Master Thesis Finance, Tilburg University, Tilburg School of Economics and Management, Department of Finance

Profitability of Technical Trading Strategies

"Double Crossover Moving Average Strategy and Contrarian Bollinger Bands Strategy"

Author : Joost de Man

ANR : S872605

Supervisor : Dr. S. Ebert

Date : 19-11-2014

Word Count : 13.304

'14

Management Summary

This Master thesis is a quantitative study on the conditions under which the Double Crossover Moving Average strategy, and the alternative to the Contrarian Bollinger Bands strategy generate abnormal returns.

It was hypothesized that in general both technical trading strategies will not generate abnormal returns, argued through the eyes of the semi-strong market efficiency theory. However, several modifications and circumstances were created where the MA strategy and the BB strategy are hypothesized to generate abnormal returns. Reducing the n-period of the simple moving averages of both technical trading strategies will increase the responsiveness to price changes, which is expected to amplify the results. In addition, it is hypothesized that when MA traders take a neutral position instead of a short position on a sell signal, abnormal returns will decrease. A simple risk-return relationship underpins this expectation. Furthermore, both technical trading strategies are expected to generate greater abnormal returns during the credit crisis, as those strategies could indicate short sell signals when or before stock prices fall. Whenever the crisis period does not produce satisfactory results, data mining will be applied for investigating abnormal returns on Bull and Bear markets.

The STOXX Europe 600 was selected as sample for this study, on which the Buy-and-Hold, MA and BB strategies were applied on all parameterizations and time periods. From here, monthly excess return portfolios, gross of transactions costs, were constructed. Finally, all portfolios were regressed on three risk-adjustment models: CAPM; Fama French 3-factor model; Carhart four-characteristic model. After regression, the following results were generated: The MA strategy does not generate abnormal returns, except, surprisingly, when traders take a neutral position on sell signals. The MA strategy does even generate negative abnormal returns while operated in Bull and Bear markets. The BB strategy with the shortest-term moving average generates the greatest abnormal returns, gross of transaction costs. During Bear market, abnormal returns are greater and seem to outperform the B&H strategy even net of transactions costs. However, this study's Bull and Bear markets suffer from data mining, therefore, further research should investigate whether it is possible for individual investors to generate abnormal returns net of transaction costs.

Nevertheless, although abnormal net returns are probably not significantly larger than zero, an investor who is considering buying or selling a stock is, *Ceteris Paribus*, better off purchasing and selling shares indicated by the BB strategy trading signals than by their own subjective, biased decisions.

Table of Content

Chapter 1: Introduction

1.1 Problem Indication

Barber and Odean (2000) concluded that trading is hazardous to your wealth. They studied 66,465 households with accounts at a large discount broker during 1991 to 1996. According to this study, individuals that traded most, underperform the market returns significantly even without taking transaction costs into account. Those results are in line with the Efficient Market Hypothesis: if the market is efficient and the price is right at any given time, then there is no point to trade, which advocates the Buy-and-Hold strategy – B&H strategy. Why then, do individuals buy and sell stocks frequently? Probably, investors believe that markets are not perfectly efficient and that they can make a profit on this through trading. This is a behavioral problem and is attributable to overconfidence (Glaser & Weber, 2007; Statman, Thorly & Vorking, 2006) and sensation seeking (Grinblatt & Keloharju, 2009). 1) Overconfidence is directly linked to attribution bias. According to Gino and Pisano (2011), individuals assign successful outcomes to their selves and unsuccessful outcomes to others or external sources, which causes overconfidence. Therefore, investors assign positive returns on trading to their own capabilities, while they blame external sources – the market – for negative returns, which makes them more likely to trade on incoming information. 2) Sensation seeking is a stable personality trait, studied in the psychology literature, which varies across individuals. Those who are sensation seekers search for novel, intense, and varied experiences generally associated with real or imagined physical, social, and financial risks. Stock trading fits with this definition. Being active in the financial market is risky in itself, however the absence of trading lacks novelty and variety. To a sensation seeker it is the novelty of a new stock or a change in one's position that creates utility (Grinblatt & Keloharj, 2009).

Those behavioral aspects are difficult to take control of, as it is in the psyche of human beings, which causes irrational behavior. I propose that only when investors gain confidence in a trading system that allow for frequently trading, the impact of both behavioral aspects can be mitigated. Therefore several studies attempted to create a tool for those investors to eventually beat the B&H strategy. For example Potvin, Soriano & Vallée (2004) developed a system – genetic programming - that generates buying and selling signals for investors. Bollinger Bands are an easy to use trading strategy for individual investors, however it reveals mixed results in terms of excess returns (Leung and Chong, 2003). Therefore, this particular trading strategy could overcome the behavioral problems of individuals. Ebert and Hilpert (2014) discuss how the Double Crossover Moving Average Strategy – MA Strategy – is valuable for investors that are less than fully rational. Returns, using the Moving Average Strategy are skewed to the right, which do sensation seeking investors prefer. Therefore, such a mechanism could be a useful guideline for overconfident, sensation seeking, irrational investors.

However, do such strategies pay off in terms of returns? How does the MA Strategy perform with respect to the B&H strategy? And what about the Bollinger Bands Strategy – BB Strategy? Under what conditions do those technical trading strategies perform better? Gunasekarage and Power (2001) investigated this issue partly in the previous decade for the South-Asian market. They concluded, with respect to the moving average strategy, that the MA strategy generated abnormal returns. Consequently, the following problem statement is formulated:

Under which conditions do the MA strategy and the BB strategy generate abnormal returns?

1.2 Literature Review

Technical analysis uses historical prices or other historical data for investment decisions. Advocates of technical analysis believe that historical data contain information that could predict future movements of the stock market. The rationale of technical trading is to be able to recognize changes in trends at an early stage and to maintain an investment strategy until the weight of the evidence indicates that the trend has reversed (Gençay, 1998). However, Barber and Odean (2000) concluded that trading is hazardous to investors' wealth. According to them, even before taking trading costs into account, excessive trading will produce negative returns relative to not trading - B&H strategy.

As trading reduces investors' wealth, and, assuming that each investor wants to maximize its value; there should be some psychological biases that cause investors to trade excessively and subsequently reduce value. Overconfidence (Glaser & Weber, 2007; Statman, Thorly & Vorking, 2006), sensation seeking (Grinblatt & Keloharju, 2009), attribution bias (Gino & Pisano, 2011) and disposition effect (Dhar & Zhu, 2006) are such psychological causes of excessive trading. Therefore, individual investors lose value when they depart from their rationality, and subsequently let their intuition determine their trading strategy.

Trading rules or strategies could be a useful investment tool for those biased investors. Although the semi-strong form of market efficiency asserts that investors should not be able to generate trading profits based on publicly available information. The suggestion, that it is possible to make trading profits on publicly available information, is made by several scholars. Park and Irwin (2007) tested different trading rules on profitability. They found especially positive returns for technical trading strategies until the early 1990's. Also Artificial Neural Networks technical trading rules were tested in 2000 on the General Index of the

Madrid Stock Market (Fernandéz-Rodriquez, González-Martel & Sosvilla-Rivero, 2000). They conclude from their study that a simple technical trading rule based on Artificial Neural Networks is superior to the B&H strategy during bear market and stable market periods, in absence of trading costs. However, during bull markets the strategy does not outperform its benchmark. Potvin, Soriano and Vallé (2004) come to a different conclusion. Trading rules generated by genetic programming are generally beneficial when the market falls or when it is stable and not when the market is rising. Gençay (1998a) found that the moving average rule provided at least a 10% forecast improvement in the volatile years of the Great Depression and in the trendy years of 1980-1988. On the other hand, the performance of technical trading rules is more moderate in periods in which there is no clear trend in either a positive or negative direction. Furthermore, Gençay (1998b) concluded that nonparametric models with technical trading rules provide significant abnormal returns after transaction costs are taken into account. Gunasekarage and Power (2001) also found abnormal returns for the moving average strategy for the investors in South Asian markets. Several technical trading strategies, like moving average, Bollinger bands, RSI, SMI and CMI, are useful technics for trading analysis, however, it would not make an investor rich by definition (Kannan, Sekar, Sathik & Arumugam 2010). According to them, half of the stock's closing price direction could be predicted by those technical trading technics. The Bollinger Bands trading strategy provided the highest profits according to that study.

According to above studies it seems that technical trading rules could generate abnormal returns, and, as a consequence, outperform individual investors who trade excessively as well. The existing literature will be used to create theoretical synergies in order to formulate well-argued hypotheses.

1.3 Contribution

Dhar and Zhu (2006) assert that the disposition effect is lower for wealthier individuals and individuals employed in professional occupations. I expect also the other behavioral biases to be larger for individuals that are less acquainted with the stock market. Therefore, this study is meant to provide an investment tool for that kind of investors, as they need a trusted trading system to overcome the behavioral biases that reduce their wealth.

As the aforementioned studies are executed in the 20th century and not on the STOXX Europe 600 index, this study will test the performance of the Double Crossover Moving Average Strategy, the Bollinger Bands Strategy, and the Buy-and-Hold strategy on the STOXX Europe 600 Index of the past decade, on abnormal returns. Furthermore, several side hypotheses will be tested in order to investigate whether those technical trading strategies generate greater abnormal returns under certain circumstances. Therefore, this Master Thesis will try to provide irrational, sensation seeking, investors with a strategic tool for trading. Through using one of those strategies, it is possible to mitigate the behavioral biases of individual investors, while maintaining the sensation seeking aspect of trading, which is important for most investors (Grinblatt & Keloharju, 2009). Furthermore, partial information leads to irrational decisions. This information discrepancy could be diminished by using technical trading strategies as trading tool. Besides, as this study investigates under which circumstances the MA strategy and BB strategy generate abnormal returns, this Thesis also contributes to the market efficiency debate.

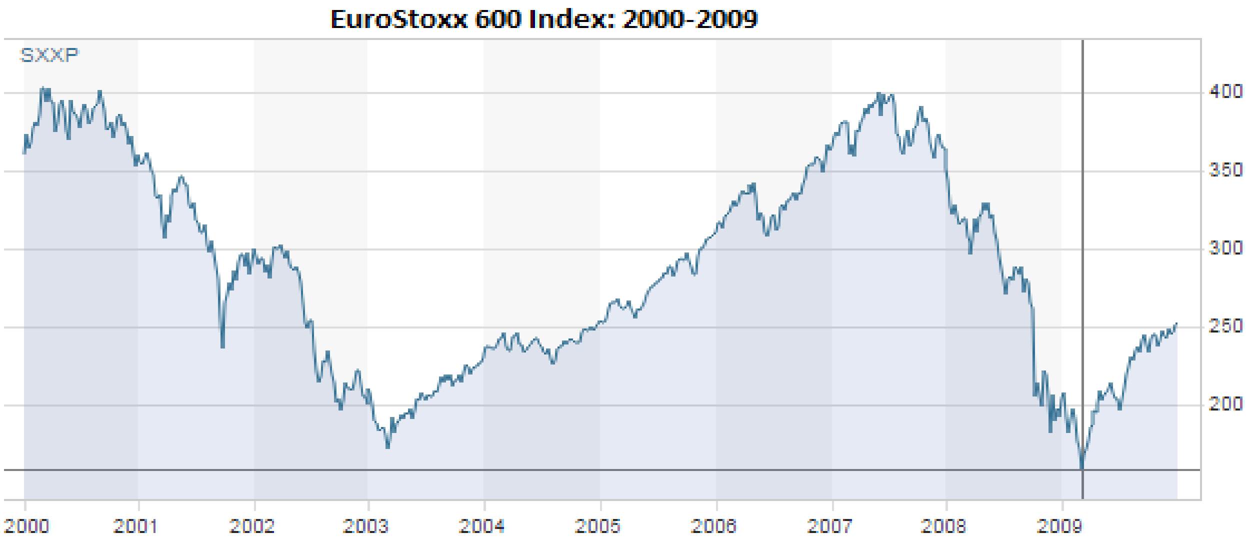
Finally, this study could be a starting point for further research, as research in this particularly field is relatively rare, especially with respect to the Bollinger Bands Strategy. The results of this Master Thesis could be tested on other markets, in other time slots and on other, self-constructed, portfolios.

The structure of this Thesis is as follows. Chapter 2 describes the use of the MA strategy and the BB strategy, from which several hypotheses are developed. Chapter 3 deals with the methodological part of this study, where data collection, data preparation, portfolio constructions and performance measures are discussed. Chapter 4 is devoted to results from the regression analyses. Finally, Chapter 5 ends this thesis with conclusions, limitations, contributions and further research sections.

Chapter 2: Theory

As the literature is mixed about the usefulness and profitability of technical trading strategies, it is interesting to test such strategies on real historical data. In this chapter the hypotheses are formulated and supported by literature research. Eventually, all hypotheses will be tested on the STOXX Europe 600 Index which is depicted below – **Figure 1**. The first half of this chapter is devoted to the Double Crossover Moving Average strategy. Subsequently, the second half is devoted to an alternative to the Contrarian Bollinger Bands strategy.

Figure 1: A graphical presentation of the daily closing prices in euros for the STOXX Europe 600 Index: 2000-2009. Source: www.stoxx.com



2.1 Double Crossover Moving Average

The MA strategy consists of a short-term- and a long-term simple moving average. Therefore, the most recent closing prices are more heavily represented in the short-term moving average, and are consequently more responsive to recent price changes. As a result, when the short-term line crosses the smooth long-term line from below (above) an upward (downward) trend is recognized, which corresponds to a buy (sell) signal, such that investors could profit from the trend. Therefore, the Double Crossover Moving Average strategy is used for this study.

Mathematically, let S_t denote the time *t* price of a stock *S.* The value of the MA line of stock *S* at a given time *t* with length *n* is the average closing price of the past *n* closing prices:

$$(1)\quad MA(t,n) = \frac{1}{n}\sum_{i=1}^{n} S_{t-i}$$

As times moves on, the oldest data used to calculate the moving average are replaced by the newest observations of the stock price. Therefore, the moving average line with fixed length n, which is constructed by the several moving averages of the stock price, reveals how the average stock price evolves over time. The Double Crossover Moving Average strategy is based on a short-term moving average (n = small) and a long-term moving average (n = large). Obviously: $n_{long} > n_{short}$.

Therefore, when the short-term MA crosses the long-term MA from below, it indicates a short-term upwards trend relative to the long-term trend. An investor who trades on the MA double-crossover strategy buys the stock at this signal. However, this investor goes short on its shares when the short-term MA crosses the long-term MA from above. As it indicates that the short-term upward trend is over, and simultaneously indicates a downward trend. The moving average strategy thus chases momentum as it buys recent winners and sells recent losers (Ebert & Hilpert, 2014).

Therefore, in this study the following rules hold with regard to the Double Crossover Moving Average simulation:

Rule 1: *The MA trader buys the stock at time t when the short-term MA line crosses the long-term MA line from below:*

$$(2) \quad MA(t-1, n_{short}) < MA\left(t-1, n_{long}\right) \text{ and } MA(t, n_{short}) \geq MA\left(t, n_{long}\right)$$

Rule 2: *The MA trader takes a short position in the stock at time t when the short-term MA line crosses the long-term MA line from above:*

$$(3) \quad MA(t-1, n_{short}) > MA\left(t-1, n_{long}\right) \text{ and } MA(t, n_{short}) \leq MA\left(t, n_{long}\right)$$

As becomes clear from above, the double-crossover MA trading strategy incorporates a moment where the MA trader has no position in a particular stock. Namely, at the beginning of the sample period until a trade signal is given by the strategy. When the MA trader has no position in a particular stock, its return will be based on the risk free rate, the neutral position, which is the UK 3 month Treasury bill rate.

Ebert and Hilpert (2014) use what they call ‘a popular parameterization’ with n_{short} = 50 for the length of the short-term MA and n_{long} = 200 for the long-term MA. The same time spans will be used for this study. However, in order to test the balance between more responsive trade signals and excessive trading, other parameterizations will be tested as well, which will be discussed in the next section.

Figure 2: Double Crossover Moving Average Strategy (50,200) for 3I Group from January 2000 to July 2006. This graph shows the 50-day MA line (yellow line) and the 200-day MA line (blue line) calculated from the 3I Group stock's daily closing prices (grey line) on the STOXX Europe 600 Index. Sell signals are accentuated in purple, buy signals in green. Besides, the sell and buy prices are included in the figure.

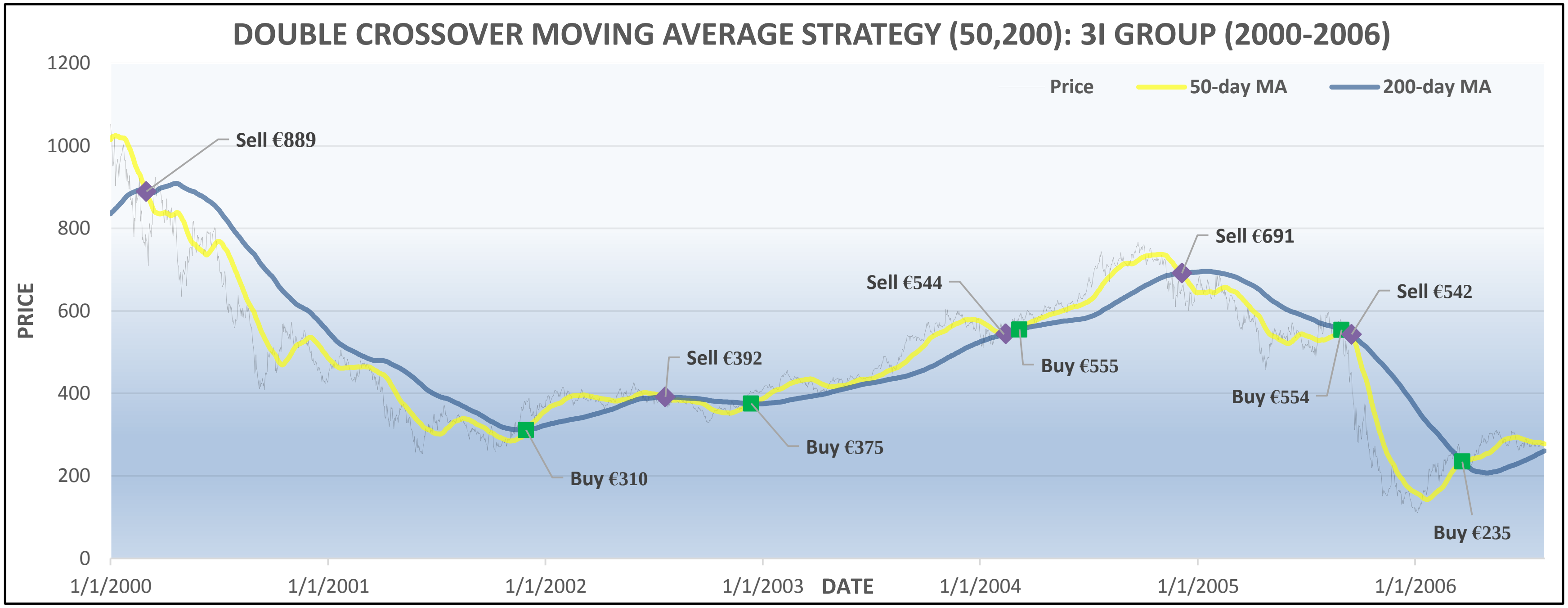


***Figure 2** illustrates the Double Crossover Moving Average Strategy with regard to the 3I Group common stock trajectory of daily closing prices on the STOXX Europe 600 Index for the period 2000-2006. Furthermore, the figure also reveals the buy and sell signals provided by this technical trading strategy. As becomes clear from the graph, an investor who trades according to the MA strategy takes a short position when the 50-MA yellow line crosses the 200-MA blue line from above. Besides, this investor buys the stock when 50-MA line crosses the 200-MA line from below. A profitable trading strategy would be selling the 3I Group stock short at the sell signal in March 2000 for 889 euro and buying it back in November 2001 at 310 euro. Buying the stock at the buy signal in December 2002 at 375 euro and going short February 2004 at 544 euro would be a profitable trade as well, indicated by the MA trading strategy signals. Minor losses would have resulted from selling short at 544 euro, February 2004 and buying it back at 555 euro a month later. Before the first trading signal – sell 889 in the beginning of 2000 – a risk-free rate position is taken.*

2.1.1 Moving Average's Abnormal Returns

As a result of above-mentioned, the random walk theory should not hold for the Double Crossover Moving Average strategy to work. This theory states that stock price changes have the same distribution and are independent of each other, which means that past movement or trend of stock prices cannot be used to predict its future movement. As emerging markets diverge more from market efficiency, random walk theory is rejected in those markets (Chaudhuri & Wu, 2003; Smith & Ryoo, 2003). Therefore, it is expected that developed, more efficient markets – like the STOXX Europe 600 Index – move according to the random walk theory. As a result, it is impossible to predict future price movements on historical data. In other words, it is impossible to generate positive alphas, even before transaction costs. Therefore, using the MA strategy will not benefit an investor. As a consequence, the MA strategy will not generate abnormal returns:

H1: The Double Crossover Moving Average strategy will not generate positive abnormal returns.

However, several studies concluded that technical trading strategies do generate abnormal returns under certain circumstances, which indicates that future stock movements can be explained by historical prices. Some adjustments to the standard MA (50,200) strategy could result in greater abnormal returns.

2.1.2 Parameterization

Moving averages with shorter time periods fluctuate more, and consequently, provide more trading signals, which increases the benefits of an upward trend and decreases the burn during a downward trend. However, transactions cost will increase, as more trading signals are provided. On the other hand, moving averages with a larger n-period will reveal a smoother average, which decreases the opportunity to profit from long- and short positions in respectively upward- and downward trends.

In the literature, there is no consensus concerning the time frames of the long- and short-term simple moving average, with n-periods diverging from 1 day to 200 days (Ebert & Hilpert, 2014; Guasekarage & Power, 2001; Gençay 1998a; Kannan et al., 2010). Therefore, several parameterizations will be tested for the MA strategy – 50,200; 37,200; 22,200; 50,100. As a result the following hypothesis is formulated:

H2: The larger the n-period difference between the short-term moving average line and the long-term one, the greater the abnormal returns of the MA strategy.

When MA investors take a neutral position – risk free rate – instead of a short position, abnormal returns are expected to decrease. This is theoretically underpinned by the commonly known risk-return relationship: potential returns rise with an increase in risk. Therefore, low levels of risk/uncertainty are accompanied by low returns. While, high levels of risk/uncertainty are associated with high potential returns (Bodie, Kane & Marcus, 2014). Therefore, the following hypothesis is defined:

H3: The MA short-sell strategy generates greater abnormal returns compared to the strategy in which a neutral position is taken on a sell signal.

2.1.3 Crisis

During the economic crisis of 2007 stock prices collapsed which caused huge losses for investors. If the MA strategy had provided the investor with a sell signal, this technical trading strategy could have generated abnormal returns.

Advocates of the MA strategy assume that stock prices move in trends, which are determined by the changing attitudes of traders towards several economic indicators, like political, economical and psychological forces (Pätäri & Vilska, 2014). Therefore, to generate positive alphas with a MA strategy, stock prices have to move in trends. During crises there exist clearly a trend as you can see in **Figure 1**. For technical traders it is important to profit from the 'main movement' (Brown, Goetzmann & Kumar, 1998). And as already mentioned in the literature review, technical trading strategies perform better when markets fall. Probably, the MA strategy is well suited to detect those falling markets through its trade signals. The crisis of 2007 could function as such a falling market. Pätäri and Vilska (2014) investigated this phenomenon on the Finnish market and concluded that MA trading profits are higher during the Credit Crisis than in the period before. In addition, this strategy outperformed the B&H strategy. As a consequence, the following is hypothesized:

H4: The MA strategy generates greater abnormal returns during economic crises than pre-crisis, before transaction costs.

2.2 Alternative Contrarian Bollinger Bands

In general the BB strategy consists of a simple moving average and two boundary lines that with 2 standard deviations from the mean should capture approximately 95% percent of the price movements – in case of normal distribution. As a result, the area above the upper Bollinger Band is considered as an overbought region, while the area below the lower Band is considered as an oversold region. In the overbought situation, investors should sell their assets as prices are expected to reverse to their fundamental value. However, it is unclear for what time the prices remain overbought, as, due to sentiment, prices could remain above fundamental value for long time periods. Therefore, it is better to wait until the stocks moves away from the overbought area. The same logic applies to the situation in which assets are oversold. Consequently, for this study a slight alternative to the Contrarian Bollinger Bands strategy is operated (Leung & Chong, 2003).

Mathematically, let S_t denote the time t price of a stock S. The simple moving average line is determined by equation (1). Based on this line and a standard deviation, σ, of the same N-period as the simple moving average with a fixed multiplier denoted by k, both the upper- and lower N-day Bollinger Bands are defined:

$$(1)\quad (\mathrm{BB}_N^k(t) = MA(t,n) \pm k\sigma_{(t,n)}$$

As times moves on, the oldest data used to calculate the moving average are replaced by the newest observations of the stock price. Therefore, the moving average line with fixed length n, which is constructed by the several moving averages of the stock price, reveals how the average stock price evolves over time. Furthermore the spread between the upper Bollinger Band and the lower Bollinger Band indicates the volatility of the stock price. Therefore, this trading strategy provides us with a relative definition of high and low.

Consequently, when stock prices are above the upper Bollinger Band, it indicates that prices are overbought. Therefore, when the stock price crosses the upper band from above investors should go short, as this could indicate a starting downward trend. Simultaneously, when stock prices are below the lower Bollinger Band, it indicates that prices are oversold. As a consequence, when the stock price crosses the lower band from below, investors should go long in the stock, as it could indicate the beginning of an upward trend (Leung & Chong, 2003)**.** Therefore, the following rules hold with regard to the above theory about the Bollinger Band trading simulation:

Rule 1: *The BB trader buys the stock at time* t *when the stock price P the lower Bollinger Band from below:*

$$(2)\quad (P_i(t-1) < BB_N^{low}(t-1) \text{ and } P_i(t) > BB_N^{low}(t)$$

Rule 2: *The BB trader takes a short position in the stock at time* t *when the stock price* P *crosses the upper Bollinger Band from above:*

$$(3)\quad P_i(t-1) > BB_N^{up}(t-1) \text{ and } P_i(t) < BB_N^{up}(t)$$

As becomes clear from above, the Bollinger Bands trading strategy incorporates a moment where the BB trader has no position in a particular stock. Namely, at the beginning of the sample period until a trade signal is given by the strategy. When the BB trader has no position in a particular stock, its return will be based on the risk free rate, which is the UK 3 month Treasury bill rate.

The parameterization of the Bollinger Bands trading strategy are traditionally set at N=20 and $k = \pm\,\sigma 2$ (Lento et al., 2007). Which means that the bands are both two standard deviations above and below the 20-day simple moving average line. Parameterization will be discussed in the next section.

2.2.1 Bollinger Bands' Abnormal Returns

As became clear from above, the BB strategy does not chase momentum like the MA strategy, as it tries to recognize the point where either an upward trend or a downward trend ends. Therefore, it speculates on reversal to the fundamental value. Namely, when a stock is overbought according to the BB strategy, this strategy expects the stock price to fall, but only signal a 'sell' when the downward trend has just began. As the bands are both two standard deviation above and below the moving average, this methodology provides a relative definition of high and low. Again, according to efficient market hypothesis stock prices always reflect the true value of the firm, and, as a consequence will be neither overbought nor oversold. Therefore, it is expected that in an efficient market, like the STOXX Europe 600 Index, the BB strategy cannot generate abnormal returns. Especially, when transaction cost are taken into account. This theory is formally formulated in the following hypothesis:

H5: The Bollinger Bands strategy does not generate abnormal returns.

However, some modifications to the BB strategy could change the sign or magnitude of this relation. Therefore, in the following subsections parameterization and crisis are investigated through a literature review.

2.2.2 Parameterization

The length of time for the simple moving average is really important, as moving averages with shorter time periods fluctuate more, and consequently, provide more trading signals. As a consequence, overbought and oversold stocks will be recognized at an earlier stage. However, transactions cost will increase, as more trading signals are provided. Moving averages with longer time periods will reveal a smoother average,

Figure 3: Bollinger Band Strategy (20,2) for 3I Group for the year 2006. This graph shows the 20-day MA line (red line) and the Bollinger Bands (2 standard deviations from the MA line) calculated from the 3I Group stock's daily closing prices (grey line) on the EURO STOXX 600. Sell signals are accentuated in purple, buy signals in green. Besides, the sell and buy prices are included in the figure.

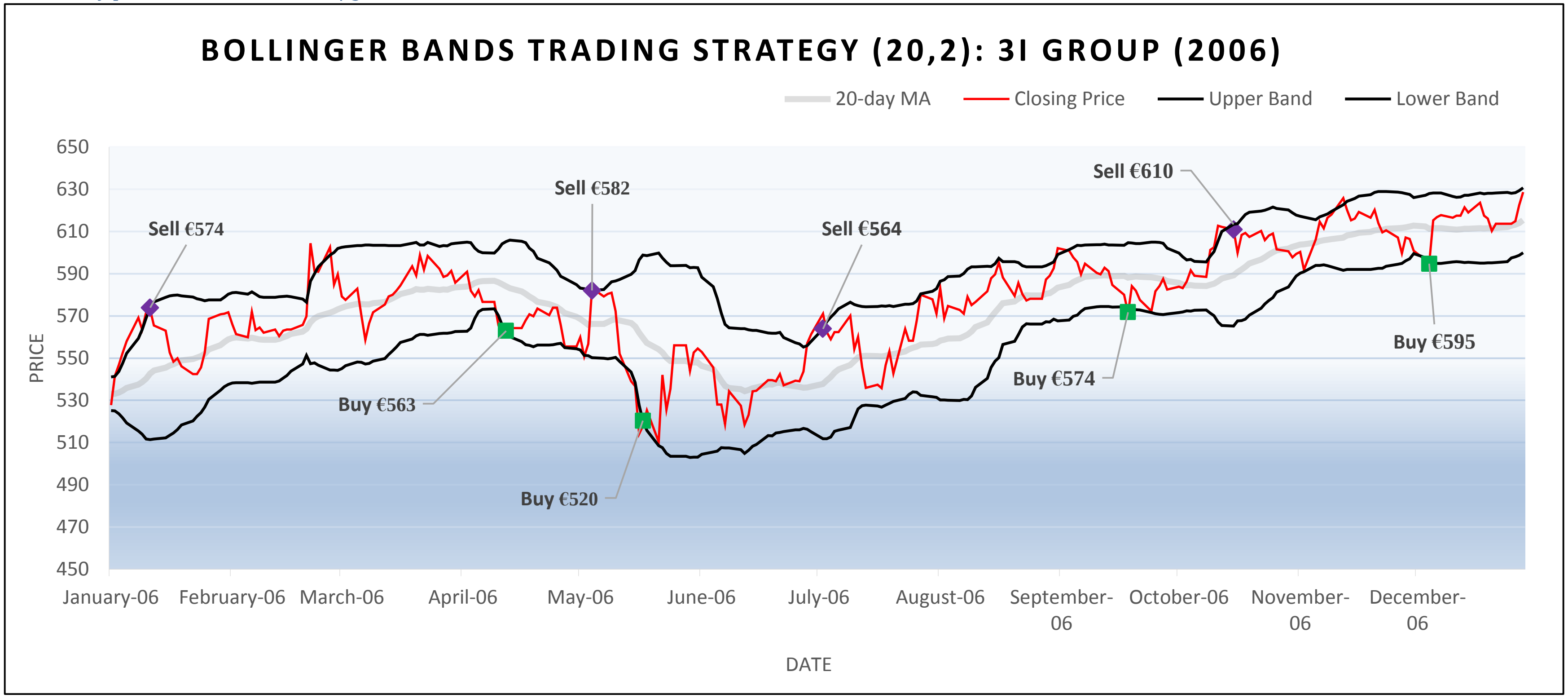


Figure 3 *illustrates the alternative to the Contrarian Bollinger Bands strategy with regard to the 3I Group common stock trajectory of daily closing prices on the STOXX Europe 600 Index for the year 2006. Furthermore, the figure also reveals the buy and sell signals provided by this technical trading strategy. As becomes clear from the graph, an investor who trades according to the BB strategy takes a short position when the 20-MA red line crosses the black Upper Band from above. Besides, this investor buys the stock when 20-MA line crosses the black Lower Band from below. For example, a profitable trading strategy would be selling the 3I Group stock short at the sell signal in the beginning of May 2006 for 582 euro and buying it back at the end of May 2006 at 520 euro. Minor losses would have resulted from selling short at 564 euro at the beginning of July 2006, and buying it back at 574 euro mid-September.*

which decreases the opportunity to profit from long- and short positions in respectively upward- and downward trends.

The most commonly used parameterization is BB (20,2) (Kannan et al., 2010; Leung and Chong, 2003; Lento et al., 2007; Liu, Huang & Zheng, 2006). John Bollinger also recommends in his book an N=50 period for calculating the moving averages and standard deviations. However, he proposes to use in that case a 2.1 interval for the upper- and lower bands (Bollinger, 2001). This Master Thesis will investigate those two parameterizations. The following hypothesis is developed:

H6: The BB strategy generates lower abnormal returns when a larger N-period is used for the simple moving average, before transactions costs.

2.2.3 Crisis

Before the start of the credit crisis of 2007, stock prices were highly overbought. If the BB strategy recognizes those overbought stocks, it will provide the investor with a sell signal. Therefore, this technical trading strategy could outperform the B&H strategy in times of crises. Most crises are preceded by economic bubbles, also called speculative bubbles, in which prices are, due to investor sentiment, far above the intrinsic value of the asset. This phenomenon of rising prices, above the fundamental value cannot last forever. The bubble will burst one day when a specific shock to the economic fundamentals amplifies a negative spiral to economic assets like stock prices (Martin & Ventura, 2011)

The original BB strategy generated lower abnormal returns than the B&H strategy during the crisis as it generated buy signals during economic decline and sell signals once it bottomed and began to recover (Chuen & Gregorio, 2014). However, as our alternative to the contrarian approach (Kannan et al., 2010) indicates the opposite signals to investors, this strategy would provide theoretically profitable signals in crisis time. As a consequence, the following hypothesis is defined:

H7: The BB strategy generates greater abnormal returns during economic crises than pre-crisis, before transactions costs.

The B&H strategy will also be investigated, which can operate as a benchmark. For the B&H strategy the security is purchased at $(t = 1)$. This long position is kept until the end of the sample period. Subsequently, those daily returns for strategies, parameterizations and time frames are transformed into monthly data in order to construct portfolios for the several models. The method of portfolio construction is described in the next chapter.

2.3 Theoretical Summary

In the previous paragraphs some modifications of both trading strategies were introduced, which are expected to affect the relation between the technical trading strategies and its abnormal returns. For every modification a hypothesis was developed on the basis of several arguments from both academic articles and logical reasoning. The theory can be divided into two sections: the MA strategy and the BB strategy.

The **MA strategy** is not expected to generate positive abnormal returns. However, when certain modifications are applied to the MA strategy it will generate positive abnormal returns. Thus, when the N-period difference between the short- and long term simple moving average is enlarged; Short Selling strategy is applied; and when the MA strategy is applied during Crises, the MA strategy will produce greater abnormal returns.

The **BB strategy** is not expected to generate positive abnormal returns compared to the B&H strategy. In addition, it is expected that when the N-period of the simple moving average increases, the abnormal returns will decrease even more. However, it is predicted that positive abnormal returns are generated when the BB strategy is tested during economic crisis. The main difference between the MA strategy and the BB strategy is that the former chases momentum and buys (sell) recent winners (losers), while the latter strategy speculates on trend reversals and buys (sell) prior losers (winners).

When the *Crisis* period does not generate significant abnormal returns, it is possible to look at '*Bull versus Bear markets'* where only the period of rising prices and decreasing prices are analyzed, respectively. The 'Bull market' starts at March 2003 and it lasts until May 2007, while the 'Bear market' starts at June 2007 and ends at February 2009. For graphical argumentation of those periods see **Figure 1**. This method of analysis suffers from data mining, however, it is a good way to test whether up- or downward trends generate higher abnormal returns for a particular technical trading strategy.

Chapter 3: Methodology

The formulated hypotheses from the previous chapter have to be empirically tested, for which data have to be collected. This chapter focuses on data collection, data description and method of analysis.

3.1 Sampling Strategy

Sampling & Data Collection

This study will investigate the abnormal returns of two technical trading strategies and the B&H strategy for stock prices of the STOXX Europe 600 Index for the 1/1/2000 – 31/12/2009 period. This index is a subset of the STOXX Global 1800 Index. It consists of 600 components and represents large, medium and small capitalization companies across several industries and 18 countries from the stan region – Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. Stock prices of the components that were included in the STOXX Europe 600 Index at 1/1/2000 are used for the entire sample period and were provided by Thomson Reuters DataStream. Otherwise, when the current components of the STOXX Europe 600 Index were used, the sample was biased towards successful companies – survivorship bias. The stock prices and the 3 Month UK Treasury bill Rate for calculating excess returns are also retrieved by means of DataStream at the UVT Library. Furthermore, the STOXX Europe 600 Index will function as a control variable, next to the Market Equity, Book-to-Market ratio, and Prior Performance, which data were retrieved via DataStream as well.

3.2 Technical Trading Strategies

Parameterization

To measure whether the parameterization of the MA strategy and the BB strategy improve the abnormal returns, several parameterizations are used. For the **MA strategy** the following n-periods for the short-term moving average and the long-term moving average are used, respectively: (50,200); (37,200); (22,200); (50,100). Therefore, all those simple moving averages are retrieved via Thomson Reuters DataStream. Furthermore, a formula for the (50,200) parameterization is incorporated in order to test for abnormal returns when going into the risk free rate at sell signals instead of selling the stock short. The **BB strategy** is tested on the following parameterizations: (20, 2) and (50, 2.1) which is the N-period simple moving average and the multiplier of the standard deviation, respectively. Consequently, the 20-day simple moving average is retrieved from DataStream as well, from which the standard deviation is calculated afterwards.

Crises

In order to measure whether both technical trading strategies generate higher abnormal returns during crises, the sample period is divided into two periods. The first period starts January 2000 and ends December 2006, which is defined as the 'pre-crisis period'. The second period starts at January 2007 and ends at the end of the sample period, December 2009, which is defined as the 'crisis period'. Subsequently, it is tested whether both the MA strategy and the BB strategy generate higher abnormal returns during the 'crisis period' compared to the 'pre-crisis period'. In addition, Bull and Bear markets are analyzed. The 'Bull market' starts at March 2003 and it lasts until May 2007, while the 'Bear market' starts at June 2007 and ends at February 2009. Those periods are consecutive months of rising (falling) stock prices for the Stoxx Europe 600 Index, respectively, **Figure 1**.

3.3 Data preparation

For calculating the monthly excess returns for each portfolio, several steps have to be made. A comparable methodology is used as in the paper of Barber et al. (2001). Their study investigated abnormal returns of portfolios through trading on analyst recommendations, while this study searches for abnormal returns of portfolios by trading on technical trading signals.

For each firm i the equally-weighted return of each portfolio p for date τ is calculated first. Denoted by $R_{p\tau}$, for portfolio p, this return is formally given by:

$$(1)\quad R_{p\tau} = \sum_{i=1}^{n_{p\tau}} R_{i\tau}$$

Where

> $R_{i\tau}$ = the adjusted return on the common stock of firm i on date τ, and
>
> $n_{p\tau}$ = the number of firms in portfolio p at the close of trading on date τ.

Equal weighting is chosen, as the individual returns of the smaller firms, which are likely to be less efficient, are relatively more heavily represented in the aggregate return than with a value weighting method. And, as mentioned in the theory, less efficient securities are more likely to generate abnormal returns when technical trading is applied.

In order to measure portfolio excess returns R_{pt} for month t on all strategies' portfolios, monthly stock returns for the entire portfolio will be used. Those stock returns are calculated through compounding the daily adjusted stock returns for the portfolio $R_{p\tau}$ over the n trading days of that month:

$$(2)\quad R_{pt} = \prod_{\tau=1}^{n}\left(1 + R_{p\tau}\right) - 1$$

Namely, daily returns are needed to determine the long- and short positions of a stock, and, consequently, the corresponding daily- and subsequently monthly returns. The trading strategies are described in Chapter 2. As a result, the monthly returns for the different trading strategies will differ from each other, such that comparison in the end is possible. When monthly returns are calculated, the risk-free rate R_{ft} is subtracted from it in order to generate the excess returns $R_{pt} - R_{ft}$. For the monthly risk free rate the 'UK 3 month Treasury bill rate' is chosen.

3.4 Performance Evaluation

Also for the performance evaluation of the portfolios the same methodology is used as in the study of Barber et al. (2001). In order to determine whether some of the selected technical trading strategies generate abnormal returns, this study will adjust the excess returns for risk. As starting point, for each portfolio the Sharpe Ratio will be calculated through dividing the portfolio excess returns by the standard deviation of the portfolio σ_p which is a simple way to generate risk-adjusted excess returns:

$$(3)\quad \text{Sharpe Ratio} = \frac{\mathrm{R_{pt}} - \mathrm{R_{ft}}}{\sigma_{\mathrm{p}}}$$

Market risk

When stocks entail higher systematic risk, they should earn higher returns. This is what the Capital Asset Pricing Model asserts about the risk-return relationship (Bodie, Kane & Marcus, 2014). Therefore, in order to test whether a particular technical trading strategy generates positive abnormal returns, one should control for risk. According to the CAPM, the asset's sensitivity to non-diversifiable risk is measured by beta. This beta is calculated by means of the excess return of the STOXX Europe 600 Index, the market return in this study. Consequently, the following formula is used to control for systematic risk, by means of the CAPM:

$$(4)\quad R_{pt} - R_{ft} = \alpha_p + \beta_p\left(R_{mt} - R_{ft}\right) + \varepsilon_{pt}$$

Where

α_p = the estimated CAPM intercept (Jensen's alpha)

β_p = the estimated market beta, and

ε_{pt} = the regression error term.

This test yields parameter estimates of α_p and β_p for each portfolio. Jensen's alpha is the parameter of interest, as it reflects the abnormal returns of the portfolio after controlling for risk.

Size

Fama and French (1993) developed the 3-factor model – FF3F. This model takes into account that small cap stocks tend to outperform large cap stocks and that value stocks outperform growth stocks in general. Therefore, in order to measure whether technical trading strategies outperform the B&H strategy, this study controls for both size and value (next subsection). This is realized by including a 'size-factor' into the model, which should capture the outperformance of small cap stocks over large ones. As those factors are not available for the European stock market, this study calculated the factors itself. The factors are calculated through first constructing 25 portfolios for each month from the STOXX Europe 600 Index, ranked on Market Equity and Book-to-Market ratio. Those portfolios are rebalanced quarterly. Subsequently, the size factor, Small-minus-Big SMB_t is calculated. SMB_t is the average monthly return on three small portfolios minus the average monthly return on three big portfolios:

$$(5) \quad SMB_t = \frac{1}{3}(\text{Small}_{\text{Value}} + \text{Small}_{\text{Neutral}} + \text{Small}_{\text{Growth}}) - \frac{1}{3}(\text{Big}_{\text{Value}} + \text{Big}_{\text{Neutral}} + \text{Big}_{\text{Growth}})$$

Value

According to Fama and French (1993), one should also control for the tendency that value stocks outperform growth stocks. This is realized by including a 'value-factor' into the model. From the same 25 portfolios, as above mentioned, the value factor, High-minus-Low HML_t is calculated. HML_t is the average monthly return on two value portfolios minus the average monthly return on two growth portfolios:

$$(6) \quad HML_t = \frac{1}{2}(\text{Small}_{\text{Value}} + \text{Big}_{\text{Value}}) - \frac{1}{2}(\text{Small}_{\text{Growth}} + \text{Big}_{\text{Growth}})$$

Through including those factors another risk-adjusted abnormal performance test is employed.
Therefore, for each portfolio the following monthly time-series regression is run:

$$(7) \quad R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + \varepsilon_{pt}$$

The regression yields parameter estimates of α_p, β_p, s_p and h_p for each portfolio. Again, Jensen's alpha is the parameter of interest, as it reflects the abnormal returns of the portfolio after controlling for risk.

Momentum

Carhart (1997) developed an extension of the Fama-French 3-factor model, which is called the Carhart 4-characteristic model – CAR4. According to that study, recent winners tend to outperform recent losers. Moskowitz, Ooi and Pedersen (2012) confirm this finding with their study about time series momentum. As a consequence, this Thesis will also control for momentum in order to test whether technical trading outperforms the B&H strategy. This is realized by including a 'momentum-factor' into the 3-factor model, which should capture the outperformance of recent winners over recent losers. Therefore, 6 portfolios are constructed based on Market Equity and Prior Returns (2-12 months), which are rebalanced monthly. Momentum, Mom_t, is the average monthly return on the two high prior return portfolios minus the average return on the two low prior return portfolios:

$$(8)\quad Mom_t = \frac{1}{2}(\text{Small}_{\text{High}} + \text{Big}_{\text{High}}) - \frac{1}{2}(\text{Small}_{\text{Low}} + \text{Big}_{\text{Low}})$$

When the Momentum factor is included in the regression model, the following regression is produced:

$$(9)\quad R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + m_p Mom_t \varepsilon_{pt}$$

The regression yields parameter estimates of α_p, β_p, s_p, h_p and m_p for each portfolio. Again, Jensen's alpha is the parameter of interest, as it reflects the abnormal returns of the portfolio after controlling for risk.

Transaction Costs

All returns calculated above are gross of transaction costs arising from the bid-ask spread, brokerage commissions, and the market impact of trading. In order to measure transaction costs the daily turnover for each equal-weighted portfolio is calculated. First of all, the average number of trades per stock is calculated, $\check{G}_i$:

$$\check{G}_i = \frac{\sum_{i=1}^{n} G_i}{P_n}$$

Where

G_i = the total number of transactions for each stock per, and

P_n = the number of stocks comprising the portfolio

$\check{G}_i$ is divided by the number of trading days of the sample period. This number is multiplied by the number of trading days per year to get to the annual turnover rate for each portfolio.

Subsequently, the methodology of Barber et al. (2001) is used to calculate round-trip transaction costs for the portfolios. They use the round-trip transaction costs of 0.727, 1.94, and 4.12 percent for respectively large, medium and small capitalization stocks. Small stocks are defined as having a market equity between €300 million and €2 billion, mid cap stocks fall between a market equity of €2 billion and €10 billion, large capitalization stocks have a market equity of above €10 billion. Large firms comprise 34% of the total portfolio, medium sized firms 46%, and small firms 20%. By means of this composition and the above mentioned round-trip transaction costs per size class, an average round-trip transaction cost of 1.95% is estimated. This implies that for each portfolio 1.95% of annual turnover equals the total annual transaction costs.

3.5 Parameter Estimates

Alpha

In the above-mentioned regressions the intercept α_p is of interest with respect to testing the hypotheses. The intercept is commonly known as Jensen's Alpha and tells you how much better the fund did than predicted by the CAPM, FF3F or CAR4 in terms of excess returns – abnormal returns of the particular technical trading strategy. And, in case of a negative alpha, how much worse it did than predicted by the model. Therefore, this study wants to test whether, and when, the alpha of technical trading strategies are significantly positive, as it provides a good measure of performance after risk-adjustment.

Also the other estimates from the regression provide information concerning the portfolio, although those are less of interest for this particular study. A value of , β_p greater (less) than one indicates the firms in portfolio p are, on average, riskier (less risky) than the market. A value of s_p greater (less) than zero indicates that small capitalization stocks perform better (worse) than large cap stocks for that particular portfolio/trading strategy. A value of h_p greater (less) than zero signifies that value stock relatively outperform (underperform) growth stocks for analyzed portfolio. Finally, a value of m_p greater (less) than zero means that good prior performing stocks do on average better (worse) than bad prior performers for that portfolio.

Chapter 4: Results

In this chapter the results of the statistical analysis will be provided. Every hypothesis will be investigated, in order to either accept or reject the predefined hypothesis. First, some preliminary results are provided in order to get some first understanding concerning the portfolio results. All regressions use excess returns gross of transaction costs.

Preliminary results

Table 1: outperformance of the technical trading strategies on the Buy-and-Hold strategy, in mean raw excess annual returns (%), underperformances are shown in parentheses. The mean annual return on the B&H portfolio $R_{pB\&H}$ is subtracted from the mean annual return on each of the technical trading strategies R_{pTT_i} listed in row 1: $R_{pTT_i} - R_{pB\&H}$.

RAW EXCESS RETURNS (1)	MA (50,200)	MA (37,200)	MA (22,200)	MA (50,100)	MA (50,200) RF	BB (20,2)	BB (50,2.1)
2000-2009	3.55	3.96	4.12	(1.31)	3.00	10.88	(0.22)
PRE-CRISIS	1.19	1.64	1.89	(4.50)	0.19	8.76	(2.34)
CRISIS	8.92	9.23	9.19	6.02	9.42	15.63	4.57

First of all the annualized mean returns for each portfolio were calculated, and, subsequently the annualized mean B&H return was subtracted from it, such that a basic comparison is possible between technical trading strategies and an investment strategy without trading. From **Table 1** one could see that most technical trading strategies are outperforming the B&H strategy in terms of raw returns, excluding the MA (50,100) and the BB (50,2.1) strategies. Furthermore, from this table it becomes clear that during *Crisis* outperformance is greater (less) than during both the *Pre-Crisis period* and the entire sample period – *2000-2009*. Those returns are not controlled for risk, therefore, before the regressions are executed, a simple risk-adjustment calculation is made by means of the Sharpe Ratio. Which is provided in **Table 2.** The Sharpe Ratio calculates the excess returns per unit of risk, measured through the standard deviation. All technical trading strategies, except BB (50,2.1) outperform the B&H strategy according to the Sharpe Ratio. Where BB (20,2) has the greatest outperformance. During *Crisis* the risk-adjusted returns are again all positive, except the BB (50,2.1) strategy, while the B&H generates a negative Sharpe Ratio in that time period.

After those preliminary findings, results look promising, however, do abnormal returns retain reliably greater than zero after the model has controlled for market risk, size, book-to-market ratio, and price-momentum effect? This is investigated by means of an OLS regression. The results are provided below.

Table 2: Sharpe Ratio for each trading strategy and time period. The portfolio's geometric mean raw excess returns are divided by the standard deviation of the portfolio.

SHARPE RATIO	MA (50,200)	MA (37,200)	MA (22,200)	MA (50,100)	MA (50,200)RF	BB (20,2)	BB (50,2.1)	B&H
2000-2009	0.1030	0.0919	0.1069	0.0202	0.1499	0.3370	-0.0157	0.0178
PRE-CRISIS	0.1175	0.0865	0.1011	0.0090	0.1711	0.3862	0.0117	0.0732
CRISIS	0.0964	0.1031	0.1189	0.0542	0.0841	0.2448	-0.1007	-0.1162

OLS Regression

First the regression analysis was conducted for al MA technical trading strategies for all three risk-adjustment models – CAPM, Fama French 3-factor model, Carhart 4-characteristic model. This table is provided below – **Table 3**. By running the forty-five regressions some interesting preliminary results were found, which will be discussed in this chapter. Secondly regression analysis was conducted for all BB strategy regressions, for investigation of the sign of the intercepts. Again, for all three risk-adjustment models. The results are provided in **Table 4** and discussed below. Both tables include the intercepts/ alphas of all regression models, with next to it the corresponding standard errors, which appear in parentheses. After those technical trading strategy results, the B&H regressions are conducted. Those are the regressions that investigate the performance of the B&H strategy during the three different time periods, from which it is possible to make some simple comparisons with the performance of the technical trading strategies. Those alphas and corresponding standard errors are presented in **Table 5.**

The betas of all variables, the F-value of all models and the R squared are tabulated in **Table 10, 11, 12** and **13** (See Appendix). Whether or not a variable or model is significant is indicated by the following signs: *$p < 0.10$; **$p < 0.05$; ***$p < 0.001$.

With regard to the R squared of the estimated models, it is noticeable that the amount of variance explained by the model varies across models and across portfolios – varying from less than 1% for the MA (50,200) CAPM model Panel B, to more than 89% for the CAR 4-characteristic model panel C. The R squared for the CAR4 model is the highest, which makes sense, as more variables are included in the model. Also during the *Crisis* period the R squared is higher for most technical trading strategies, except the BB (20,2) strategy. This particular strategy does produce overall relatively low R squared numbers. It seems that the

BB (20,2) behave differently in comparison with the other portfolios. With respect to the predictive power of the model as a whole, the F-value for each model is analyzed in **Table 10, 11, 12** and **13**. The models with a significant F-value are most suitable to draw conclusions about hypotheses. Most of the OLS regressions generate significant F-values. Only the MA (50,200) strategy does not contain a significant F-value for Panel A and B. In addition the BB (20,2) strategy has not a significant F-value for Panel C, *Crisis* period. Consequently, most of the regression models are suitable to draw conclusions concerning its parameter coefficients, which will be executed in the next section.

Also the Betas of all variables are provided in **Table 10, 11, 12** and **13**. It is interesting to see that the market excess return beta for the technical trading strategies is in some cases not significant, much closer to zero, and even negative for the Bollinger Bands strategies, in comparison to this particular beta for the B&H model. This makes sense, as the technical trading strategies go short and long continuously, and therefore do not move in accordance with market returns. Logically, the market return beta for the MA (50,200) RF strategy, which does not go short on sell signals, is significantly larger than zero and closer to the B&H market return beta.

4.1 Results

Double-crossover Moving Average strategy **(Table 3)**

The first hypothesis asserts that the MA strategy will not generate abnormal returns. In order to test this hypothesis, the excess returns for the most commonly used parameterization **MA (50,200)** for the *2000-2009* time period, are regressed on the several risk-adjustment models. The intercepts of the MA (50,200) are not significantly different from zero, although they are positive. This is in accordance with the hypothesis. When the MA (50,200) alpha is compared to the benchmark's, B&H, alpha, it becomes clear that the abnormal returns of the CAPM and the CAR4 model are significantly greater than zero at a 10% significance level – 0.0054; 0.0047 respectively – and robust for the *Pre-Crisis* period. Therefore, the MA strategy underperforms the B&H strategy even before transactions costs, which is in accordance with the main literature about the Double Crossover Moving Average strategy. However, according to the efficient market hypothesis the B&H strategy should not generate abnormal returns. A possible explanation for this result is discussed in the limitations. In the next analyses it will be tested whether abnormal returns can be generated through changes in parameterization and by regressing during the crisis.

For testing hypothesis 2 it is investigated whether larger differences between the N-period of the short-term versus the long-term simple moving average generate higher alphas, and, whether a smaller difference in this parameterization generates lower alphas. None of the intercepts are significantly greater than zero, therefore, hypothesis 2 is rejected. However, it is possible to draw conclusions about the direction of the relation – see **Figure 4** in the Appendix. As the alphas are considered, much lower intercepts are generated for **MA (37,200)** and **MA (22,200)** than for the baseline strategy, **MA (50,200)**. On the other hand, **MA (50,100)** generates lower and even negative alphas, which is in line with the hypothesized direction. When this hypothesis is scrutinized during the *Crisis*, the hypothesized direction does hold – see **Figure 5** in the Appendix. In short, hypothesis 2 is rejected, as none of the alphas are significant. Especially as the portfolio alphas move in the opposite direction when the N-period difference for the moving averages increases with respect to the baseline MA strategy. However, when the N-period difference between the long- and short term moving average decreases, the direction of the hypothesis hold, although not significantly.

Hypothesis 3 predicts that an MA strategy, which takes a short position on sell signals generate higher abnormal returns than an MA Strategy that takes on a neutral position at a sell signal. First of all, the Sharpe Ratio draws an opposite conclusions, as this measurement is higher for the **MA (50,200) RF**. Which means that according to the Sharpe Ratio, the **MA (50,200)** strategy is not enough compensated for the extra risk it takes in comparison with the MA (50,200) RF strategy. Furthermore, Jensen's alpha of MA (50,200) RF is significantly above zero for all three risk-adjustment models – 0.0048; 0.0039; 0.0037, respectively, at a 5% significance level. Therefore, hypothesis 3 is rejected. In addition, the hypothesis is significant in the opposite direction, as MA (50,200) RF is generating significantly higher abnormal returns than the MA (50,200) strategy, and, diminishes the outperformance by the B&H strategy. With respect to the FF3F model the MA (50,200) RF strategy is even outperforming the B&H strategy in terms of abnormal returns, as the B&H strategy is not generating abnormal returns significantly greater than zero. As a consequence, hypothesis 3 is rejected.

With respect to hypothesis 4, the performance of the several **MA** strategies is analyzed during ***Pre-Crisis*** and ***Crisis***. Subsequently, those two time-periods are compared to each other. The alphas are not significant, which makes it difficult to draw conclusions about those intercepts. Therefore, hypothesis 4 is rejected. However, it is possible to discuss the hypothesized direction. Analyzing the corresponding alphas on whether higher alphas are generated by the several MA strategies during the crisis compared to pre-crisis reveals mixed results. The FF3F and CAR4 alphas of MA (37,200); MA (22,200); and MA (50,100) reveal higher intercepts during the crisis period. However, MA (50,200) FF3F; CAR4; and MA (50,200) RF, FF3F generate lower alphas during the crisis. The Sharpe Ratio in **Table 2** shows the same pattern. On the

*Table 3: Both raw monthly returns and raw annual returns are tabulated in column two and three. Intercepts are tabulated in columns 4, 5 and 6 for OLS regressions on CAPM, Fama-French 3 factor model, and Carhart 4-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the five different Double-Crossover Moving Average strategies and for the three different time periods. Standard errors appear in parentheses. *p < 0.10. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Portfolio (1)	Raw Monthly Returns (2)	Raw Annual Returns (3)	Intercept from CAPM (4)	Intercept from FF3F (5)	Intercept from CAR4 (6)
Panel A: 2000-2009					
MA (50,200)	0.65	8.02	0.0187 (0.0187)	0.0181 (0.0189)	0.0176 (0.0189)
MA (37,200)	0.68	8.43	0.0013 (0.0028)	0.0005 (0.0028)	-0.0001 (0.0020)
MA (22,200)	0.69	8.59	0.0017 (0.0027)	0.0010 (0.0027)	0.0004 (0.0020)
MA (50,100)	0.26	3.16	-0.0008 (0.0026)	-0.0014 (0.0026)	-0.0019 (0.0022)
MA (50,200) RF	0.60	7.47	**0.0048**** (0.0020)	**0.0039**** (0.0019)	**0.0037**** (0.0018)
Panel B: Pre-Crisis					
MA (50,200)	0.73	9.09	0.0267 (0.0265)	0.0256 (0.0271)	0.0239 (0.0273)
MA (37,200)	0.76	9.55	0.0018 (0.0035)	0.0001 (0.0033)	-0.0019 (0.0023)
MA (22,200)	0.78	9.79	0.0022 (0.0034)	0.0006 (0.0032)	-0.0013 (0.0023)
MA (50,100)	0.28	3.41	-0.0009 (0.0034)	-0.0021 (0.0033)	-0.0038 (0.0026)
MA (50,200) RF	0.65	8.10	0.0055 (0.0026)	0.0037 (0.0023)	0.0032 (0.0022)
Panel C: Crisis					
MA (50,200)	0.44	5.46	-0.0002 (0.0048)	0.0011 (0.0047)	0.0027 (0.0039)
MA (37,200)	0.47	5.76	0.0001 (0.0048)	0.0015 (0.0047)	0.0030 (0.0039)
MA (22,200)	0.47	5.73	0.0007 (0.0046)	0.0020 (0.0046)	0.0033 (0.0040)
MA (50,100)	0.21	2.55	-0.0004 (0.0040)	0.0004 (0.0039)	0.0012 (0.0037)
MA (50,200) RF	0.48	5.95	0.0029 (0.0025)	0.0031 (0.0026)	0.0035 (0.0025)

*Table 4: Both raw monthly returns and raw annual returns are tabulated in column two and three. Intercepts are tabulated in columns 4, 5 and 6 for OLS regressions on CAPM, Fama-French 3 factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the two different Contrarian Bollinger Bands strategies and for the three different time periods. Standard errors appear in parentheses. *p < 0.10; ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Portfolio (1)	**Raw Monthly Returns (2)**	**Raw Annual Returns (3)**	**Intercept from** CAPM (4)	**Intercept from** FF3F (5)	**Intercept from** CAR4 (6)
			Panel A: 2000-2009		
BB (20,2)	1.20	15.35	**0.0088***** (0.0022)	**0.0091***** (0.0022)	**0.0092***** (0.0022)
BB (50,2.1)	0.35	4.25	0.0010 (0.0024)	0.0016 (0.0023)	0.0020 (0.0019)
			Panel B: Pre-Crisis		
BB (20,2)	1.29	16.67	**0.0093***** (0.0024)	**0.0098***** (0.0024)	**0.0104***** (0.0023)
BB (50,2.1)	0.45	5.57	0.0014 (0.0031)	0.0026 (0.0030)	**0.0042*** (0.0024)
			Panel C: Crisis		
BB (20,2)	0.96	12.17	0.0075 (0.0048)	0.0078 (0.0050)	**0.0087*** (0.0048)
BB (50,2.1)	0.09	1.11	-0.0001 (0.0032)	-0.0008 (0.0032)	-0.0015 (0.0030)

*Table 5: Both raw monthly returns and raw annual returns are tabulated in column two and three. Intercepts are tabulated in columns 4, 5 and 6 for OLS regressions on CAPM, Fama-French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the three different time periods. Standard errors appear in parentheses. *p < 0.10. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Portfolio (1)	Raw Monthly Returns (2)	Raw Annual Returns (3)	Intercept from CAPM (4)	Intercept from FF3F (5)	Intercept from CAR4 (6)
			Panel A: 2000-2009		
B&H	0.36	4.47	**0.0054*** (0.0028)	0.0044 (0.0027)	**0.0047*** (0.0026)
			Panel B: Pre-Crisis		
B&H	0.64	7.90	**0.0069*** (0.0036)	0.0052 (0.0035)	**0.0062*** (0.0033)
			Panel C: Crisis		
B&H	-0.29	-3.47	0.0015 (0.0035)	0.0005 (0.0033)	-0.0004 (0.0030)

contrary, when the raw excess returns are compared from **Table 1** all MA strategies produce greater annual returns – compared to the B&H strategy – during crisis in comparison with the pre-crisis period. In short, during crises the MA strategy performs better than pre-crisis, except the (50,200) parameterizations, although insignificantly.

Alternative Contrarian Bollinger Bands Strategy **(Table 2)**

The fifth hypothesis predicts that the BB strategy does not generate abnormal returns, which is statistically tested by means of Jensen's Alpha. The alphas of all three risk-adjustment models of the **BB (20,2)** portfolio are highly significant above zero at the 1% level – 0.0088; 0.0091; 0.0092 respectively. The abnormal returns are robust over the three different time periods for the CAR4 model. This is also revealed in **Table 1** and **2** in terms of raw excess returns and Sharpe Ratio, respectively**.** Besides, Jensen's alpha is higher than the, significant, B&H benchmark. Therefore, for BB (20,2), hypothesis 5 is rejected: Namely, the Bollinger Bands strategy does generate abnormal returns. This strategy generates even greater abnormal returns than the B&H strategy when the magnitude of both intercepts is analyzed. Especially, within the FF3F regression model, the B&H strategy does not generate significant abnormal returns, while the BB strategy does. The opposite holds for the **BB (50,2.1)** regressions, which are insignificant and lower than the alphas of the B&H strategy. The alpha of this particular trading strategy does not score high on robustness as the CAR4 alpha pre-crisis is significantly positive ($p < 0.10$) and during crisis insignificantly negative. The change of signs is also shown in **Table 1** and **2**. In short, hypothesis 5 is rejected as the BB (20,2) strategy does generate abnormal returns.

This brings us to hypothesis 6, which asserts that a BB strategy with a larger N-period for the simple moving average generates lower abnormal returns than with a smaller N-period. The **BB (20,2)** strategy produces significant positive alphas for all three risk-adjustment models at the $p < 0.001$ level – **Table 4**, while the **BB (50,2.1)** alphas are insignificant and lower, which is in favor of the hypothesis. Furthermore the strategy with the smaller N-period simple moving average generates both much higher Sharpe Ratios and Raw Excess Returns. Those findings are robust as BB (20,2) outperforms BB (50,2.1) in all time periods, although, not significantly during crisis – except CAR4 model. However, in that period the larger N-period simple moving average generates insignificant negative alphas for both FF3F and CAR4. To summarize, hypothesis 6 is accepted.

With respect to hypothesis 7, the performance of both **BB** strategies is analyzed during the periods ***Pre-Crisis*** and ***Crisis***. Subsequently, those two time-periods are compared to each other. The Raw Excess

Returns over the B&H strategy increase sharply during the Crisis Period in comparison with the Pre-Crisis Period – **Table 1**. To the contrary, The BB (20,2) strategy generates positive and significant alphas for all risk-adjustment model during the pre-crisis period at the 1% significance level – 0.0093; 0.0098; 0.0104 respectively. The BB (50,2.1) strategy reveals also a positive and significant alpha for the CAR4 regression during the pre-crisis period at the 10% level – 0.0042**.** During the Crisis period those alphas are, in contradiction with the hypothesis, closer to zero and insignificant. And, with respect to the BB (50,2.1) strategy, even insignificantly negative. This is confirmed by the Sharpe Ratio in **Table 2**. On the other hand, under the CAR4 model, the BB (20,2) strategy generates a significant positive alpha during *Crisis* at the 10% level – 0.0087. While the B&H strategy does not generate an intercept significantly different from zero. While B&H did produce a significant Jensen's Alpha *Pre-Crisis*. Despite that, hypothesis 7 is rejected.

Bull and Bear market

As both technical trading strategies do not generate abnormal returns during the *Crisis* period, and, even underperform the *Pre-Crisis* period with respect to the Bollinger Bands strategy, this subsection will investigate whether the MA strategy and the BB strategy outperform the B&H strategy during 'Bull' or 'Bear markets'. Those sample periods were defined in the methodological section. The abnormal returns in terms of Jensen's Alpha are presented in **Table 6**. The Carhart four-characteristic model generates significantly negative abnormal returns for the MA strategy – MA (50,200) 0.0046 $p< 0.05$; MA (37,200) 0.0043 $p< 0.10$; MA (22,200) 0.0039 $P< 0.10$ – and when regressed on the CAPM, positive abnormal returns for the MA strategy which takes a neutral position on sell signals – MA (50,200) RF 0.0074 $p< 0.10$ – for the Bull market period. While the BB (20,2) strategy produces significantly positive abnormal returns for this period at a 5% significance level – 0.0068. The alpha of the B&H strategy does not significantly differ from zero, except the CAPM model. In short *the MA short sell strategies generate negative abnormal returns in bull markets, and underperform the B&H strategy. On the other hand, the BB strategy generates positive abnormal returns in bull markets, and thus, outperforms the B&H strategy.*

During the Bear market all different MA strategies are generating significantly negative abnormal returns at a 5% significance level for all three risk-adjustment models. On the other hand, the BB strategies generate significantly positive abnormal returns at the 5% level for all three risk-adjustment models – 0.0186; 0.0192; 0.0191, respectively. While at the same time the B&H intercepts do not differ significantly from zero. Therefore, *the MA strategy generates negative returns during bear markets, and consequently, underperforms the B&H strategy. While the BB strategy generates positive abnormal returns during bear markets, and outperforms the B&H strategy.*

*Table 6: Both raw monthly returns and raw annual returns are tabulated in column two and three. Intercepts are tabulated in columns 4, 5 and 6 for OLS regressions on CAPM, Fama-French 3 factor model, and Carhart 4-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for all trading strategies and for the Bull- and Bear market time periods. Standard errors appear in parentheses. *$p < 0.10$ **$p < 0.05$. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero. All returns are gross of transaction costs.*

Portfolio (1)	**Raw Monthly Returns (2)**	**Raw Annual Returns (3)**	**Intercept from** CAPM (4)	FF3F (5)	CAR4 (6)
			Panel D: Bull Market		
MA (50,200)	0.73	9.05	0.0006 (0.0037)	-0.0037 (0.0034)	**-0.0046**** (0.0022)
MA (37,200)	0.73	9.10	0.0009 (0.0036)	-0.0034 (0.0033)	**-0.0043*** (0.0022)
MA (22,200)	0.72	8.99	0.0011 (0.0034)	-0.0030 (0.0032)	**-0.0039*** (0.0021)
MA (50,100)	0.37	4.54	-0.0016 (0.0032)	-0.0033 (0.0033)	-0.0041 (0.0026)
MA (50,200) RF	1.43	18.57	**0.0074*** (0.0041)	0.0004 (0.0029)	0.0002 (0.0029)
BB (20,2)	0.84	10.61	**0.0059**** (0.0020)	**0.0066**** (0.0020)	**0.0068**** (0.0020)
BB (50,2.1)	0.28	3.42	0.0001 (0.0029)	0.0027 (0.0030)	0.0033 (0.0024)
B&H	2.19	29.72	**0.0121**** (0.0054)	0.0043 (0.0044)	0.0048 (0.0043)
			Panel E: Bear Market		
MA (50,200)	0.74	9.28	**-0.0118**** (0.0043)	**-0.0124**** (0.0048)	**-0.0118**** (0.0039)
MA (37,200)	0.77	9.67	**-0.0118**** (0.0042)	**-0.0124**** (0.0048)	**-0.0118**** (0.0038)
MA (22,200)	0.77	9.60	**-0.0118**** (0.0042)	**-0.0122**** (0.0048)	**-0.0166**** (0.0038)
MA (50,100)	-0.00	-0.04	**-0.0121**** (0.0042)	**-0.0133**** (0.0042)	**-0.0130**** (0.0042)
MA (50,200) RF	-0.48	-5.62	**-0.0043*** (0.0021)	**-0.0049**** (0.0023)	**-0.0047**** (0.0021)
BB (20,2)	1.27	16.48	**0.0186**** (0.0077)	**0.0192**** (0.0087)	**0.0191**** (0.0090)
BB (50,2.1)	-0.04	-0.44	**0.0083**** (0.0034)	**0.0100**** (0.0035)	**0.0098**** (0.0035)
B&H	-2.50	-26.19	-0.0043 (0.0047)	-0.0043 (0.0051)	-0.0046 (0.0051)

Buy-and-Hold

For the 2000-2009 sample period, the alphas for the Buy-and-Hold regressions are slightly significant for the CAPM and CAR4. Which is contradictory to the efficient market hypothesis. During Bull markets the intercepts are insignificant, except for the CAPM regression. In the Bear market period Jensen's Alpha is negative and insignificant. Therefore, one could conclude that the BB (20,2) strategy is outperforming the B&H strategy during both bear and bull markets.

4.2 Transaction Costs

All returns presented thus far have been gross of transactions costs associated with the bid-ask spread, brokerage commissions, and the market impact of trading. As you can see from **Table 7,** the most profitable trading strategy, BB (20,2), also contains by far the most trading signals. The advantage of this large amount of trading signals is that this trading strategy recognizes trend reversals at an earlier stage. The downside is, that all those trades come at a cost. According to the methodology of Barber et al. (2001), the round-trip transaction costs accumulate to 1.95%. However, with 45 trades on average for each stock in the period 2000-2009 transactions costs will be excessive, and, let probably disappear the abnormal returns of the BB (20,2) strategy. Decreasing the responsiveness of the BB strategy through increasing N, reduces transactions costs, however, trading less frequently also reduces abnormal gross returns significantly.

Table 7: mean number of trading signals per stock, for each short sell technical trading strategy. Mean number of trades per year appear in parentheses.

Trading Strategy	**MA (50,200)**	**MA (37,200)**	**MA (22,200)**	**MA (50,100)**	**BB (20,2)**	**BB (50,2.1)**
Transactions 2000-2009	11 (1.1)	12 (1.2)	15 (1.5)	21 (2.1)	45 (4.5)	19 (1.9)

This is revealed in **Table 8** where the annual turnover per portfolio/technical trading strategy is provided with the corresponding annual transaction costs. It becomes clear that for the most profitable trading strategy, BB (20,2), the annual transaction costs are the largest. One way to lower the transaction costs is to increase the n-period for calculating the simple moving average, BB (50,2.1). As you could see from the table, annual transaction costs for this strategy decrease to 3.69%, however, significant abnormal returns disappear as well. The BB (20,2) strategy generated between 11.09% and 11.61% annual abnormal returns.

Therefore, when subtracting the 8.79% transaction costs from it, returns remain positive, however, the returns will probably not differ significantly from zero anymore. On the other hand, the B&H strategy does not suffer from large transaction costs, and are negligible for a 10 year period. The B&H strategy generates abnormal returns between 5.79% and 6.68%, which is therefore net of transaction costs, greater than the most profitable technical trading strategy in this study, BB (20,2).

Table 8: annual turnover for each portfolio in percentages in row 2, with in row 3 the annual transaction costs calculated through multiplying the annual turnover with the round-trip transaction costs of 1.95%

Trading Strategy	**MA (50,200)**	**MA (37,200)**	**MA (22,200)**	**MA (50,100)**	**BB (20,2)**	**BB (50,2.1)**
Annual Turnover (%)	108.27	119.31	145.28	212.29	450.67	189.16
Annual Transaction Cost (%)	2.11	2.33	2.83	4.14	8.79	3.69

Although, abnormal net returns are probably not significantly larger than zero, an investor who is considering buying or selling a stock is, *Ceteris Paribus*, better off purchasing and selling shares indicated through the BB (20,2) signals than by their own subjective, biased decisions as studied in the paper of Barber and Odean (2000).

In order to test whether it is possible to generate abnormal returns net of transaction costs, the BB (20,2) strategy transaction costs are calculated for both the Bull- and Bear market periods. Especially, as this strategy revealed the greatest abnormal returns during Bear market – between 1.869% and 1.92% monthly or between 24.75% and 25.64% annually. The number of transactions (annually), Annual Turnover and Annual Transaction Costs for the several BB (20,2) sample periods are presented in **Table 9**.

Table 9: annual turnover for the Bull- and Bear market periods for the BB (20,2) strategy, and the corresponding annual transaction costs calculated through multiplying the annual turnover with the round-trip transaction costs of 1.95%. The mean number of trading signals per stock, for each time period. Mean number of trades per year appear in parentheses.

BB (20,2) strategy sample periods	**Transactions**	**Annual Turnover (%)**	**Annual Transaction Costs (%)**
Bull Market	22 (5.2)	519.97	10.14
Bear Market	9 (5.4)	541.01	10.55

As becomes clear from the table, the Bear market sample would have had annual transaction costs of 10.55%, which are the largest transaction costs this study encountered thus far, implying frequent trading during Bear market. When this costs are subtracted from the annual abnormal returns of this period, abnormal returns net of transaction costs between 14.20% and 15.09% annually are generated by the BB (20,2) strategy. This is larger than the B&H strategy annual abnormal returns which differs between 5.79% and 6.68%. As a result the Bollinger Bands strategy outperforms the B&H strategy during the Bear market net of transaction costs.

Based on the analytical results, conclusions can be drawn, managerial implications can be suggested, limitations can be mentioned and further research can be suggested. This will be treated in the following chapter.

Chapter 5: Conclusion

This Master Thesis investigated under which conditions technical trading strategies could generate positive abnormal returns, and in addition, compared the abnormal returns to the B&H strategy. This was done through hypothesis testing. Based on these key results, managerial implications are provided. Besides that, a paragraph is allocated to describe the theoretical contribution of this study. Finally, limitations are discussed and suggestions for further research are provided.

5.1 Summary of key results

In order to answer the problem statement this study selected two technical trading strategies. By means of several modifications for each strategy, certain conditions were created under which those strategies were expected to generate abnormal returns. First of all, the MA (50,200), and all other MA short sell strategies did not generate abnormal returns, which is in accordance with literature. However, when the MA trader takes a neutral position on a sell signal, instead of a short position, this particular technical trading strategy generates positive abnormal returns - 0.39% per month or 4.78% per year. While under the Fama French 3-factor model, B&H strategy does not have a significant alpha, and thus outperforms the B&H strategy.

Abnormal returns were also produced by the Bollinger Bands strategy (20,2) with N = 20 for the calculation of the simple moving average and a standard deviation of 2 for determining the upper- and lower bands. With a significant alpha at the 1% level of 0.0091 for the 3-factor, this strategy performs 0,91% per month better than the risk-adjustment model would have predicted. Which corresponds to 11.48% per year. This strategy also outperforms the BB (50,2.1) strategy. Next, the BB (20,2) strategy has also a significant positive intercept during crisis. The B&H strategy does not generate abnormal returns during *Crisis*, therefore, assuming 0% abnormal return for the B&H strategy, this strategy outperforms the B&H strategy with 0.87% with equals 10.95% annually.

During both Bull and Bear markets, the MA strategies generate significantly negative abnormal returns, while the BB strategies generate positive and significant abnormal returns during those periods. Therefore, it seems that during periods of steady up- or downward trends the BB strategy is generating significant abnormal returns compared to the B&H strategy. For example, during the bear market period, the BB strategy produces monthly abnormal returns of 1.91%, which corresponds to 25.49% annually, under the CAR4 model. While the B&H strategy generates even negative abnormal returns, although insignificant.

During the bull market, monthly abnormal returns were equal to 0.68% or 8.47% annually. Therefore, bear markets are better suited for the BB strategy compared to bull markets. Concerning the Bull and Bear markets, it is very interesting to see that during periods with clear downward or upward trends the MA strategies produce negative abnormal returns, while the BB strategies generate positive abnormal returns. This difference is caused, because the MA strategy speculates on trends, while the BB strategy speculates on mean reversal.

Therefore, technical trading strategies do generate abnormal returns when the alternative to the Contrarian Bollinger Bands technical trading strategy is applied, and, with the right parameterization. In addition, the sample period plays an important role, as during periods with clear downward- or upward trends, this strategy even performs better. As a result, based on the statistical hypothesis tests, it is possible to draw conclusions with respect to the problem statement:

The Double Crossover Moving Average strategy (50,200) does not generate positive abnormal returns, except when the MA trader takes a neutral position on sell signals.

*The (*alternative *to the) Contrarian Bollinger Bands trading strategy (20,2) generates positive abnormal returns. During bull markets those abnormal returns are even greater.*

5.2 Managerial implications

As was mentioned in the Problem Indication, individual investors lose value relative to the B&H strategy, even before transaction costs, due to excessive trading and behavioral biases like for example overconfidence (Barber & Odean, 2000). Furthermore, sensation seeking plays an important role (Grinblatt & Keloharj, 2009). Which is the reason that investors prefer a 'trading' strategy to the B&H strategy. A technical trading strategy could overcome this problem, as such a strategy provides the investor with objective trading signals, instead of subjective, biased signals from the market or trading on intuition. This study concluded that a particular alternative to the Contrarian Bollinger Bands trading strategy generates positive abnormal returns, although before transaction costs. Those abnormal returns were even greater than the abnormal returns of the B&H strategy. Therefore, behavioral biased and sensation seeking investors can reduce their losses by applying the BB strategy, as this strategy generates positive abnormal returns, instead of losing value asserted by abovementioned study, before transaction costs.

5.3 Theoretical Contribution

This study contributed to the existing literature in several ways. First of all this study investigated the profitability of technical trading strategies in the European stock market. The same sample was used as the paper of Ebert and Hilpert (2014), who concluded that applying the MA strategy skews the distribution to the right, which is attractive for investors that are less than fully rational. This Master Thesis also tried to provide a trading strategy to those investors who are less than fully rational and prefer sensation seeking. Therefore, this study tested the same sample on profitability for three different time periods and three different risk adjustment models. None of the short-sell modifications significantly generated positive abnormal returns, which confirms the general theory about the Double Crossover Moving Average strategy. Contradictory to the main literature, the MA strategy that takes a neutral position at a sell signal, generates abnormal returns.

Furthermore, the Bollinger Bands strategy is also applied on the same dataset, which contributes to the existing literature, as there exist not much literature concerning this technical trading strategy. Especially, concerning the alternative to the Contrarian The Bollinger Bands strategy, used in this study. The BB strategy generates significant abnormal returns, and, produce higher returns than the B&H strategy, before transaction costs. This is in contrast with Barber and Odean (2000) who concluded that excessive trading by investors will underperform the B&H strategy, even before transaction costs. Therefore, this alternative to the Contrarian Bollinger Bands strategy is an objective technical trading strategy that takes into account sensation seeking in terms of frequently trading.

In addition, the SMB, HML and Mom factors were not available for the European stock market. This study calculated those factors itself through constructing portfolios from the Stoxx Europe 600 Index, as explained in the methodology. Consequently, the calculated factors fit the sample of this study better than when the standard factors were used. Besides, those factors could be used for further research.

5.4 Limitations and Further research

Limitations

First of all, this study used equal-weighted portfolio compositions, in which the small capitalization stocks are more heavily represented in the portfolios. According to the literature, those stocks capture higher risk and consequently have higher expected returns. When value-weighted portfolios were created, different returns would have been generated. Therefore, the equal-weighted portfolio could be an explanation for the abnormal returns of the B&H strategy under the CAPM regressions, as abnormal returns disappear when the FF3F model controls for size effects.

Furthermore, generalizability is a limitation as well. Only two technical trading strategies with a limited amount of modifications were analyzed in this Master Thesis. Which makes it impossible to conclude about profitability of technical trading in general. Also the sample period of the data was limited, as only one decade was scrutinized, which is less reliable in terms of robustness. Besides, the particular technical trading strategies are only tested on the European STOXX Euro 600 index, which reduces generalizability on other stock markets or other securities.

Another limitation could be data snooping. This phenomenon is the problem of determining whether the apparent performance of a particular trading rule is genuine and not simply due to luck and the abuse of data mining (Bajgrowicz & Scaillet, 2012). As already mentioned in the theory, the bull/bear market analysis suffered from data mining. In addition, it could be that the Bollinger Bands strategy just by chance fits this particular sample period, therefore, this sample period was divided into three different time periods, and eventually even five periods. It would even be better to test the trading strategies on the 20th century period. Furthermore, in order to overcome the data snooping problem, it was beforehand determined which technical trading strategies, including the different parameterizations, would be used in this study.

According to Bajgrowicz and Scaillet (2012), another concern is how investors could beforehand determine what the best performing technical trading strategy is in the future. Especially, because this study wanted to investigate whether technical trading strategies could assist investors in their trading behavior. Investors should beforehand know, based on historical data, which technical trading strategy to use, and whether they should use, in this case, the Bollinger Bands strategy. A persistence test could demonstrate whether the performance of a particular trading strategy persists over time. Consequently, investors learn what strategy to use for certain periods – based on antecedents from historical data.

Further Research

As this Master Thesis concluded that the alternative to the Contrarian Bollinger Bands trading strategy generated positive abnormal returns, it is interesting to investigate more modifications, parameterizations, time periods, and other samples with respect to this strategy. Especially, as literature concerning Bollinger Bands is still relatively rare.

In addition, further research could investigate whether insignificant abnormal returns of the MA strategy could be improved through increasing the quality and quantity of the sample. For example through regressing on industry. Or using an emerging market sample, as those markets are less efficient and thus the random walk probably will not apply on such markets, which is in favor of technical trading strategies that chase on trends. With respect to MA strategies, it is especially interesting to further investigate the MA (50,200) strategy, as it generated the highest insignificant alphas during the *2000-2009* period and the *Pre-Crisis* period. In addition, this strategy indicated on average the lowest amount of trading signals, which increases returns net of transaction costs.

Besides it is recommended to test performance of technical trading during bull and bear markets on other samples and time periods. Namely, in those periods, the MA strategy was generating negative abnormal returns, while the BB strategy generated positive abnormal returns, which accentuated the difference between both technical trading strategies: trend chasing MA strategy; reversal speculating BB strategy. For this study, those results could be addressed to data mining. Investors who want to choose a well-suited technical trading strategy are obviously not able to do this. Therefore, it could be interesting for further research to test whether it is possible to predict such trends. Sentiment could be a decent variable for such a study. Schmeling (2009) asserts that consumer confidence as a proxy for sentiment can predict future returns.

With regard to the coefficient of the SMB it is interesting that it has a negative (significant) sign for the BB strategies, while the MA strategies reveal positive (significant) signs for this particular coefficient – (**See Appendix**). Probably, small capitalization stocks perform worse than expected when the BB strategy is applied on them compared to the MA strategy. A reasonable argumentation for this could be that, as the BB strategy speculates on overbought (oversold) prices to reverse to their fundamental value, the small capitalization stocks are less suited for such a strategy. Namely, small caps are expected to be less efficient and less transparent, therefore, investors tend to remain their position in overbought shares due lack of knowledge of the fundamental value and sentiment, which limits the possibility of arbitrage, also in the long-term (Schleifer & Vishny, 1997). Consequently, this makes predicting reversals for the BB strategy more difficult. Further research could investigate the difference in performance between small- and large capitalization firms.

Finally, other technical trading strategies could be investigated in order to provide individual irrational investors with an investment tool, which generates higher abnormal returns than their current subjective, behavioral biased trading patterns.

References

Al-Khazali, O.M., Ding, D.K., & Pyun, C.S. (2007). A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit. *The Financial Review, 42,* 303-317.

Bajgrowicz, P.G., & Scaillet, O. (2012). Technical Trading Revisited: False Discoveries, Persistence Tests, and Transaction Costs. *Journal of Financial Economics, 106*, 473-491.

Barber, B.M., & Odean, T. (2000). Trading Is Hazardous to Your Wealth:The Common Stock Investment Performance. *The Journal of Finance, 2,* 773-806.

Barber, B.M., Lehavy, R., McNichols, M., & Trueman, B. (2001). Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. *The Journal of Finance, 56 (2)*, 531-563.

Bodie, Z., Kane, A., & Marcus, A.J. (2014). *Investments* (10th ed.). New York, NY: McGraw-Hill.

Bollinger, J. (2002). *Bollinger on Bollinger Bands*. New York, NY: McGraw-Hill.

Brown, S.J., Goetzmann, W.N., & Kumar, A. (1998) The Dow theory: William Peter Hamilton's track record reconsidered. *Journal of Finance, 53*, 1311–1333.

Carhart, M.M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52,* 57-82.

Chaudhuri, K., & Wu, Y. (2003). Random walk versus breaking trend in stock prices: Evidence from emerging markets. *Journal of Banking & Finance, 27,* 575-592.

Chuen, D.L.K., & Gregorio, G.N. (2014). *REIT's, Trading, and Fund Performance* (2nd ed.). San Diego, CA: Elsevier.

Dhar, R., & Zhu, N. (2006). Up Close and Personal: Investor Sophistication and the Disposition Effeect. *Management Science, 52 (5)*, 726-740.

Ebert, S., & Hilpert, C. (2014). The Trend Is Your (Imaginary) Friend – A Behavioral Perspective on Technical Analysis. *Not published.*

Fama, E.F., & French, K.R. (1993). Common Risk Factors in the Returns on Stock and Bonds. *Journal of Financial Economics, 33,* 3-56.

Fernandéz-Rodriquez, F., González-Martel, C., & Sosvilla-Rivero, S. (2000). On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market. *Economic Letters, 69,* 89-94.

Gençay, R. (1998a). The predictability of security returns with simple technical trading rules. *Journal of empirical Finance, 5*, 347-359.

Gençay, R. (1998b). Optimization of technical trading strategies and the profitability in security markets. *Economics Letters, 59,* 249-254.

Glaser, M., & Weber, M. (2007). Overconfidence and Trading Volume. *Geneva Risk Insurance Review, 32,* 1-36.

Grinblatt, M., & Keloharju, M. (2009). Sensation Seeking, Overconfidence, and Trading Activity. *The Journal of Finance, 64 (2),* 549-578.

Guasekarage, A., & Power, D.M. (2001) The Profitability of Moving Average Trading Rules in South Asian Stock Markets, *Emerging Markets Review, 2 (1),* 17-33.

Kannan, K.S., Sekar, P.S., Sathik, M.M., & Arumugam, P. (2010). Financial Stock Market Forecast using Data Mining Techniques. *Proceedings of the International MultiConference of Engineers and Computer Scientists. 1.*

Lento, C., & Gradojevic, N. (2007). The Profitability Of Technical Trading Rules: A combined Signal Approach. *Journal of Applied Business Research, 23 (1),* 13-28.

Leung, J., & Chong, T. (2003). An Empirical Comparison of Moving Average Envelopes and Bollinger Bands. *Applied Economics Letters, 10,* 339-341.

Liu, W., Huang, X., & Zheng, W. (2006). Black-Scholes' Model and Bollinger bands. *Physica, A371,* 565-571.

Moskowitz, T.J., Ooi, Y.H., & Pedersen, L.H. (2012). Time Series Momentum. *Journal of Financial Economics, 104,* 228-250.

Park, C.H., Irwin, S.H. (2007). What do we know about the Profitability of Technical Analysis? *Journal of Economic Surveys 21*, 786–826.

Pätäri, E., & Vilska, M. (2014). Performance of moving average trading strategies over varying stock market conditions: the Finnish evidence. *Applied Economics, 46 (24),* 2851-2872.

Potvin, J.Y., Soriano, P., & Vallée, M. (2004). Generating trading rules on the stock markets with genetic programming. *Computers & Operations Research, 31,* 1033-1047.

Saunders, M., & Lewis, P. (2012). *Doing Research in Business & Management: An Essential Guide to Planning Your Project.* Harlow, England: Prentice Hall.

Schleifer, A., & Vishny, R. (1997). The Limits of Arbitrage. *Journal of Finance*, *52 (1)*, 35-55.

Schmeling, M. (2009). Investor Sentiment and stock returns: Some international evidence. *Journal of Emperical Finance*, 394-408.

Smith, G., & Ryoo, H.J. (2003). Variance ratio tests of the random walk hypothesis for European emerging stock markets. *The European Journal of Finance, 9,* 290-300.

Snow, C. (1994). Field Research Methods in Strategic Management: Contributions to Theory Building and Testing. *Journal of Management Studies, 31 (4),* 457.

Statman, M., Thorley, S., & Vorking, K. (2006). Investor Overconfidence and Trading Volume. *The Review of Financial Studies, 19 (4),* 1.

Websites:

STOXX® Europe 600. (n.d.). Retrieved on 13th November, on http://www.stoxx.com/indices/index_information.html?symbol=SXXP

Appendix

Figure 4: Intercepts of the Carhart four-characterstic model during the 2000-2009 sample period. The monthly intercepts are graphically represented for each of the four Double-Crossover Moving Average (Short Sell) strategies.

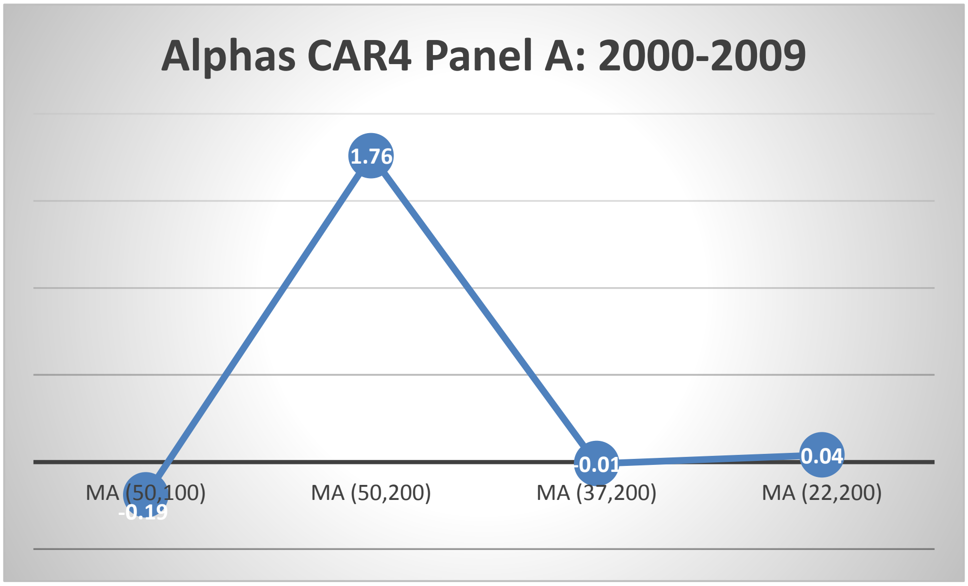


Figure 5: Intercepts of the Carhart four-characterstic model during the Crisis sample period. The monthly Intercepts are graphically represented in percentages per month for each of the four Double-Crossover Moving Average (Short Sell) strategies.

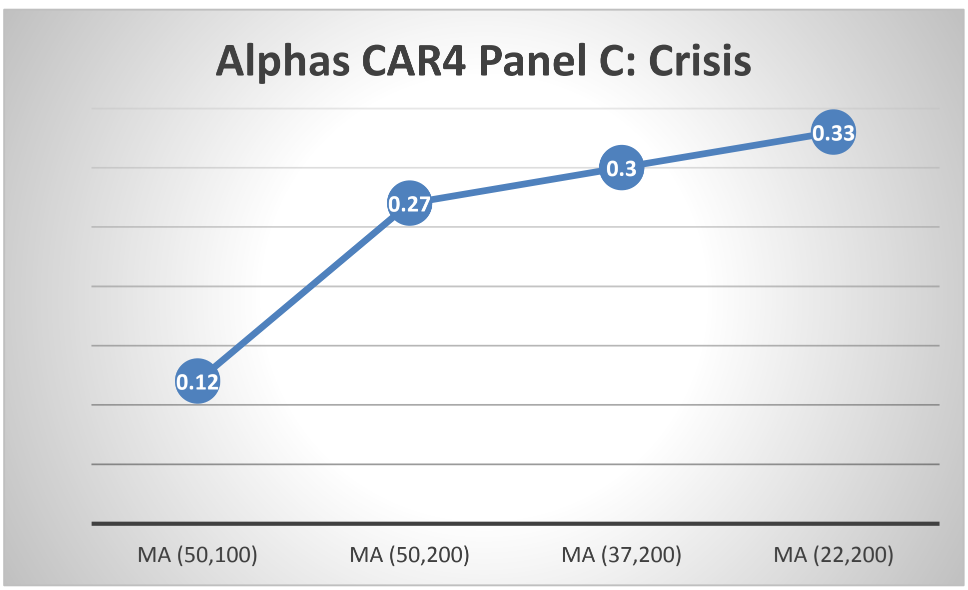


*Table 10: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the MA (50,200) and the MA (37,200) strategies on the three different time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	MA (50,200) CAPM	MA (50,200) FF3F	MA (50,200) CAR4	MA (37,200) CAPM	MA (37,200) FF3F	MA (37,200) CAR4
			Panel A: 2000-2009			
R_{pt} - R_{ft}	-0.3969	-0.2625	-0.0764	**-0.3402*** **	**-0.2848*** **	-0.0599
SMB	-	0.7321	0.6909	-	0.1735	0.1237
HML	-	-0.2318	-0.1982	-	0.1509	**0.1916** **
Mom	-	-	0.3345	-	-	**0.4044*** **
F-Value	1.2135	0.6644	0.6967	**39.4906*** **	**16.3311*** **	**48.6728*** **
R-Square	0.0102	0.0169	0.0237	0.2507	0.2969	0.6287
			Panel B: Pre-Crisis			
R_{pt} - R_{ft}	-0.4546	-0.3922	-0.2286	**-0.3392*** **	**-0.1888** **	0.0067
SMB	-	0.8116	0.8491	-	0.0082	0.0530
HML	-	-0.4156	-0.4930	-	**0.4181** **	**0.3256** **
Mom	-	-	0.3633	-	-	**0.4339*** **
F-Value	0.6179	0.3731	0.3842	**20.0346*** **	**12.1144*** **	**39.7104*** **
R-Square	0.0075	0.0138	0.0191	0.1964	0.3124	0.6678
			Panel C: Crisis			
R_{pt} - R_{ft}	**-0.3565*** **	**-0.2415** **	-0.0908	**-0.3432*** **	**-0.2230** **	-0.0776
SMB	-	0.3651	0.2318	-	0.3826	0.2540
HML	-	-0.2785	-0.0923	-	-0.2904	-0.1109
Mom	-	-	**0.3082*** **	-	-	**0.2972*** **
F-Value	**22.3002*** **	**8.8989*** **	**13.7895*** **	**20.8834*** **	**8.6228*** **	**12.9555*** **
R-Square	0.3961	0.4548	0.6402	0.3805	0.4470	0.6257

*Table 11: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the MA (22,200) and the MA (50,100) strategies on the three different time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	MA (22,200) CAPM	MA (22,200) FF3F	MA (22,200) CAR4	MA (50,100) CAPM	MA (50,100) FF3F	MA (50,100) CAR4
			Panel A: 2000-2009			
R_{pt} - R_{ft}	**-0.3429*****	**-0.2898*****	-0.0760	**-0.2540*****	**-0.2120*****	-0.0348
SMB	-	0.1680	0.1206	-	0.1301	0.0908
HML	-	0.1415	**0.1801****	-	0.1179	**0.1499***
Mom	-	-	**0.3844*****	-	-	**0.3185*****
F-Value	**42.8354*****	**17.3829*****	**47.5974*****	**24.8677*****	**10.1418****	**24.8842*****
R-Square	0.2663	0.3101	0.6234	0.1741	0.2078	0.4640
			Panel B: Pre-Crisis			
R_{pt} - R_{ft}	**-0.3453*****	**-0.2058****	-0.0172	**-0.3129*****	**-0.2083****	-0.0332
SMB	-	0.0113	0.0546	-	0.0723	0.1125
HML	-	**0.3850****	**0.2957****	-	**0.2422***	0.1594
Mom	-	-	**0.4187*****	-	-	**0.3886*****
F-Value	**22.2831*****	**12.4380*****	**39.3175*****	**18.3645*****	**8.4879****	**24.5151*****
R-Square	0.2137	0.3181	0.6656	0.1830	0.2414	0.5538
			Panel C: Crisis			
R_{pt} - R_{ft}	**-0.3416*****	**-0.2243****	-0.0913	**-0.1812****	-0.1113	-0.0333
SMB	-	0.3977	0.2801	-	0.0237	-0.0453
HML	-	-0.2589	-0.0945	-	**-0.3658****	-0.2694
Mom	-	-	**0.2720****	-	-	**0.1595***
F-Value	**21.7429*****	**8.8696*****	**12.0645*****	**8.2440*****	**4.4928****	**4.9768****
R-Square	0.3901	0.4540	0.6089	0.1952	0.2964	0.3910

*Table 12: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the MA (50,200) RF, and the BB (20,2) strategies on the three different time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	**MA (50,200) RF CAPM**	**MA (50,200) RF FF3F**	**MA (50,200) RF CAR4**	**BB (20,2) CAPM**	**BB (20,2) FF3F**	**BB (20,2) CAR4**
			Panel A: 2000-2009			
R_{pt} - R_{ft}	**0.2069*** **	**0.2666*** **	**0.3311*** **	**0.0930** **	0.0537	0.0398
SMB	-	**0.1846** **	**0.1703** **	-	**-0.1724* **	**-0.1693* **
HML	-	**0.1671** **	**0.1788** **	-	-0.0123	-0.0148
Mom	-	-	**0.1161** **	-	-	-0.0250
F-Value	**28.8903*** **	**17.5535*** **	**16.8967*** **	**4.7310** **	**3.0249** **	**2.3368* **
R-Square	0.1967	0.3122	0.3702	0.0385	0.0762	0.0752
			Panel B: Pre-Crisis			
R_{pt} - R_{ft}	**0.2582*** **	**0.4196*** **	**0.4647*** **	**0.1175** **	0.0825	0.0185
SMB	-	0.0939	0.1042	-	**-0.2469** **	**-0.2616** **
HML	-	**0.3866*** **	**0.3652*** **	-	0.0815	0.1118
Mom	-	-	**0.1002** **	-	-	**-0.1422** **
F-Value	**20.5894*** **	**19.7506*** **	**16.7514*** **	**4.8693** **	**3.8179** **	**5.4466*** **
R-Square	0.2007	0.4255	0.4589	0.0561	0.1252	0.2162
			Panel C: Crisis			
R_{pt} - R_{ft}	**0.1409** **	**0.1584** **	**0.2062*** **	0.0609	0.0842	0.1729
SMB	-	0.1400	0.0977	-	-0.0198	-0.0982
HML	-	0.0417	0.1007	-	-0.1494	-0.0399
Mom	-	-	**0.0977* **	-	-	0.1813
F-Value	**12.2952*** **	**4.2565** **	**4.4587** **	0.6501	0.3654	1.2308
R-Square	0.2656	0.2852	0.3652	0.0188	0.0331	0.1370

*Table 13: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the BB (50,2.1) and the B&H strategies on the three different time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	**BB (50,2.1) CAPM**	**BB (50,2.1) FF3F**	**BB (50,2.1) CAR4**	**B&H CAPM**	**B&H FF3F**	**B&H CAR4**
			Panel A: 2000-2009			
R_{pt} - R_{ft}	**0.2524*** **	**0.2015*** **	0.0448	**0.7852*** **	**0.8421*** **	**0.7384*** **
SMB	-	**-0.1877***	**-0.1530***	-	0.1555	0.1785
HML	-	-0.0842	-0.1125	-	**0.1990** **	**0.1802***
Mom	-	-	**-0.2819*** **	-	-	**-0.1865*** **
F-Value	**30.4973**	**13.0687*** **	**27.8886*** **	**214.2886*** **	**79.5405** **	**69.3531*** **
R-Square	0.2054	0.2526	0.4924	0.6449	0.6729	0.7069
			Panel B: Pre-Crisis			
R_{pt} - R_{ft}	**0.2777*** **	**0.1745** **	0.0164	**0.8442*** **	**0.9906*** **	**0.8926*** **
SMB	-	-0.1411	**-0.1773***	-	0.1481	0.1256
HML	-	-0.1883	-0.1135	-	**0.3049** **	**0.3513** **
Mom	-	-	**-0.3509*** **	-	-	**-0.2174** **
F-Value	**16.8989*** **	**8.4488*** **	**23.4140*** **	**112.6973*** **	**45.1779*** **	**40.3379*** **
R-Square	0.1709	0.2406	0.5424	0.5788	0.6288	0.6713
			Panel C: Crisis			
R_{pt} - R_{ft}	**0.2196*** **	**0.1578** **	0.0892	**0.7067*** **	**0.6262*** **	**0.5403*** **
SMB	-	-0.1555	-0.0949	-	-0.0557	0.0203
HML	-	0.1900	0.1053	-	**0.3934** **	**0.2873** **
Mom	-	-	**-0.1402** **	-	-	**-0.1756** **
F-Value	**18.8662*** **	**7.2052*** **	**67.5737*** **	**161.8647*** **	**65.1618*** **	**63.5364*** **
R-Square	0.3569	0.4032	0.4942	0.8264	0.8593	0.8913

*Table 14: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the MA (50,200) and the MA (37,200) strategies on the Bull Market and Bear Market time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	**MA (50,200) CAPM**	**MA (50,200) FF3F**	**MA (50,200) CAR4**	**MA (37,200) CAPM**	**MA (37,200) FF3F**	**MA (37,200) CAR4**
			Panel D: Bull Market			
R_{pt} - R_{ft}	**0.1919***	**0.2560***	**0.2697*****	**0.1876***	**0.2528****	**0.2663*****
SMB	-	0.2691	**0.3204****	-	0.2917	**0.3421****
HML	-	**0.5523****	**0.3733****	-	**0.5367****	**0.3608****
Mom	-	-	**0.4385*****	-	-	**0.4312*****
F-Value	**2.8964***	**7.4327*****	**30.6469*****	**2.8097***	**7.4707*****	**29.7983*****
R-Square	0.0548	0.3172	0.7229	0.0532	0.3183	0.7172
			Panel E: Bear Market			
R_{pt} - R_{ft}	**-0.5013*****	**-0.5183*****	**-0.3750*****	**-0.4948*****	**-0.5111*****	**-0.3660*****
SMB	-	-0.1077	0.0076	-	-0.1021	0.0147
HML	-	-0.0239	0.0275	-	-0.0218	0.0303
Mom	-	-	**0.2760****	-	-	**0.2795****
F-Value	**68.9604*****	**20.9540*****	**26.1322*****	**68.7492*****	**20.8549*****	**26.9140*****
R-Square	0.7840	0.7871	0.8673	0.7835	0.7863	0.8706

*Table 15: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the MA (22,200) and the MA (50,100) strategies on the Bull Market and Bear Market time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	MA (22,200) CAPM	MA (22,200) FF3F	MA (22,200) CAR4	MA (50,100) CAPM	MA (50,100) FF3F	MA (50,100) CAR4
			Panel D: Bull Market			
R_{pt} - R_{ft}	**0.1961***	**0.2588****	**0.2714*****	**0.2171****	**0.2446****	**0.2559****
SMB	-	**0.2999***	**0.3468****	-	0.2821	**0.3243****
HML	-	**0.4878****	**0.3241****	-	0.0005	-0.1467
Mom	-	-	**0.4012*****	-	-	**0.3606*****
F-Value	**3.4275***	**7.5895*****	**27.7554*****	**4.9446****	**2.5340***	**11.2481*****
R-Square	0.0642	0.3217	0.7026	0.0900	0.1367	0.4891
			Panel E: Bear Market			
R_{pt} - R_{ft}	**-0.5017*****	**-0.5151*****	**-0.3655*****	**-0.3437*****	**-0.3621*****	**-0.3097****
SMB	-	-0.0734	0.0471	-	-0.3004	-0.2582
HML	-	-0.0065	0.0473	-	-0.2062	-0.1874
Mom	-	-	**0.2886****	-	-	0.1008
F-Value	**70.5332*****	**21.1992*****	**28.5048*****	**33.4021*****	**14.4056*****	**11.1612*****
R-Square	0.7878	0.7891	0.8769	0.6374	0.7177	0.7362

*Table 16: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the MA (50,200) RF, and the BB (22,2) strategies on the Bull Market and Bear Market time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	MA (50,200) RF CAPM	MA (50,200) RF FF3F	MA (50,200) RF CAR4	BB (20,2) CAPM	BB (20,2) FF3F	BB (20,2) CAR4
			Panel D: Bull Market			
R_{pt} - R_{ft}	**0.4097****	**0.5137*****	**0.5179*****	**-0.1433****	**-0.1578****	**-0.1596****
SMB	-	**0.4396****	**0.4553****	-	**-0.2460****	**-0.2529****
HML	-	**0.8912*****	**0.8362*****	-	0.1390	0.1634
Mom	-	-	**0.1347***	-	-	-0.0596
F-Value	**10.3875****	**29.1306*****	**24.0557*****	**5.5053****	**3.7806****	**3.2275***
R-Square	0.1720	0.6455	0.6718	0.0992	0.1911	0.2155
			Panel E: Bear Market			
R_{pt} - R_{ft}	**0.0566***	0.0256	0.0695	**0.2397****	0.2701	0.2552
SMB	-	-0.0355	-0.0002	-	0.0308	0.0188
HML	-	0.1130	**0.1287***	-	-0.1145	-0.1199
Mom	-	-	**0.0844***	-	-	-0.0287
F-Value	**3.6200***	1.9297	**2.3881***	**4.9176****	1.5293	1.0859
R-Square	0.1600	0.2540	0.3738	0.2056	0.2125	0.2135

*Table 17: coefficient estimates are tabulated for the CAPM, Fama French 3-factor model, and Carhart 4 factor-characteristic model, respectively, on the monthly portfolio excess returns. Results are regressed for the BB (50,2.1) and the B&H strategies on the Bull Market and Bear Market time periods. In addition, the F-value for each regression model is given and in the last row of each Panel the R-Square is provided. *p < 0.10; **p < 0.05 ***p < 0.001. P-values are calculated with the T-statistics that pertain to the hypothesis that the mean risk-adjusted abnormal return is zero.*

Variable	**BB (50,2.1) CAPM**	**BB (50,2.1) FF3F**	**BB (50,2.1) CAR4**	**B&H CAPM**	**B&H FF3F**	**B&H CAR4**
			Panel D: Bull Market			
R_{pt} - R_{ft}	**-0.1797***	**-0.2204****	**-0.2298****	**0.6005*****	**0.7162*****	**0.7096*****
SMB	-	**-0.3345****	**-0.3695****	-	**0.4348***	**0.4102***
HML	-	-0.1188	0.0036	-	**1.0692*****	**1.1550*****
Mom	-	-	**-0.2999*****	-	-	**-0.2103****
F-Value	**3.9792***	**3.6183****	**10.6630*****	**12.8968*****	**20.0124*****	**17.0055*****
R-Square	0.0737	0.1844	0.4757	0.2050	0.5557	0.5914
			Panel E: Bear Market			
R_{pt} - R_{ft}	**0.3233*****	**0.3718*****	**0.3174*****	**0.6243*****	**0.6024*****	**0.5504*****
SMB	-	0.2796	0.2359	-	0.1302	0.0883
HML	-	0.0426	0.0231	-	0.2317	0.2130
Mom	-	-	-0.1046	-	-	-0.1002
F-Value	**46.7237*****	**17.3448*****	**14.0852*****	**87.6806*****	**30.5502*****	**22.7864*****
R-Square	0.7109	0.7537	0.7788	0.8219	0.8435	0.8507