined.

Alternative Hypothesis 6. If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount can be determined.

Design. The design for the computation of Hypothesis 6 helped me to evaluate the optimal trading frequency according to nine different investment amounts. The independent variables for the equation 18 were the overlapping MA MOM strategy portfolio returns, the portfolio returns standard deviations, and the returns of the risk free rate that I obtained from experiment 4, from individual computations, and from the Fama and French (1993) risk factor data. The dependent variables were the computed abnormal Sharpe ratios. The sample considered nine different portfolio returns according to six different trading frequencies, nine different investment amounts, and resulted in ($n_{Abnormal\ Sharpe\ ratios}$ = 486 values).

Analysis. I obtained from experiment 4 the net monthly overlapping MA MOM strategy returns, differentiated by six different trading frequencies. I computed the monthly standard deviations for each MA MOM portfolio: (a) By first transforming the stock prices through the application of the natural log into continuous portfolio returns; (b) I computed the excess-returns for each portfolio ($x-\bar{x}$); (c) then, I computed a covariance-variance matrix (Σ); (d) and from the covariance-variance matrix and the portfolio weights vectors ($\omega^T\Sigma\omega$), I could obtain the variance and the monthly standard deviation; (e) while remodeling the continuous results back into discrete returns (e^x-1). Further, I considered the monthly standard deviation from the DIJA index returns, and I computed the monthly geometric mean for the portfolio risk-free rates and for the DJIA index. These computations that I conducted allowed me to compute the Share ratios to each investment amount and trading frequency. I tested the computed Sharpe ratios for their significant difference, compared to the DJIA Sharpe ratio. I considered the estimated standard deviation for this parametric significance test according to equation 19. Then, I subtracted the DJIA Sharpe ratio from the MA MOM Sharpe ratios to obtain the abnormal net monthly overlapping MA MOM Sharpe ratios. I applied the significant findings to the obtained abnormal Sharpe ratio table. I provided the tables to the abnormal Sharpe ratio computations at the end of the study, in the Appendix section. Subsequently, Figure 5 displays the results for an initial investment amount of $30,000 and the distributions of the abnormal monthly Sharpe ratios for six different trading frequencies. I selected $30,000, because all abnormal Sharpe ratios were in this example positive or profitable at the investment amount of $30,000 and above.

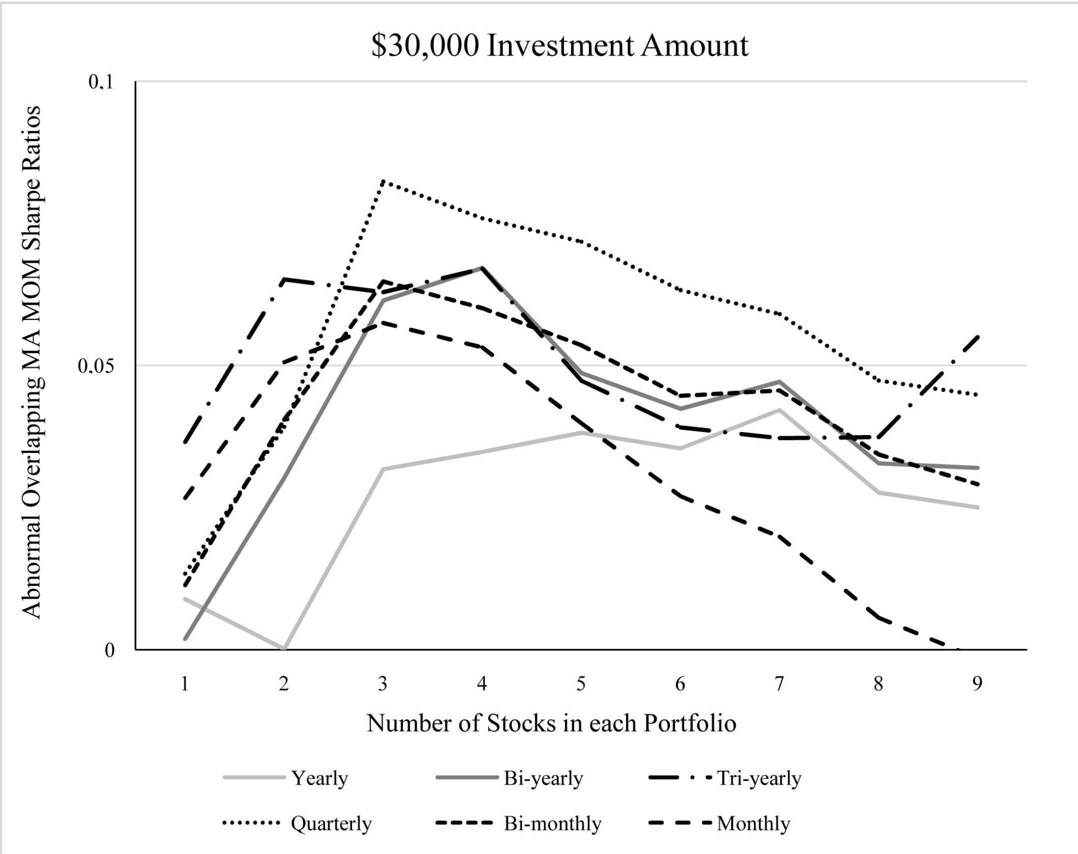

Figure 5. Monthly abnormal overlapping MA MOM Sharpe ratios = overlapping MA MOM Sharpe ratios minus the DJIA benchmark Sharpe ratio. This figure displays the abnormal Sharpe ratios for nine different portfolios, six different trading frequencies, and for an initial investment amount of $30,000. Adapted from “Profitable momentum trading strategies for individual investors” by B. Foltice and T. Langer, 2015, *Financial*

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Discussion

Through the monthly abnormal overlapping MA MOM Sharpe ratios, that I computed in three tables and that I placed in the appendix, the optimal trading frequency for the overlapping MA MOM strategy could be assessed. In Figure 5, I displayed the abnormal Sharpe ratios for an initial investment of $30,000, differentiated by six different trading frequencies. From the diagram, I could see that the abnormal Sharpe ratios increased for one until three stock overlapping MA MOM portfolios as the trading frequency increased, from a yearly towards a monthly trading frequency. For example, the optimal trading frequency for a three stock overlapping MA MOM portfolio was a quarterly trading frequency with (abnormal MA MOM Sharpe ratio = 0.08***).

From the computation of the portfolio's volatility, I could find that diversification effects were present in the portfolios, meaning the volatility decreased if the stock amount was increased and if the trading frequency was increased. In Figure 5, a peak was reached for the abnormal Sharpe ratios between three and four stock overlapping MA MOM portfolios. Especially after the peak was reached, the transaction costs started to impact the returns of the overlapping MA MOM portfolios largely. For example, a significant transaction cost effect and a significant volatility decrease effect on the overlapping MA MOM returns were displayed in the diagram for the monthly trading frequency. In consequence, the initial investment amounts were impacted by the transaction costs and the volatility, which affected the decreasing speed of the abnormal Sharpe ratios according to the trading frequencies for portfolios above four stocks.

However, at a level of $100,000 the transaction costs did not impact anymore the overlapping MA MOM returns largely. Essentially, I could conclude that the Null Hypothesis 6 could not be rejected, since not all abnormal Sharpe ratios in the tables in the Appendix were significant at a 1% alpha level, when determining the optimal frequencies for overlapping MA MOM strategy according to the investment amounts.

Hypothesis 7

Null Hypothesis 7. If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the MA MOM strategy returns are not greater than the MOM strategy returns.

Alternative Hypothesis 7. If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the MA MOM strategy returns are greater than the MOM strategy returns.

QE Design. The selected design allowed me to determine the optimal trading frequencies, returns, and alphas for the overlapping MA MOM strategy. And, the selected design allowed me to conduct a comparison between the overlapping MA MOM strategy findings and the yearly MOM strategy findings. The following values were important for the comparison: (a) CAPM and FF3FM alpha values, (b) GRS values, (c) investment amounts, (d) maximum stocks traded, and (e) net monthly returns for the top five values. I determined the optimal values for the overlapping MA MOM strategy according to the top five Sharpe ratio values. I selected the optimal values for the overlapping MA MOM strategy from a sample of six different trading frequencies, nine different investment amounts, and nine different overlapping MA MOM portfolio sizes, which led to ($n_{MA\ MOM\ sample}$ = 6 frequencies x 9 investment amounts x 9 portfolios = 486 potential result-values).

Analysis. The experiment 6 was essential for the analysis of optimal values for the overlapping MA MOM strategy. I considered the top five highest Sharpe ratio values per investment amount and per trading frequency to determine the optimal trading frequency for the overlapping MA MOM strategy. After I determined the optimal trading frequencies for the overlapping MA MOM strategy, I could select the following values from the previous experiments 4 and 5: (a) Net monthly returns, (b) GRS values, (c) CAPM alphas, (d) FF3FM alphas, and (e) maximum stocks traded (e.g., in Table 7; 3 until 84 stocks). I obtained the net monthly returns of the yearly MOM strategy from experiment 2 for a comparison of both strategies. I computed and selected the CAPM alpha values and the FF3FM alpha values together with the GRS values for the yearly MOM strategy, to complement the comparison between both strategies.

The optimal trading frequencies differed in three forms, depending on the investment amount, ranging from: (a) bi-yearly, (b) quarterly, to (c) monthly. The optimal net monthly overlapping MA MOM returns ranged from ($r_{MA\ MOM}$ = 0.90% until 1.57%), while the net monthly yearly MOM returns ranged from (r_{MOM} = 0.96% until 1.19%). I could find from a paired sample *t*-test that the optimal overlapping MA MOM strategy lowest returns did not differ significantly from the yearly MOM strategy lowest returns, with no significance at a 5% alpha level $t(8) = 1.358$, $p = .211$. However, the optimal overlapping MA MOM strategy highest returns differed significantly from the yearly MOM strategy highest returns, with significance at a 5% alpha level $t(8) = 10.270$, $p < .001$; and partial $\eta^2 = .353$ displaying a low effect. The risk-adjusted returns presented in this comparative analysis a different picture. The lowest alphas differed significantly with $t(8)=10.469$; $p<.001$ for the CAPM and $t(8)=15.344$; $p<.001$ for the FF3FM at a 5% alpha level. The highest CAPM and FF3FM alpha values did not differ significantly in a comparison of both strategies.

The CAPM alphas below ($alpha_{CAPM} \leq 0.55\%$) were not significant in the analysis of the alpha values, which occurred for investment amounts ≤ $15,000, and the FF3FM alphas below ($alpha_{CAPM} \leq 0.70\%$) were not significant, which occurred for investment amounts ≤ $10,000. The CAPM model displayed smaller GRS values for all values, compared to the FF3FM GRS values with (GRS_{CAPM} = 0.55-17.23 versus GRS_{FF3FM} = 3.95-22.25) in the comparison of both strategies. All findings for the analysis of Hypothesis 7 are displayed in the subsequent Table 7.

Table 7

Overlapping MA MOM strategy compared to the MOM strategy

Amount	Frequency	Overlapping MA MOM strategy					Maximum
		Net monthly return	$CAPM_{\alpha}$	$FF3FM_{\alpha}$	$CAPM_{GRS}$	$FF3FM_{GRS}$	stocks
$ 5,000	Tri-yearly	0.90-1.85 %	0.44-2.09	0.69-1.75	5.09	8.76	3-15
$ 10,000	Quarterly	0.99-1.34 %	0.50-1.00	0.68-1.31	8.52	10.49	8-24
$ 15,000	Quarterly	1.01-1.45 %	0.52-1.01	0.70-1.24	8.52	10.49	12-28
$ 30,000	Quarterly	1.12-1.51 %	0.63-1.07	0.81-1.30	8.52	10.49	12-28
$ 50,000	Quarterly	1.17-1.53 %	0.68-1.09	0.86-1.32	8.52	10.49	12-28
$ 100,000	Quarterly	1.20-1.55 %	0.71-1.11	0.89-1.34	8.52	10.49	12-28
$ 250,000	Quarterly	1.22-1.56 %	0.73-1.12	0.91-1.35	8.52	10.49	12-28
$ 500,000	Quarterly	1.23-1.45 %	0.74-1.12	0.92-1.35	8.52	10.49	12-28
$ 1,000,000	Monthly	1.22-1.57 %	0.67-1.18	0.98-1.44	17.23	22.25	36-84

Amount	Frequency	Yearly MOM strategy			Maximum
		Net monthly return	$CAPM_{\alpha}$	$FF3FM_{\alpha}$	stocks
$ 5,000	Tri-yearly	1.02-1.25 %	0.22-1.40	0.35-2.85	2-6
$ 10,000	Quarterly	1.09-1.15 %	0.29-1.00	0.42-1.87	2-7
$ 15,000	Quarterly	0.96-1.17 %	0.11-1.02	0.09-1.89	2- 9
$ 30,000	Quarterly	0.99-1.18 %	0.14-1.03	0.12-1.91	2- 9
$ 50,000	Quarterly	1.00-1.18 %	0.16-0.65	0.14-1.22	2-9
$ 100,000	Quarterly	1.01-1.19 %	0.17-0.66	0.15-1.23	2-9
$ 250,000	Quarterly	1.02-1.19 %	0.17-0.66	0.15-1.24	2- 9
$ 500,000	Quarterly	1.02-1.19 %	0.18-0.67	0.16-1.24	2-9
$ 1,000,000	Monthly	1.02-1.19 %	0.18-0.67	0.16-1.24	2-9
		GRS	0.68	3.81	

Note. The frequencies for each investment amount are based on the highest significant abnormal Sharpe ratios for the top five portfolios. To provide a variety to the quarterly frequency, the second highest abnormal Sharpe ratios were considered for $1 mllion. CAPM below 0.55% alphas and FF3FM below 0.70% alpha in this table were not significant. The GRS-test values are average values according to the trading frequencies. The Maximum stocks are the numbers of stocks traded at any given time period in the MA MOM portfolio. The net monthly returns represented the real turnover portfolio values. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29* (2), p. 101. Copyright 2018 by Ulrich R. Deinwallner.

Discussion

According to the significance tests between the returns of the overlapping MA MOM strategy and the yearly MOM strategy, the highest return values differed significantly and the lowest return values did not differ significantly (e.g., analysis section H7). After computing the means for both strategies, I could find from a pared sample *t*-test that the overlapping MA MOM strategy return-means differed significantly compared to the yearly MOM strategy return-means, at a 1% alpha level, with $t(8)$ =

4.740; $p < .001$; partial $\eta^2 = .974$ displaying a strong effect. I can speculate that the lowest overlapping MA MOM returns seemed to be equally, negatively impacted by cost effects for both strategies, even with an optimal risk and return relation. For the highest overlapping MA MOM returns compared to the highest yearly MOM returns, the overlapping method could fully enfold its potential, in connection to the positive impacts of the MA adjustment for the overlapping MA MOM strategy. I can conclude that the overlapping MA MOM strategy returns are on average greater than the yearly MOM strategy returns. In other words, I could reject the Null Hypothesis 7 at a 1% alpha level through the result of the conducted significance test.

I can make the following conclusions in regard of the optimal trading frequency decisions for an investor. For portfolios with an (investment amount = \$5,000) the overlapping MA MOM strategy should be traded with a tri-yearly trading frequency. Portfolios between (investment amount = \$10,000 and \$500,000) should be traded with a quarterly trading frequency for the overlapping MA MOM strategy. In order to trade the overlapping MA MOM strategy profitable and optimal, for portfolios (investment amount ≥ \$1,000,000), it was even possible to trade a monthly trading frequency. For example, this means that for an investor with a small portfolio of two stocks and an investment amount of \$5,000, positive abnormal returns could be achieved, by trading a tri-yearly overlapping MA MOM strategy, earning up until ($r_{MA\ MOM}$ = 1.64% net monthly return), with risk-adjusted returns of ($alpha_{CAPM}$ = 1.41%; $alpha_{FF3FM}$ = 1.46%), while holding 6 stocks over a holding period of 1 year, during the time period from 1992 until 2010.

Research question

Through the final analysis of Hypothesis 7, I can now provide an answer to the research question of the study. The research question was: What MA setting as a strategy adjustment can improve the MOM strategy performance for small portfolios of U.S. stocks? From a heuristic determination of an optimal MA setting for the MOM strategy, I can find that a 6 months versus 36 months SMA combination that led to double-crossover was an optimal MA to adjust the MOM strategy. The net monthly return-means of the overlapping MA MOM strategy are at a 1% alpha level, with $t(8) = 4.740$; $p<.001$; partial $\eta^2 = .974$ significantly more profitable compared to the yearly MOM strategy return-means, for a holding period of 1 year and a formation period of 6 months. I can conclude that the overlapping MA MOM strategy can improve the yearly MOM strategy by ($\bar{r}_{difference} = 0.16\%$ net monthly return) on average. Especially in the top, optimal application, the overlapping MA MOM strategy can improve the yearly MOM strategy by ($\bar{r}_{difference} = 0.25\%$ net monthly return) on average. The optimal application of the overlapping MA MOM strategy varied in this study, depending on the considered investment amount. The different investment amounts required a tri-yearly, quarterly, or monthly optimal trading frequency for the optimal application of the overlapping MA MOM strategy, all displayed in Table 7.

Summary

In this chapter, I summarize the results of testing the seven hypotheses and related to my research question. First, I state each of the seven alternative hypotheses and then the result of the test on that hypothesis. H1: If the MA strategy is tested at a stock market index and different MA number of day settings and different MA computation types are compared, then the optimal MA number of day setting and the optimal MA computation type can be found to adjust the MOM strategy. From the QE's, I could find that the 6v36 SMA double-crossover signals exhibited the optimal values to adjust the MA MOM strategy. Thus, H1 was supported by my data

H2: If the DJIA index (benchmark), the MOM strategy, and the MA MOM strategy returns are compared, then the MA MOM strategy returns are greater than the DJIA index and the MOM strategy returns. The yearly MA MOM strategy returns were greater compared to the yearly MOM strategy returns; however, only at a significance level of alpha 10%. I found that main issues occurred through high volatility of the stocks in the MA MOM portfolios and in the MOM portfolios when trading a yearly trading frequency. My data did not support H2 at a 1% alpha level.

H3: If the costs are factored for the MA MOM strategy, then the MA MOM strategy is still profitable. It appeared that I could confirm the Hypothesis 3 through my analysis; however, circa 6 until 9 stock MA MOM portfolios were not significantly more profitable compared to the benchmark, for (investment amounts < $30,000) and especially for (investment amounts = $5,000). From the results, I could not reject the Null Hypothesis 3 at a 1% alpha level. Therefore, my data did not support H3 at a 1% alpha level.

H4: If the overlapping MA MOM strategy varies by different trading frequencies and varies by different investment amounts in comparison, then volatility effects and cost effects occur for the returns of the MA MOM strategy. I could confirm the Hypothesis 4 through my analysis, the trading frequency in connection to the transaction costs had a significant negative effect on the returns of the varied overlapping MA MOM portfolios, especially below an (investment amount < $30,000). The data I analyzed supported H4 at a 1% alpha level.

H5: If the CAPM and the FF3FM alphas are computed for the overlapping MA MOM strategy, varied by different trading frequencies and varied by different trading amounts, then the alphas are still positive. I could confirm Hypothesis 5 for most alphas; exceptions occurred for quarterly, bi-monthly, and monthly trading frequencies with small (investment amounts ≤ $15,000). Therefore, I could not support H5 at a 1% alpha level for all CAPM and FF3FM alphas.

H6: If the overlapping MA MOM strategy Sharpe ratios, varied by the trading frequencies and varied by the investment amounts, are compared, then the optimal trading frequency according to the investment amount can be determined. I could find from my analysis that the optimal trading frequencies dependent on the investment amount and were tri-yearly, quarterly, and even monthly for trading the overlapping MA MOM strategy optimal. However, since not all abnormal Sharpe ratio returns of the tested portfolios were significant at a 1% alpha level, the data did not support H6.

H7: If the overlapping MA MOM strategy returns are compared to the MOM strategy returns, differentiated by different investment amounts and assessed for the optimal trading frequencies for the MA MOM strategy, then the MA MOM strategy returns are greater than the MOM strategy returns. I can support Hypothesis 7 through my analysis at a 1% alpha level, the overlapping MA MOM strategy was significantly more profitable than the yearly MOM strategy in its top, optimal application, with a ($\bar{r}_{difference}$ = 0.25% net monthly return) higher on average (during the time period 1992 until 2010).

Finally, I could answer the research questions; what MA setting as strategy adjusts can improve the MOM strategy performance for small portfolios of U.S. stocks? The optimal MA setting to improve the MOM strategy performance was a 6v36 SMA double-crossover signal combination, while trading the overlapping MA MOM strategy on a yearly holding period basis and a 6 month formation period, with a tri-yearly ($5,000), quarterly ($10,000 until $500,000), and even monthly (>$1,000,000) optimal trading frequency, depending on the investment amount.

Chapter 5: Discussion, Conclusions, and Recommendations

In this quantitative study, the purpose was to examine the relationship between different MA settings, the MOM strategy, and the performance of the returns from the construction of small U.S. stock portfolios. I selected a quasi-experimental design for the study to answer the research questions. I determined the optimal MA indicator setting as one of the key findings of the study. This means that I introduced a new combined methodology for the MOM strategy on how to avoid larger losses in declining stock market phases. I conducted a comparison between the overlapping MA MOM strategy, MA MOM strategy, MOM strategy, and BH strategy through which I could find significant differences between the compared strategies. The target population of the study consisted of 30 DJIA stocks and the DJIA index. The findings of the study could contribute to the scholarly literature of the momentum strategy and to the issue of portfolio management.

Interpretation of Findings

For the first pair of hypotheses that I tested in the study, I analyzed what optimal indicator setting was required to complement the MOM strategy. I found through a heuristic analysis and through a quasi-experiment that the 6 months versus 36 months SMA double-crossover signals could adjust the MOM strategy optimal for the given time period. I could determine through the application of the 6v36 SMA indicator three major bull phases in the selected time period between 1992 until 2010. The method of adjusting the MOM strategy with an MA was oriented at Cohen and Cliffer’s (2014) determination of Bull and Bear phases for the S&P 500 index and implied an easy to use methodology for private investors to adjust the MOM strategy. The 6v36 SMA result corroborated Glabadanidis (2015) findings for a monthly based MA trading, where Glabadanidis saw a SMA and the day combinations of [6, 12, 36, 48, and 60 months] as most effective.

For the second pair of hypotheses that I tested in the study, the main question was if the yearly MA MOM strategy can outperform the yearly MOM strategy and the DJIA index. The MA MOM strategy outperformed the BH strategy in the comparison conducted in the study. However, the MA MOM strategy was only significantly more profitable at a 10% alpha level with $t(8) = 2.043$, $p = .075$; partial $\eta^2 = .732$ compared to the MOM strategy. The insight that a MA MOM strategy can improve the MOM strategy extended Foltice and Langer's (2015) findings, who recommended testing the MOM strategy with the application of a timing indicator. I found through the analysis that larger deviations and higher volatility could be observed for one stock MA MOM portfolios and MOM portfolios, which implied that different trading frequencies and the application of the overlapping strategy could lead to more significant results as Foltice and Langer similarly reported in their study. I did not find support for the Alternative Hypothesis 2.

For the third pair of hypotheses that I tested in the study, the question was if the yearly MA MOM strategy is still profitable after factoring the transaction costs. I found that the yearly MA MOM strategy, with a holding period of 1 year and a formation period of 6 months, was still profitable after applying the transaction costs for all investment amounts, ranging from 0.86% until 1.73% net monthly return. Investment amounts above $50,000 were significantly more profitable compared to the BH returns even after applying the transaction costs. Foltice and Langer (2015) reported higher returns for S&P 500 values when applying the MOM strategy in their study compared to the DJIA returns that I considered in my analysis. The aspect of different considered stock sizes (or market capitalizations) implied that the DJIA MA MOM returns were lower on average by circa 1% (for the largest values) compared to Foltice and Langer's (2015) S&P 500 MOM returns. A reason for this aspect can be that my analysis only considered large cap stocks for the analysis, and the outperforming tendency that was reported by Akhtar (2017) for small stocks, was not represented in the MA MOM portfolios in my study. I did not find support for the Alternative Hypothesis 3.

For the fourth pairs of hypotheses that I tested in the study, the main question was if volatility effects and cost effects impact the overlapping MA MOM strategy. I found that the trading frequencies and the transaction costs had a significant negative effect on the overlapping MA MOM portfolios returns, at and below ≤ $30,000. My findings corroborated Foltice and Langer's (2015) results that MA MOM net monthly returns or MOM net monthly returns for portfolios with only one or two stocks start out with positive returns. However, with an increasing amount of traded stocks for the MA MOM portfolios, a higher trading frequency diminishes positive returns due to the aspect of higher transaction costs. These implications were especially true for smaller investment amounts at and below ≤ $30,000. From the data, I could reject the Null Hypothesis 4 at a 1% alpha level.

For the fifth pair of hypotheses that I tested in the study, the main question was if the CAPM alphas and the FF3FM alphas for the overlapping MA MOM portfolios were positive? The alphas were mostly positive for the overlapping MA MOM strategy in the study. However, positive alphas could not be confirmed for investment amounts at and below ≤ $15,000 and for trading frequencies that were quarterly, bi-monthly, or monthly. Especially for the one stock portfolio and a yearly trading frequency, differences occurred here between my research findings and Foltice and Langer's (2015) findings. A reason could be that diversification effects were not at present for one stock MA MOM portfolio which led to a high volatility for the portfolio returns and depending on which month the formation of the overlapping MA MOM portfolio started, the result seemed to vary significantly. For example, depending if January or June was selected as the start of the formation period, then large volatility caused differences in the net monthly returns, which could be observed in the comparison between Foltice and Langer and my alpha value results. Therefore, a different starting date of the formation period could be an indication why my results were here different compared to Foltice and Langer's findings. Null Hypothesis 5 could not be rejected, since not all CAPM and FF3FM alphas were significantly positive at a 1% alpha level.

For the sixth pair of hypotheses that I tested in the study, the Sharpe ratios were of interest to assess the optimal trading frequency for the overlapping MA MOM portfolios. The analysis of the Sharpe ratios of the overlapping MA MOM strategy was especially relevant for the subsequent analysis of Hypothesis 7. For the analysis of Hypothesis 7, the top five largest Sharpe ratio values were assessed for the overlapping MA MOM strategy. The selection of the top Sharpe ratio values allowed me determining the optimal trading frequency of the overlapping MA MOM strategy, differentiated by nine different investment amounts. Foltice and Langer (2015) saw here five different trading frequencies as profitable to trade the overlapping MOM strategy (bi-yearly, tri-yearly, quarterly, bi-monthly, and monthly). My findings corroborated some of Foltice and Langer's results and confirmed that \$5,000 should be traded tri-yearly; \$15,000 until \$500,000 should be traded quarterly; and ≥ \$1 million can be traded on a monthly basis for the overlapping MA MOM strategy. The results obtained for the overlapping MA MOM strategy and the overlapping MOM strategy exhibited several commonalities in comparison, even though Foltice and Langer applied the overlapping MOM strategy to S&P 500 stocks, and I applied the overlapping MA MOM strategy to DJIA stocks. Essentially, I could not reject the Null Hypothesis 6 because not all abnormal Sharpe ratios were significant at a 1% alpha level.

The analysis of the seventh pair of hypotheses allowed me to answer the research question: *What MA setting as a strategy adjustment can improve the MOM strategy performance for small portfolios of U.S. stocks?* I could find from the results that the net monthly average returns of the overlapping MA MOM strategy were significant at a 1% alpha level, with $t(8) = 4.740$; $p<.001$; partial $\eta^2 = .974$ and were significantly more profitable by ($\bar{r}_{difference}$ = 0.16% net monthly return) compared to the yearly MOM strategy net monthly average returns. The data of my analysis supported the Alternative Hypothesis 7. This means that the MOM strategy can be improved and adjusted by an MA. In specific, the MOM strategy can be adjusted by a 6v36 SMA to determine bull and bear market phases, in order to decide when to trade and when to stop trading the MA MOM strategy. The computation and the decision making for the timing signals in this study were aligned with Glabadanidis's (2015) recommendations for the number of day settings of a monthly MA; Cohen and Cliffer's (2014) Bull and Bear market phase demonstrations; Dolvin's (2014) computation methodology of the SMA, EMA, and decision making of MA signals. Therefore, I concluded that the overlapping MA MOM strategy can adjust the MOM strategy and is more profitable than the yearly MOM strategy. The findings of my study addressed a gap in the MOM strategy body of evidence that was relevant for private investors, who trade small stock portfolios. I could contribute with the findings of the study to the scholarly literature regarding the momentum effect, portfolio management, and the momentum strategy, to which major findings were reported by Foltice and Langer (2015), Hung and Banerjee (2014), and Jegadeesh and Titman (1993).

Limitations of the Study

As presented in Chapter 1 in the limitation section, I assumed that the subsequent main aspects to the: (a) stocks; (b) quasi-experiment; (c) methodology; (d) strategy; and (e) time period could impact the generalizability, validity, and reliability of this study.

I make the first limitations for the considered stocks and for the consideration of quasi-experiments in this study. Through the selection of quasi-experiments in the study, unknown variables could have impacted the presence of the momentum effect. Bornholt, Dou, and Malin (2015) mentioned that a lower individualistic culture score could diminish the momentum effect when applying the MOM strategy, in for example Asian countries. Hung and Banerjee (2014) reported the observation of a missing momentum effect in Taiwan, Hong Kong, and Korean stock markets, which could mean that the MA

MOM strategy could not be applied in these Asian regions; the results of my study might not be generalizable for these Asian regions; and the MA MOM method might not be reliable for Asian countries stock markets. Not all U.S. stocks had the possibility to be selected for the sample, for the allocation of the stocks to the quasi-experiment in the study. The corporation size of the selected MA MOM stocks did impact the portfolio returns. In a comparison between my study and the study of Foltice and Langer (2015), I found that depending if DJIA stocks or S&P 500 stocks were considered for the MOM strategy, the maximal return values differed and led to lower maximum DJIA return values. Therefore, I limit the validity, reliability, and generalization of this study's findings to large cap stock results of U.S. stock markets.

In regard of the validity of the methodology, I had to limit the application of the MA MOM methodology in the study. The MA signals of the MA MOM strategy need to be obtained from the same stock index, from which the selected stocks are from. This means if the MA signals for the MA MOM strategy are obtained from the DJIA index, then the stocks also need to be selected from the DJIA index. For example, the results of this study cannot be assumed as valid, if the MA signals of the MA MOM strategy would be obtained from the Japanese Nikkei 225 index, but the stocks of the MA MOM portfolio would be selected from the S&P 500. Therefore, I needed to limit the MA MOM methodology to MA signals that were obtained from the same index, from which the selected stocks of the MA MOM portfolio are obtained.

The findings for the MA MOM strategy in this study might also not apply to the momentum strategy as it was intended in the momentum strategy origin. Through the former momentum strategy, presented by Jegadeesh and Titman (1993), both directions of a financial market are traded, long and short. This means that where I received from the MA MOM strategy a signal to stop trading the stock markets, the momentum strategy starts to benefit from short sales that can lead to positive excess returns for a momentum trader. In consequence, the MA adjustment of the MA MOM strategy method that was introduced in this study, cannot adjust the original form of the momentum strategy. The MA strategy adjustment of the MA MOM strategy presented in this study should not be generalized to other momentum strategy variations. The MA adjustment of the MA MOM strategy needs to be limited to only adjust a MOM strategy in order to be valid.

Biases could have occurred for the results of this study through the selected time period. The selected time period in the study represented a progression and declining market phases that provided an average of two extremes for the test of the MA MOM strategy and for stock market trading. The selected time period was therefore a representation of the most common market conditions in one period. For example, if the market conditions for the selected time period were: (a) permanent positive, then a MA adjustment would be irrelevant; (b) permanent declining, then no trading of the MA MOM strategy would have occurred at all; or (c) permanent oscillating sideways, then high frequent entry and exit signals would have occurred, which could have undermined the potential of the overlapping strategy. It is a task of the investor to decide if fair market conditions are present, if the market is efficient, and if the market situation allows the investor to trade (e.g., efficient markets; Fama, 1970). Therefore, the time period that was considered for the results led to findings that are valid in semi efficient markets and not extreme market conditions. I limited the findings of this study to a time period (or market conditions) of average oscillating and semi efficient markets, which excludes the three former described extremes.

Recommendations

In this section, I present the recommendations that could be made for additional research potential that was found during the investigation and development of this study. In specific, the recommendations in this section were obtained from the strengths, limitations, and literature review sections that were presented in this study and indicated the potential for further research for other researchers.

The first recommendation is that the MA MOM strategy, as it was performed in this study, is not the only way how momentum portfolios can be constructed. Moskowitz at al. (2012) reported that the TSM strategy could be more profitable compared to a CSM approach, when trading a momentum strategy. A comparison between trading the MA MOM strategy with a CSM approach and a TSM approach could be of interest to test Moskowitz at al.'s proclamations. Therefore, the first recommendation that I could make would be to compare a CAM approach and a TSM approach for the MA MOM strategy by other researchers.

The second recommendation is that the MA method that I introduced in this study to adjust the MOM strategy could be corroborated or advanced by other researchers. I selected the MA method, related to Cohen and Cliffer's (2014) determination of Bull and Bear market phases, because the method is easy to use especially for private investors. Other studies, for example from Park (2015), mentioned that MA signals could also be determined for each stock and not only for one stock index, when applying a MA MOM strategy. The method of Park would mean for example that each stock would be rebalanced according to an individual MA signal when trading the MA MOM strategy. For a monthly overlapping MA MOM strategy this would require the investor, in the worst case, to monitor (i.e., nine stocks in a portfolio x 12 months = 108 MA signals per month) to rebalance the stocks. An opportunity for research could be, to solve the described monitoring issue and to find a more stringent method to advance the MA MOM strategy.

The third recommendation is that the momentum effect has still not been explained sufficiently in the scholarly literature. Barberis et al. (1998), Chan et al. (1996), and Hong and Stein (1999) have assumed that investors' overreactions or underreactions could be causal for a momentum effect in financial markets, which I agree on. However, many other contributions have been made to the issue of the momentum effect in the momentum literature (e.g., momentum effect section in this study). Fama and French (1996) reported that more than one factor could be causal for explaining the momentum effect, and that a multifactor model could bring a solution. Therefore, I would recommend for other researchers to investigate multifactor models to explain the occurrence of a momentum effect in the financial markets of countries with a high individualistic culture score.

Implications for Positive Social Change

The first implication for positive social change is that investors with small portfolios can improve their investment performance when applying the MA MOM strategy compared to the MOM strategy. In the study, a MA adjustment for the MOM strategy was tested, and an optimal MA setting was found with the disposition 6v36 SMA crossover signals to adjust and to improve the MOM strategy. From my analysis I found that investors who apply the MA MOM strategy can reduce the volatility or the risk in their MA MOM portfolios compared to MOM portfolios. I further found that the application of the MA adjustment allowed investors to stay longer profitable with their MA MOM portfolios and achieve higher returns ($\bar{r}_{difference}$ = 0.16% net monthly return) with the overlapping MA MOM strategy compared to the yearly MOM strategy. Therefore, the application of the MA MOM strategy can bring positive social change to the portfolio management of private investors, managers of organizations, or managers of institutions.

The findings that I reported in this study could fill a gap in the scholarly momentum literature. Foltice and Langer (2015) mentioned that the MOM strategy needed to be tested in connection with timing signals. Other researchers, like Nedeltcheva (2015) and Dolvin (2014) have reported how to apply MA's; however, little connections were made in the literature to the issue of MA's and to momentum trading. My study introduced a new methodology how to trade the MOM strategy more profitable. The main objective of my study was to find an easy to use methodology in order to apply an MA to the MOM strategy. My idea was that investors could manage a multiple stock MA MOM portfolio, while orienting at only one MA signal that is obtained from one stock market index, for the investor to make buying and selling decisions. The easy form to apply the MA to the MOM strategy will allow especially private investors to manage their portfolio effectively. Therefore, the study provided an easy to apply methodology for private portfolio managers and addressed a literature gap found in the scholarly momentum and portfolio management literature.

Conclusions

I examined in this study: What MA setting as a strategy adjustment can improve the MOM strategy performance for small portfolios of U.S. stocks? The general problem of the study was that it was unclear when to enter and when to exit declining financial markets, to avoid larger losses and to improve the overall performance with the MOM strategy. Therefore, the purpose of the study was to examine the relationship between different MA settings to adjust the MOM strategy, in order to improve the performance for investors with small U.S. stock portfolios. The key findings of the study were that with the setting 6v36 SMA and with double-crossover signals, the investor could identify Bull and Bear market phases from a stock market index, to decide when to apply the MA MOM strategy to generate excess returns. The yearly MA MOM strategy outperformed the yearly MOM strategy significantly at a 10% alpha level and on average by ($\bar{r}_{difference}$ = 0.07% monthly return), during the tested time period (1992 until 2010). The aspect that the investment amount was not reinvested in bonds during the trading breaks, and volatility effects that could be observed in comparison for the yearly MA MOM strategy and for the yearly MOM strategy, impacted the testing results.

I investigated the performance results of the overlapping MA MOM strategy, and I determined the optimal trading frequencies for the overlapping MA MOM strategy, differentiated by nine investment amounts. The overlapping MA MOM strategy, with a 6 months formation period and an 1 year holding period, was significantly more profitable at a 1% alpha level and on average by ($\bar{r}_{difference}$ = 0.25% net monthly return) compared to the yearly MOM strategy. The optimal trading frequencies, differentiated by nine investment amounts, are displayed in Table 7 as an overview. From the Table 7, the investor can decide what optimal trading frequency, investment amount, and stocks amount to choose, and what returns can be expected when following the overlapping MA MOM strategy. Essentially, I found out in the study that a 6v36 SMA as a strategy adjustment can improve the MOM strategy performance for small portfolios of U.S. large cap stocks.

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Appendix: Tables and Computations to the Study

Table A1

Cost adjusted MA MOM returns by subtracting transaction costs (%) full turnover, yearly trading frequency DJIA return: 0.56

Initial $ amount / stocks	1	2	3	4	5	6	7	8	9
Unadjusted MA Mom returns	1.74	1.19	1.46	1.31	1.31	1.23	1.28	1.21	1.17
$ 5,000	1.69***	1.09*	1.31***	1.10*	1.05*	0.92	0.92	0.80	0.71
$ 10,000	1.71***	1.12*	1.36***	1.17**	1.14**	1.02	1.04*	0.93	0.86
$ 15,000	1.71***	1.13**	1.37***	1.19**	1.16**	1.06*	1.08*	0.98	0.91
$ 30,000	1.72***	1.14**	1.39***	1.22**	1.19**	1.09*	1.12*	1.02	0.96
$ 50,000	1.72***	1.15**	1.40***	1.22**	1.20**	1.10*	1.13**	1.04*	0.98
$ 100,000	1.72***	1.15**	1.40***	1.23**	1.21**	1.11*	1.14**	1.05*	0.99
$ 250,000	1.72***	1.15**	1.40***	1.24**	1.22**	1.12*	1.15**	1.06*	1.00
$ 500,000	1.72***	1.15**	1.41***	1.24**	1.22**	1.12*	1.15**	1.06*	1.01
$ 1,000,000	1.72***	1.15**	1.41***	1.24**	1.22**	1.12*	1.15**	1.07*	1.01
Full trade amount	14	28	42	56	70	84	98	112	126

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 93. Copyright 2018 by Ulrich R. Deinwallner. The trading amount represents a full trade, meaning one buying action and one selling action. All stocks were bought and sold at each trading opportunity over the entire time period to obtain the full turnover. The costs were computed according to a low spread average of 0.212%, since the market capitalizations of the stocks were all greater than $11,365.8 m. The equation was ((2 * $10 commission) + (2 * 0.5 * 0.75% spread) + 0.003333% SEC fee). The DJIA standard deviation = 4.30%; statistical significance was mostly given by a parametric *t*-test that compared the portfolio monthly average returns with the DJIA monthly average return. Significant at alpha levels of: *p < 10%, **p < 5%, ***p < 1%.

Table A2

CAPM – net monthly alphas (in %)

	1	2	3	4	5	6	7	8	9
3 x year									
$ 5,000	2.09***	1.41***	1.01***	0.77**	0.44	0.28	0.14	0.03	0.04
$ 10,000	2.14***	1.50***	1.15***	0.95***	0.65*	0.52	0.42	0.34	0.38
$ 15,000	2.16***	1.53***	1.19***	1.01***	0.72**	0.61*	0.51	0.45	0.50
$ 30,000	2.17***	1.56***	1.24***	1.07***	0.79**	0.69**	0.60*	0.55	0.61*
$ 50,000	2.18***	1.58***	1.26***	1.10***	0.82**	0.72**	0.64*	0.59*	0.66*
$ 100,000	2.18***	1.59***	1.27***	1.11***	0.84***	0.74**	0.67*	0.62*	0.69**
$ 250,000	2.19***	1.59***	1.28***	1.12***	0.86***	0.76**	0.69**	0.64*	0.71**
$ 500,000	2.19***	1.59***	1.28***	1.13***	0.86***	0.76**	0.69**	0.65*	0.72**
$ 1,000,000	2.19***	1.59***	1.28***	1.13***	0.86***	0.77**	0.69**	0.65*	0.72**
GRS Average									5.09
4 x year									
$ 5,000	1.41***	0.89**	0.79**	0.55	0.42	0.20	0.07	-0.05	-0.18
$ 10,000	1.47***	1.00***	0.96***	0.77**	0.68**	0.50	0.41	0.32	0.23
$ 15,000	1.49***	1.04***	1.01***	0.84**	0.76**	0.60*	0.52	0.45	0.37
$ 30,000	1.51***	1.08***	1.07***	0.92***	0.85***	0.70**	0.63**	0.57*	0.50
$ 50,000	1.51***	1.09***	1.09***	0.95***	0.88***	0.74**	0.68**	0.62*	0.56*
$ 100,000	1.52***	1.11***	1.11***	0.97***	0.91***	0.77**	0.71**	0.66**	0.60*
$ 250,000	1.52***	1.11***	1.12***	0.98***	0.92***	0.79**	0.73**	0.68**	0.63*
$ 500,000	1.52***	1.12***	1.12***	0.99***	0.93***	0.80**	0.74**	0.69**	0.63*
$ 1,000,000	1.53***	1.12***	1.13***	0.99***	0.93***	0.80**	0.74**	0.69**	0.64*
GRS Average									8.52

Note. Adapted from “Profitable momentum trading strategies for individual investors” by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 96. Copyright 2018 by Ulrich R. Deinwallner. The CAPM regression equation 14 was used to compute the monthly alphas. The variables for the equation 14 were the risk factor (IV) and the net monthly portfolios returns (DV). The risk free rate and risk factor were obtained from French's data webpage. The GRS Average represents the average value of the GRS-test. The MA MOM net monthly returns were compared to the DJIA monthly return of 0.56% and were significant at an alpha level of: *p < 10%, **p < 5%, ***p < 1%.

Table A3

CAPM – net monthly alphas (in %)

	1	2	3	4	5	6	7	8	9
6 x year									
$ 5,000	1.39***	0.81*	0.63*	0.36	0.15	-0.11	-0.24	-0.42	-0.58
$ 10,000	1.48***	0.98**	0.88**	0.68*	0.52	0.33	0.26	0.13	0.03
$ 15,000	1.51***	1.04***	0.96***	0.79**	0.65*	0.48	0.43	0.32	0.24
$ 30,000	1.54***	1.10***	1.05***	0.89***	0.77**	0.63*	0.60*	0.50	0.44
$ 50,000	1.56***	1.12***	1.08***	0.93***	0.82**	0.69**	0.67*	0.58*	0.53
$ 100,000	1.56***	1.14***	1.11***	0.97***	0.86***	0.73**	0.72**	0.63*	0.59*
$ 250,000	1.57***	1.15***	1.12***	0.98***	0.88***	0.76**	0.75**	0.67**	0.62*
$ 500,000	1.57***	1.15***	1.13***	0.99***	0.89***	0.76**	0.76**	0.68**	0.64*
$ 1,000,000	1.57***	1.16***	1.13***	0.99***	0.89***	0.77**	0.76**	0.68**	0.64*
GRS Average									8.52
12 x year									
$ 5,000	1.49***	0.66	0.20	-0.20	-0.58**	-0.95***	-1.23***	-1.55***	-1.81***
$ 10,000	1.66***	1.01**	0.69*	0.44	0.18	-0.06	-0.23	-0.42**	-0.56**
$ 15,000	1.72***	1.12***	0.85**	0.65*	0.43	0.23	0.11	-0.05	-0.15
$ 30,000	1.78***	1.23***	1.02***	0.86**	0.68**	0.53	0.44	0.33	0.27
$ 50,000	1.81***	1.28***	1.08***	0.94***	0.78**	0.65*	0.58	0.48	0.43
$ 100,000	1.83***	1.31***	1.13***	1.01***	0.86***	0.74**	0.68**	0.59*	0.56
$ 250,000	1.84***	1.33***	1.16***	1.05***	0.91***	0.79**	0.74**	0.66*	0.62*
$ 500,000	1.84***	1.34***	1.17***	1.06***	0.92***	0.81**	0.76**	0.68**	0.65*
$ 1,000,000	1.84***	1.34***	1.18***	1.06***	0.93***	0.82**	0.77**	0.69**	0.67*
GRS Average									17.23

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 96. Copyright 2018 by Ulrich R. Deinwallner. The CAPM regression equation 14 was used to compute the monthly alphas. The variables for the equation 14 were the risk factor (IV) and the net monthly portfolios returns (DV). The risk free rate and risk factor were obtained from French's data webpage. The GRS Average represents the average value of the GRS-test. The MA MOM net monthly returns were compared to the DJIA monthly return of 0.56% and were significant at an alpha level of: *p < 10%, **p < 5%, ***p < 1%.

Table A4

FF3FM - net monthly alphas (in %)

	1	2	3	4	5	6	7	8	9
3 x year									
$ 5,000	1.75***	1.46***	1.25***	1.01**	0.69	0.53	0.35	0.16	0.15
$ 10,000	1.80***	1.55***	1.39***	1.19***	0.90*	0.77	0.63	0.47	0.49
$ 15,000	1.82***	1.58***	1.43***	1.25***	0.97**	0.85*	0.72	0.57	0.60
$ 30,000	1.83***	1.61***	1.48***	1.31***	1.04**	0.93**	0.81*	0.68	0.72*
$ 50,000	1.84***	1.62***	1.50***	1.33***	1.07**	0.97**	0.85*	0.72*	0.76*
$ 100,000	1.84***	1.63***	1.51***	1.35***	1.09***	0.99**	0.88*	0.75*	0.80**
$ 250,000	1.85***	1.64***	1.52***	1.36***	1.11***	1.01**	0.90**	0.77*	0.82**
$ 500,000	1.85***	1.64***	1.52***	1.36***	1.11***	1.01**	0.90**	0.77*	0.83**
$ 1,000,000	1.85***	1.64***	1.52***	1.37***	1.11***	1.01**	0.90**	0.78*	0.83**
GRS Average									8.76
4 x year									
$ 5,000	1.96***	1.20**	1.01**	0.84	0.62	0.38	0.25	0.10	-0.05
$ 10,000	2.02***	1.31***	1.18***	1.06**	0.88**	0.68	0.58	0.47	0.36
$ 15,000	2.03***	1.35***	1.24***	1.13**	0.96**	0.78*	0.70	0.59	0.50
$ 30,000	2.05***	1.39***	1.30***	1.20***	1.05***	0.88**	0.81**	0.71*	0.63
$ 50,000	2.06***	1.4***	1.32***	123***	1.08***	0.92**	0.86**	0.76*	0.69*
$ 100,000	2.07***	1.42***	1.34***	1.25***	1.11***	0.95**	0.89**	0.80**	0.73*
$ 250,000	2.07***	1.42***	1.35***	1.27***	1.12***	0.97**	0.91**	0.82**	0.75*
$ 500,000	2.07***	1.43***	1.35***	1.27***	1.13***	0.98**	0.92**	0.83**	0.76*
$ 1,000,000	2.07***	1.43***	1.35***	1.27***	1.13***	0.98**	0.92**	0.83**	0.77*
GRS Average									10.49

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 97. Copyright 2018 by Ulrich R. Deinwallner. The FF3FM regression equation 15 was used to compute the monthly alphas. The variables for the equation 15 were the risk factors (IV's) and the net monthly portfolios returns (DV). The risk free rate and risk factors were obtained from French's data webpage. The GRS Average represents the average value of the GRS-test. The MA MOM net monthly returns were compared to the DJIA monthly return of 0.56% and were significant at an alpha level of: *p < 10%, **p < 5%, ***p < 1%.

Table A5

FF3FM - net monthly alphas (in %)

	1	2	3	4	5	6	7	8	9
6x year									
$ 5,000	2.03***	1.11*	0.94*	0.67	0.46	0.14	-0.02	-0.24**	-0.44**
$ 10,000	2.12***	1.28**	1.19**	0.99*	0.84	0.58	0.48	0.32	0.18
$ 15,000	2.15***	1.34***	1.28***	1.10**	0.96*	0.72	0.65	0.51	0.39
$ 30,000	2.18***	1.40***	1.36***	1.20***	1.09**	0.87*	0.82*	0.69	0.59
$ 50,000	2.19***	1.42***	1.39***	1.24***	1.14**	0.93**	0.89*	0.76*	0.67
$ 100,000	2.20***	1.44***	1.42***	1.28***	1.17***	0.97**	0.94**	0.82*	0.74*
$ 250,000	2.20***	1.45***	1.43***	1.29***	1.20***	1.00**	0.97**	0.85**	0.77*
$ 500,000	2.20***	1.45***	1.44***	1.30***	1.20***	1.01**	0.98**	0.86**	0.78*
$ 1,000,000	2.21***	1.45***	1.44***	1.30***	1.21***	1.01**	0.98**	0.87**	0.79*
GRS Average									11.91
12x year									
$ 5,000	1.79***	0.90	0.46	0.08	-0.31**	-0.71***	-1.02***	-1.38***	-1.67***
$ 10,000	1.97***	1.24**	0.95*	0.71	0.45	0.17	-0.02	-0.26**	-0.43**
$ 15,000	2.03***	1.35***	1.12**	0.92*	0.70	0.47	0.32	0.12	-0.02
$ 30,000	2.09***	1.47***	1.28***	1.14**	0.96**	0.76	0.65	0.49	0.40
$ 50,000	2.11***	1.51***	1.35***	1.22***	1.06**	0.88*	0.79	0.64	0.56
$ 100,000	2.13***	1.55***	1.40***	1.28***	1.13***	0.97**	0.89**	0.75*	0.69
$ 250,000	2.14***	1.57***	1.43***	1.32***	1.18***	1.02**	0.95**	0.82*	0.76*
$ 500,000	2.14***	1.57***	1.44***	1.33***	1.19***	1.04**	0.97**	0.84**	0.79*
$ 1,000,000	2.15***	1.58***	1.44***	1.34***	1.20***	1.05**	0.98**	0.86**	0.80*
GRS Average									22.25

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 97. Copyright 2018 by Ulrich R. Deinwallner. The FF3FM regression equation 15 was used to compute the monthly alphas. The variables for the equation 15 were the risk factors (IV's) and the net monthly portfolios returns (DV). The risk free rate and risk factors were obtained from French's data webpage. The MA MOM net monthly returns were compared to the DJIA monthly return of 0.56% and were significant at an alpha level of: *p < 10%, **p < 5%, ***p < 1%.

Table A6

Abnormal Overlapping MA MOM Sharpe Ratios

	1	2	3	4	5	6	7	8	9
5,000									
Yearly	0.01***	0.00***	0.03***	0.03***	0.03***	0.02***	0.02***	0.01***	0.00***
Bi-yearly	0.00	0.02***	0.05***	0.05***	0.02***	0.01**	0.01	-0.01**	-0.02***
Tri-yearly	0.03***	0.05***	0.04***	0.03***	0.00	-0.01***	-0.03***	-0.04***	-0.04***
Quarterly	0.01	0.02***	0.05***	0.03***	0.01***	-0.01***	-0.03***	-0.05***	-0.07***
Bi-monthly	0.00	0.01***	0.02***	-0.01*	-0.03***	-0.06***	-0.08***	-0.11***	-0.14***
Monthly	0.00	0.00	-0.04***	-0.08***	-0.13***	-0.18***	-0.24***	-0.29***	-0.35***
10,000									
Yearly	0.01***	0.00***	0.03***	0.03***	0.03***	0.03***	0.04***	0.02***	0.02***
Bi-yearly	0.00	0.03***	0.06***	0.06***	0.04***	0.03***	0.03***	0.02***	0.01***
Tri-yearly	0.03***	0.06***	0.05***	0.05***	0.03***	0.02***	0.01**	0.01	0.02***
Quarterly	0.01**	0.03***	0.07***	0.06***	0.05***	0.03***	0.02***	0.01*	0.00
Bi-monthly	0.01*	0.03***	0.05***	0.03***	0.02***	0.00	-0.01	-0.02***	-0.04***
Monthly	0.02***	0.03***	0.02***	.00	-0.03***	-0.06***	-0.08***	-0.11***	-0.14***
15,000									
Yearly	0.01***	0.00***	0.03***	0.03***	0.04***	0.03***	0.04***	0.02***	0.02***
Bi-yearly	0.00	0.03***	0.06***	0.06***	0.04***	0.04***	0.04***	0.02***	0.02***
Tri-yearly	0.04***	0.06***	0.06***	0.06***	0.04***	0.03***	0.02***	0.02***	0.04***
Quarterly	0.01***	0.04***	0.08***	0.07***	0.06***	0.05***	0.04***	0.03***	0.02***
Bi-monthly	0.01**	0.03***	0.06***	0.05***	0.04***	0.02***	0.02***	0.01***	-0.01
Monthly	0.02***	0.04***	0.04***	0.03***	0.01***	-0.02***	-0.03***	-0.05***	-0.07***

Note. Adapted from “Profitable momentum trading strategies for individual investors” by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 109. Copyright 2018 by Ulrich R. Deinwallner. Abnormal Sharpe ratios that are compared to the DJIA index and are differentiated by trading frequency and investment amount. The Sharpe ratios were computed by equation 18. The abnormal monthly Sharpe ratios are computed by the monthly Sharpe ratio of each portfolio which is subtracted from the monthly Sharpe ratio of the DJIA index (1992 - 2010). The statistical significance levels were assessed by a conventional parametric *t*-tests: * 10 %; ** 5 %; *** 1 %

Table A7

Abnormal Overlapping MA MOM Sharpe Ratios

	1	2	3	4	5	6	7	8	9
30,000									
Yearly	0.01***	0.00***	0.03***	0.03***	0.04***	0.04***	0.04***	0.03***	0.03***
Bi-yearly	0.00	0.03***	0.06***	0.07***	0.05***	0.04***	0.05***	0.03***	0.03***
Tri-yearly	0.04***	0.07***	0.06***	0.07***	0.05***	0.04***	0.04***	0.04***	0.05***
Quarterly	0.01***	0.04***	0.08***	0.08***	0.07***	0.06***	0.06***	0.05***	0.04***
Bi-monthly	0.01***	0.04***	0.06***	0.06***	0.05***	0.04***	0.05***	0.03***	0.03***
Monthly	0.03***	0.05***	0.06**	0.05***	0.04***	0.03***	0.02***	0.01	0.00
50,000									
Yearly	0.01***	0.00***	0.03***	0.04***	0.04***	0.04***	0.04***	0.03***	0.03***
Bi-yearly	0.00	0.03***	0.06***	0.07***	0.05***	0.05***	0.05***	0.04***	0.04***
Tri-yearly	0.04***	0.07***	0.06***	0.07***	0.05***	0.04***	0.04***	0.04***	0.06***
Quarterly	0.01***	0.04***	0.09***	0.08***	0.08***	0.07***	0.07***	0.06***	0.05***
Bi-monthly	0.01***	0.04***	0.07***	0.07***	0.06***	0.05***	0.06***	0.05***	0.04***
Monthly	0.03***	0.06***	0.07***	0.06***	0.05***	0.04***	0.04***	0.03***	0.03***
100,000									
Yearly	0.01***	0.00***	0.03***	0.04***	0.04***	0.04***	0.04***	0.03***	0.03***
Bi-yearly	0.00	0.03***	0.06***	0.07***	0.05***	0.05***	0.05***	0.04***	0.04***
Tri-yearly	0.04***	0.07***	0.07***	0.07***	0.05***	0.05***	0.05***	0.05***	0.07***
Quarterly	0.01***	0.04***	0.09***	0.08***	0.08***	0.07***	0.07***	0.06***	0.06***
Bi-monthly	0.01***	0.04***	0.07***	0.07***	0.07***	0.06***	0.06***	0.05***	0.05***
Monthly	0.03***	0.06***	0.07***	0.07***	0.06***	0.06***	0.06***	0.05***	0.05***

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 109. Copyright 2018 by Ulrich R. Deinwallner. Abnormal Sharpe ratios that are compared to the DJIA index and are differentiated by trading frequency and investment amount. The Sharpe ratios were computed by equation 18. The abnormal monthly Sharpe ratios are computed by the monthly Sharpe ratio of each portfolio which is subtracted from the monthly Sharpe ratio of the DJIA index (1992 - 2010). The statistical significance levels were assessed by a conventional parametric *t*-tests: * 10 %; ** 5 %; *** 1 %

Table A8

Abnormal Overlapping MA MOM Sharpe Ratios

	1	2	3	4	5	6	7	8	9
250,000									
Yearly	0.01***	0.00***	0.03***	0.04***	0.04***	0.04***	0.05***	0.03***	0.03***
Bi-yearly	0.00	0.03***	0.06***	0.07***	0.05***	0.05***	0.05***	0.04***	0.04***
Tri-yearly	0.04***	0.07***	0.07***	0.07***	0.05***	0.05***	0.05***	0.05***	0.07***
Quarterly	0.01***	0.04***	0.09***	0.08***	0.08***	0.08***	0.07***	0.06***	0.07***
Bi-monthly	0.01***	0.05***	0.07***	0.07***	0.07***	0.06***	0.07***	0.06***	0.06***
Monthly	0.03***	0.06***	0.07***	0.08***	0.07***	0.06***	0.06***	0.06***	0.06***
500,000									
Yearly	0.01***	0.00***	0.03***	0.04***	0.04***	0.04***	0.05***	0.03***	0.03***
Bi-yearly	0.00	0.03***	0.06***	0.07***	0.05***	0.05***	0.05***	0.04***	0.04***
Tri-yearly	0.04***	0.07***	0.07***	0.07***	0.06***	0.05***	0.05***	0.05***	0.07***
Quarterly	0.01***	0.04***	0.09***	0.09***	0.08***	0.08***	0.08***	0.07***	0.07***
Bi-monthly	0.01***	0.05***	0.07***	0.07***	0.07***	0.07***	0.07***	0.06***	0.06***
Monthly	0.03***	0.06***	0.08***	0.08***	0.07***	0.07***	0.07***	0.06***	0.06***
1,000,000									
Yearly	0.01***	0.00***	0.03***	0.04***	0.04***	0.04***	0.05***	0.03***	0.03***
Bi-yearly	0.00	0.03***	0.06***	0.07***	0.05***	0.05***	0.05***	0.04***	0.04***
Tri-yearly	0.04***	0.07***	0.07***	0.07***	0.06***	0.05***	0.05***	0.05***	0.07***
Quarterly	0.01***	0.04***	0.09***	0.09***	0.08***	0.08***	0.08***	0.07***	0.07***
Bi-monthly	0.01***	0.05***	0.07***	0.07***	0.07***	0.07***	0.07***	0.06***	0.06***
Monthly	0.03***	0.06***	0.08***	0.08***	0.07***	0.07***	0.07***	0.06***	0.07***

Note. Adapted from "Profitable momentum trading strategies for individual investors" by B. Foltice and T. Langer, 2015, *Financial Markets and Portfolio Management, 29*(2), p. 109. Copyright 2018 by Ulrich R. Deinwallner. Abnormal Sharpe ratios that are compared to the DJIA index and are differentiated by trading frequency and investment amount. The Sharpe ratio was computed by equation 18. The abnormal monthly Sharpe ratios are computed by the monthly Sharpe ratio of each portfolio which is subtracted from the monthly Sharpe ratio of the DJIA index (1992 - 2010). The statistical significance levels were assessed by a conventional parametric *t*-tests: * 10 %; ** 5 %; *** 1 %