Erasmus University Rotterdam

Erasmus School of Economics

Master Thesis Financial Economics

Technical analysis in Western-European equity markets

ERASMUS UNIVERSITEIT ROTTERDAM

ERASMUS SCHOOL OF ECONOMICS

Irene Thijen | 383580

Supervisor: Dr. E. Smajlbegovic

Second assessor: Dr. Q. Mao

August 21st, 2017

Preface and acknowledgments

Over the past few months, I have been working on this final thesis of my studies at the Erasmus School of Economics. This thesis is not only the result of researching for several months, but it is also the result of great in depth studying during my four years at the Erasmus University Rotterdam. I am very grateful for all the opportunities I had to develop and improve the knowledge I have now obtained.

This thesis would not have been completed without the help of my loved ones, who were always ready to help me out and give me advice. I want to especially thank my supervisor, Mr. Smajlbegovic, who was of great help during the process. His enthusiasm, feedback, and quick response were a big help during the writing of this thesis.

Abstract

This research looks at the possible significant risk-adjusted returns, generated by technical strategies. The sample is set in four different Western-European countries over the timespan of 1999-2015. Three different widespread technical strategies are tested for significant risk-adjusted returns, namely the Moving Average (MA), the Relative Strength Index (RSI) and the Support and Resistance (SR) strategy. After this, a combined strategy will also be tested. The risk-factors considered in this research are the size- and value factors of Fama & French and the momentum factor of Carhart. The results show that most strategies will generate a significant positive return, regardless of sub-time periods or different time frames, but not all strategies create a significant alpha after correcting for market- and risk-factors. It seems like a combined strategy of the MA- and SR-strategy would perform best, generating a significant return of 0,043% per day. Additionally, this strategy would generate significant alphas in the French and German markets. The strategies separately mostly create a significant alpha in the German market only or no alpha at all. Lastly, significant relations have been found between individual strategies and the risk-factors, but none is consistent with each market. Overall, it seems to be possible to generate significant risk-adjusted returns using technical strategies; however, this is dependent on which market and strategy are chosen.

Keywords

Technical strategy, equity market, long/short strategy, risk-factors, creating alpha

Table of contents

1. Introduction

For as long as financial theory exists, one fundamental problem always comes up. Why do different assets have different returns? One of the most widely known models to explain returns is the CAPM, which is based on the concept of risk. This model is mostly used for empirical asset pricing studies, on which investors base their decisions. Private investors and asset managers aim at creating portfolios that beat the market. A systematic outperforming portfolio would, however mean that there is either mispricing in the market or that there is another risk than market risk.

Most of these outperforming portfolios are based on certain anomalies, which can be considered as profit opportunities. These are empirical results that seem to be inconsistent with maintained theories of asset-pricing behavior, such as one of the most well-known economic theories; the efficient market hypothesis, constructed by Fama (1970). These anomalies indicate either market inefficiency or inadequacies in the underlying asset-pricing model (Schwert, 2003).

An upcoming method of detecting mispricing is the use of technical analysis. This type of analysis uses historical stock prices to predict future market movements. When information about stocks is very uncertain, fundamental signals are likely to be imperfect, and so investors have a tendency to rely more heavily on technical strategies. Many top traders and investors use it, and it is one of the major information variables used for modern quantitative portfolio management (Han, Yang, & Zhou, 2013).

Most empirical studies on whether technical strategies are profitable have found inconclusive evidence. However, some have shown some significant results. For example, Neely et al. (2013) find that technical indicators work just as good as common macroeconomic variables in projecting the stock market and Goh et al. (2013) show that this type of analysis can even yield more precise forecasts than the macroeconomic variables in the bond market. Zhu and Zhou (2009) show that technical analysis can be a valuable learning tool under uncertainty about market dynamics, while Neely et al. (2013) summarize various theoretical arguments for the use of technical analysis.

In the field of technical analysis, most of the research that has been done so far was based on U.S. markets. However, recent literature states that this type of strategy has become more popular in international markets as well. Menkhoff (2010) shows that while most fund managers still show an overall preference for fundamental analysis, the preference for technical analysis is higher among European fund managers than for U.S. fund managers. For example, German fund managers show that in their overall use of analysis, 29,6% is based on technical analysis and 22,8% for Italian fund managers. U.S. fund managers show that of their overall analysis, merely 16,1% is based on technical analysis. Although popularity in technical strategies is rising internationally, there has still been relatively more research done in U.S. markets than in international markets. The few papers on technical strategies in international markets show that technical strategies should perform just as well. For example, a paper by Neely, Weller and Dittmar (1997) shows that technical analysis performs just as well in European markets as in U.S. markets. They find strong evidence of economically significant excess returns to those rules for each of six exchange rates over the period 1981-1995. Another paper by Levich and Thomas (1991) also tests technical strategies in European markets. They argue that simple technical trading rules have often led to profits that are highly unusual.

This thesis will focus on several types of technical strategies and test whether these can generate significant risk-adjusted portfolio returns. Furthermore, this type of strategy is becoming more popular on an international level, and so the research question is as follows:

> *To what extent will technical analysis be able to generate significant risk-adjusted portfolio returns on Western-European equities?*

This research will focus on three different widespread types of technical strategies: Moving Average, Relative Strength Index and the Support and Resistance Rule strategy. These strategies will be implemented in the markets of the following Western-European markets: France, Germany, the Netherlands and the United Kingdom, in the time period 1999-2015. The dataset will contain daily data and will be tested for profitable returns by using the long/short strategy. With this strategy, one takes a long position in the most profitable stocks according to an individual strategy, and a short position in the stocks that are supposedly the least profitable. This strategy will be implemented for each type of technical analysis and in every country.

Once these returns have been calculated, they will be tested using a regression analysis, to see how much can be explained by the common market- and risk-factors. Based on this, one could test if a significant positive alpha can be generated. A robustness check will be done by testing different subperiods and timeframes for the strategies. When analysing this research question, the outcome could provide sufficient information on enhancing and optimizing one's investment strategy using technical strategies. Next to that, it could point out where the current investment strategies might be flawed and how this could be improved.

The results show that most strategies will generate a significant positive return, regardless of subperiods or different timeframes, but not all strategies create a significant alpha after correcting for the market- and risk-factors. It looks like all strategies generate on average a significant positive return, but a combination of several strategies creates higher daily returns (0,043% vs. 0,031%). Additionally, several strategies create a significant alpha, but either only in the German of French market and none in the Dutch or UK market. The combination strategy generates a significant positive alpha in both the German and French market.

When looking at the strategies solely, it looks like the MA-strategy generates the most diverse returns (both the highest returns and the lowest, country wise), while the SR-strategy seems to be the safest strategy, generating the “worst” high returns but also the “least worst” low returns. Lastly, significant relations have been found between individual strategies and the risk-factors, but none has been found to be consistent with each market and each country. Overall, it seems to be possible to generate significant risk-adjusted returns using technical strategies; however, this is dependent on which market and strategy are chosen.

The remaining part of this paper will discuss the concept of technical strategies at first. There will be a discussion on different types of technical strategies and on the long/short strategy, which might lead to a significant alpha. The data description will follow up. At first data collection will be discussed, followed by the specific variables used. The methodology will follow up on how the strategies are constructed. Finally, an elaboration on the results will be given, followed by the conclusion. Lastly, the encountered implications and suggestions for further research will be discussed.

2. Theoretical framework

This section gives a summary of the concepts that will be used in this paper. Firstly, the general concept of trading strategy analysis is discussed. Afterwards, more in-depth information on technical strategy analysis is given. Since this is an empirical research, several technical trading strategies will be used for analysis. The most common groups of technical analysis are discussed in both theoretical background and earlier findings. Next to this, different types of pricing models are elaborated upon. Lastly, the existence of alphas, generated by long-short strategies, that yield positive returns accounting for the market will be examined.

2.1 General concept of trading strategies

Ever since the beginning of trading in financial assets, investors have been searching for trading strategies that can "beat the market." They believed that if they could find a returning pattern in stock returns, they could turn these into strategies that would generate "abnormal" profits. This is one of the main reasons for an increasing interest in the predictability of asset returns, based on their history or fundamental values. Many of today's techniques have already been used for over sixty years.
These techniques for discovering unknown connections in stock returns can vary from extremely simple to quite sophisticated (Brock, Lakonishok, & LeBaron, 1992).

Most of these trading strategies are based on the concept of an anomaly. This is a term describing the phenomenon of when there is a structural, replicable pattern, which cannot be explained in the framework of existing financial theory but can be economically explained (Conrad & Kaul, 1998). An anomaly could potentially be evidence that certain assumptions to a pricing model do not hold in practice. Practitioners usually cannot make optimal use of a certain anomaly, due to trading restrictions or trading fees. If this turns out to be correct and the anomaly is not profitable, it is not anomalous after all. Most anomalies that have been found occur concerning asset pricing models and with CAPM in particular. Several anomalies that have been observed since the formation of CAPM are used as a basis for disproving the model (more on this can be found in section 2.4. pricing models). The model may not always hold up in empirical studies, but this does not mean that the model does not hold any utility. For example, unlike other return models, CAPM takes into account systematic risk, is quite easy of use and allows the investor to hold a diversified portfolio.

Based on the possibility of making abnormal returns, investors have developed trading strategies over time, which are meant to profit from this mispricing in the markets. When looking at academic literature, most articles focus on strategies based on either fundamental or technical analysis. The focus of this research lies in technical analysis, but to give a complete view of trading strategies, fundamental analysis will be shortly discussed. Fundamental investors base their trading strategy on fundamental analysis, which examines things like corporate events such as actual or expected earnings reports, stock splits, reorganizations or acquisitions. Financial data which is most commonly used is earnings per share (EPS), revenues/sales and cash flows. Two of the most famous anomalies found based on fundamental analysis, are the SMB (small minus big) and HML (high minus low) factors, constructed by Fama & French in 1993. These factors focus on size and the book-to-market (BM) ratio respectively, in which it is anticipated that smaller companies are more profitable than bigger companies and that companies with high BM ratios are more profitable than low ratios. These anomalies have become so popular, that they are now known as the Fama & French three-factor model, which is viewed as an addition to the CAPM. More on this is discussed in section 2.4. Pricing models.

2.2 Technical strategy analysis

Technical analysis is considered by many to be the original form of investment analysis, dating back to the 1800s (Brock, Lakonishok, & LeBaron, 1992). In general, technical analysis studies the historical price patterns or trends or any other clues that are suggestive of future price movements (Chong & Ng, 2008). One of the main differences between academic finance and practice is the divide that exists between technical analysts and their academic critics. In contrast to fundamental analysis, which was quick to be adopted by the scholars of modern quantitative finance, technical analysis has been "an orphan from the very start" (Lo, Mamaysky, & Wang, 2000). Despite the critics, technical analysis has had a comeback on Wall Street. Nowadays, all larger financial institutions publish technical commentary on the market and individual securities.

The biggest difference between fundamental and technical analysis is that the latter is primarily visual whereas the first has a focus on more algebraic and numerical reasoning. This is one of the reasons why technical analysis uses mostly tools of geometry and recognition of patterns, and fundamental analysis uses mathematical analysis and probability theory of statistics. Over the past years, fundamental analysis has overtaken technical analysis, based on popularity. Nonetheless, technical analysis has survived through the years, probably because the visual aspects are more useful with human cognition and pattern recognition is one of the few repetitive activities for which computers do not have an absolute advantage (Lo, Mamaysky, & Wang, 2000). The biggest challenge of technical analysis is that there are hundreds of technical indicators available. Besides that, no single indicator stands out as "the best," since each indicator might be applicable only to specific circumstances (Van Bergen, 2016).

2.3 Different types of technical strategies

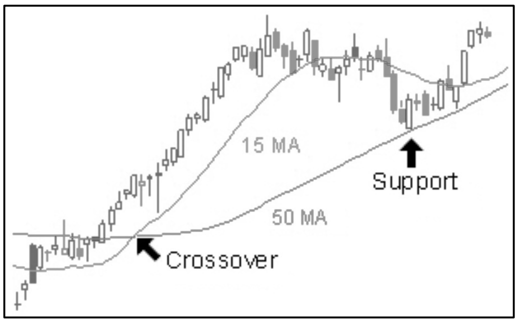
As mentioned earlier, there are several hundreds of signals used in technical analysis. In this section, some of the most common groupings are discussed. It should be stated that these groupings are only applicable to individual stocks. In general, there are five major styles of trading: scalping, momentum trading, technical trading, fundamental trading and swing trading (Van Bergen, 2016). For a schematic breakdown of these types of traders and their description, have a look at Appendix A. Next to this, an overview of different types of technical strategies can be found in Appendix B. The most popular ones will be discussed in this chapter.

2.3.1. Moving Average

The first and most common technical strategy is the trend analysis (or, Moving Average strategy). It looks at short- and long-term trend and tries to identify crossovers, where prices cross over their long-term averages. These are referred to as moving averages, where a price range is smoothed over a period of time, by averaging a series of prices and plotting the smoothed line against the actual price line of the stock. This method is applicable in many ways and different forms. There is the simple crossover, the MACD or the ribbon, but it can also be applied in combination with fundamental strategy.

In its most simple form, this strategy is formulated as buying (or selling) when the short-period MA rises above (or falls below) the long-period MA. The idea behind computing moving averages is to smooth out an otherwise volatile series. When the short-period MA enters the long-period MA, a trend is considered to be initiated (Brock et al., 1992).

An example of this can be seen in the graph on the right. The graph shows the historic stock price movement and its corresponding moving averages, which are in this case 15- and the 50-day moving average. At the crossover one can see that the short-MA crosses above the long-MA. Notice how an upward momentum has been build up since this crossover, initiating a buy-signal.



Graph 1: Example of the Moving Average strategy. The short-MA crosses above the long-MA and initiates an upward momentum. At this moment a buy-signal is triggered.

The moving average convergence divergence (MACD) uses exponential moving averages which put more weight on recent prices and shows the relationship between moving averages of prices. It is employed to identify crossovers, divergence and convergence, and overbought and oversold conditions. The MACD will be used in this research. The ribbon-type is the simple-type, but this ribbon is shaped by placing a large number of different moving averages (with different time-periods) into the same chart. The trend can be defined as strong when all these different averages move into the same direction. When they start to cross over and head into the opposite direction, a reversal could emerge.

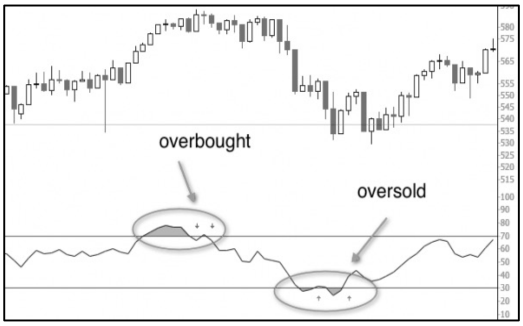
In the paper of Han, Yang & Zhou (2013), the authors apply the moving average strategy to portfolios sorted by volatility or other aspects of the stocks that display information uncertainty. The profitability of the strategy relies on whether there are detectable trends in the cross section of the stock market. They find that the application of a moving average timing strategy generates investment timing portfolios, which substantially outperform the buy-and-hold strategy. They find that especially the combination with the volatility anomaly is of great economic significance. Their paper shows that the moving average technique could enhance an investment strategy. Han, Huang & Zhou (2015) argue that most anomalies are based on low-frequency attributes and therefore ignore higher frequency information. In their research, they implement higher frequency data to test the consistency of the anomalies. The moving average technique is used to rebalance their portfolios. They find that by doing so, significant economic value will be added. They find that for the eight major anomalies used in their research, the enhanced anomalies can double the average returns while having similar or lower risks.

In another paper, written by Brock, Lakonishok & LeBaron (1992), the authors test two trading strategies: the moving average and the trading range break (see section 2.3.2.). Their results provide strong support for both technical strategies. The returns obtained from these strategies are inconsistent with the four common null models: the random walk, the AR(1), the GARCH-M and the exponential GARCH. Next to that, they find that buy signals consistently generate higher returns than sell signals and these signals are also less volatile.

2.3.2. Relative Strength Index

The second common technical strategy is the relative strength index (RSI). This is a momentum indicator, founded by technical analyst Welles Wilder, that presents a relative evaluation of the strength of a security's current price performance (Chong & Ng, 2008). This measure is mostly used to analyse overbought or oversold conditions when trading an asset. RSI values range from 0 to 100. The standard time frame for comparing up periods to down periods is 14 trading days. The usual way of interpreting the RSI is that an asset is becoming overbought (or overvalued) when the indicator value is 70 or higher. This means that it may signal a trend reversal or corrective pullback in price. On the other hand, an asset is becoming oversold (or undervalued) when the indicator value is 30 or lower. This might signal a trend change or corrective price reversal to the upside.

An example can be seen in the graph on the right. One can see the historical stock price movement and below, the relative strength index. Once the RSI indicator passes the threshold of either 70 or 30, a buy- or sell-signal will be given respectively, since it is believed that the stock is either overbought or oversold.



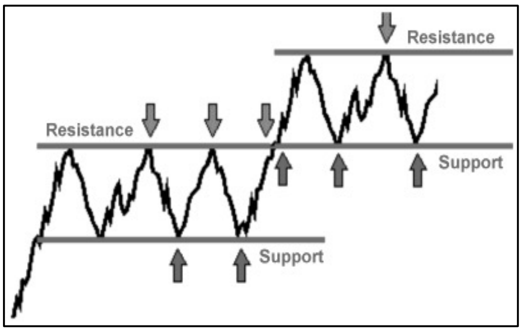
Graph 2: Example of the Relative Strength Index strategy. Once the RSI passes the threshold of 70 (30), a sell (buy) signal is given.

In a paper by Chong & Ng (2008), the authors performed a technical analysis of the London stock exchange, using the RSI rules and the FT30 (similar to the Dow Jones Industrial Average). This is the longest UK index and has a sample period from July 1935 to January 1994. They divided the sample into three subperiods. Overall, they concluded that the RSI rule outperformed the standard buy-and-hold strategy. Next to this, another paper researching the RSI rule specifically found that it appears that superior profits can be achieved by investing in securities which historically have been relatively strong in price movement (Levy, 1967).

2.3.3. Support and Resistance

The third trading strategy that is widely used is the support and resistance strategy, also called the trading ranges strategy. A trading range exists when a certain asset moves up and down between a consistently high and low for a long period of time (days, weeks or months). Stocks will be traded with this strategy, when the price is flexible enough to manoeuvre at, e.g., a 5-point range or more. A breakout occurs when the price maintains a movement, even for a short period, above or below the range. The strategy will signal a buy-indicator when the price of the asset breaks through the resistance level, that is defined as the local maximum. Technical analysis indicates that investors will sell their assets when the price is at the peak. This selling pressure will cause opposition to a price rise above the previous peak. On the other side, if the price rises too much, it will break through the resistance area. This breakout is then considered to be a buy signal. Similarly, a sell-signal is generated when the price of the asset breaks through the support level which is at the minimum price. In essence, technical analysts suggest buying when the price rises above its last peak and selling when the price drops below its last dip (Brock, Lakonishok, & LeBaron, 1992). A paper by Ming-Ming and Siok-Hwa (2006) examined the profitability of the trading range breakout on nine popular daily Asian market indices from 1988 to 2003. The test results provided strong support for the technical trading rule, stating that it offers many profit opportunities for market participants.

In the graph on the right, one can see an example of the support and resistance strategy. The stock price seems to move up at first, but it has been thought that a certain resistance pulls it back down. The flexibility of the price allows it to do so. This happens a few times but at some points, the price breaks through this resistance and this point is considered a buying-signal.



Graph 3: Example of the Support and Resistance strategy. If the price rises too much and breaks through the resistance area, a buy-signal is triggered.

2.3.4. Other common technical strategies

So far the technical strategies that will be used in this research have been discussed. There are two other common used strategies, however less popular than the ones named above. The fourth strategy is the pattern analysis. When applying this strategy, an analyst will look at certain price charts (the movement of a stock price over a certain time period) and analyse it for specific returning patterns that have historically emerged in the same stock (or for common patterns in many stocks). Some of the most commonly observed patterns are the head-and-shoulders patterns, triangle-up or triangle-down patterns, rounded tops or rounded bottoms and cup-and-handle formation. The definition of a chart pattern is a distinct formation on a stock chart that could produce a trading signal or a sign of expected price movements (Van Bergen, 2016)

One of the most researched patterns is the head-and-shoulder pattern (HS-pattern). The formalization of the geometry of an HS-pattern is as follows: three peaks, with the middle peak higher than the other two (Lo, Mamaysky, & Wang, 2000). The head-and-shoulders pattern is considered by practitioners to be the most reliable of all chart pattern, as stated by Osler & Chang (1995). The authors state that to summarize the predictive power of their trading strategy, they investigate profits from speculating in all six currencies simultaneously over the same time horizon. Their findings show that these aggregate profits would have been both statistically and economically meaningful regardless of transaction costs, interest differentials or risk. They conclude that head-and-shoulders signals have some predictive power for the German and Japanese currency during the twenty years since the advent of floating exchange rates. This would mean that as an investor, one would have to locate the neckline, wait till the pattern is complete and when the neckline breaks, on should invest.

In the paper of Lo, Mamaysky & Wang (2000), the authors compared several types of technical pattern analysis. The authors propose a systematic and automatic approach, using nonparametric kernel regression. They find that several technical indicators indeed provide significant information and may have some practical value. However, the evidence is relatively not as strong as the RSI strategy. They claim that the patterns are most difficult to quantify analytically.

The fifth and last common strategy group is gap analysis. In this type of strategy, a gap occurs when the opening price of a stock and the closing price of the previous day, differ significantly. A possible explanation for this could be if the company released some significant news overnight. The investor is concerned with this gap since it could indicate future movement in a certain direction. Gap analysis could also refer to the process through which a company compares its actual performance to its anticipated performance to determine whether it is meeting expectations and using its resources effectively (Van Bergen, 2016). If an investor is on time identifying these gaps, it can create a profitable strategy based on this.

2.4 Pricing models

After elaborating extensively on different types of technical strategies, this section will move further into different types of pricing models. When testing if the strategies mentioned above are profitable, the most common model to use is the CAPM. However, results might be different if other pricing models are used. This section will further elaborate upon this.

Up until several decades ago, the CAPM functioned as a benchmark. This model was introduced by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966) independently, building on earlier work of Markowitz on diversification and modern portfolio theory. CAPM is formulated as:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \quad (1)$$

Where $E(R_i)$ is the expected return on the capital asset, R_f is the risk-free rate of interest, such as interest arising from government bonds, β_i is the sensitivity of the expected excess asset returns to the expected excess market returns, $E(R_m)$ is the expected market return and $E(R_m) - R_f$ is known as the market premium. Nowadays, due to the discovery of some highly significant anomalies, there are models with some additions to the CAPM.

The three-factor model is introduced by Fama and French in 1993 and can be seen below, in formula 2. It is an addition to the CAPM, which contains the risk premium, but also a size factor and a value factor. As was mentioned earlier, it is assumed that smaller firms generate higher excess returns than bigger firms (small minus big, SMB) and companies with a high book-to-market ratio generate higher excess returns than low ratios (high minus low, HML). These two factors will now shortly be discussed.

$$E(R_i) = R_f + \beta_{1i}\big(E(R_m) - R_f\big) + \beta_{2i}SMB + \beta_{3i}HML \quad (2)$$

The magnitude of the size anomaly is around 2-4% per annum. There are two economic motivations for the size anomaly. First, small firms receive less analyst attention. This means that their prices are updated less often, meaning that this would carry a risk for which compensation would be required. Second, small firms are not traded much. This means that their prices refresh less often and that they are less liquid (and that they bear higher transaction costs). Repeatedly, this carries a risk for which compensation would be required (Fama & French, 1993).

According to the value anomaly, value stocks (stocks with a high B/M-ratio) gain higher returns than growth stocks (stocks with a low B/M-ratio), even after revisions have been made for their market risk. The magnitude of this anomaly is around 4-6% per annum. The economic motivation behind the value anomaly starts from the fact that ultimately asset prices are determined by (expected) pay-outs. If market value is near the book value (high B/M), the firm seems to be in dire shape (no growth possibilities that have any value) and is therefore riskier. This risk raises the required return.

Carhart builds further on the three-factor model, by adding a fourth factor in 1997 and can be seen below in formula 3. He found a momentum factor in which companies that could be considered as "winners," would outperform the "losers" (winners minus losers, WML).

$$E(R_i) = R_f + \beta_{1i}\big(E(R_m) - R_f\big) + \beta_{2i}SMB + \beta_{3i}HML + \beta_{4i}WML \qquad (3)$$

The momentum anomaly pronounces that, based on middle-long term autocorrelation, assets (stocks) that have performed well in the current past (say 3-12 months) will outperform 'losers' for another year. The magnitude of this anomaly is mostly 4-6% per year but can be as high as 2% per month. This outperformance can be achieved by sorting past 'winners' and 'losers' and then (for example) buy the 20% best-performing stocks and finance this by short selling the 20% worst performing stocks. This requires precise selection and rebalancing because at some time winners stop winning and losers stop losing. The momentum anomaly is not composed into the CAPM because from an economic point of view as it has nothing to do with risk. This emphasizes the importance of incorporating this model in this research, as the focus will be on technical strategies which are also based on historical stock price performance solely.

Trading on this anomaly has two possible downsides. First, there are trading costs. The short positions are costly to purchase and maintain. There are also transaction costs that can make it expensive to replicate the strategy. Second, there are illiquidity effects. Especially in smaller stocks, short-selling might be encountered by illiquidity. Illiquid stocks may fall a lot further if an investor tries to sell them in a decreasing market. Both explanations are based on market imperfections. The momentum anomaly is rather robust. Moreover, illiquidity effects are hard to measure, so testing on this is also hard to do.

2.5 Creating Alpha

To measure whether a specific strategy is performing well, several financial ratios are applicable: alpha, beta, standard deviation, R-squared and the Sharpe ratio. All of these indicators are used in modern portfolio theory (MPT) and are used to help investors determine the risk-return portfolio. Alpha is most often considered the active return on investment. Derived from statistics, alpha is used in connection with an assumed linear relationship between the returns on a particular asset or portfolio and the returns to some factors or a benchmark (Chung, Schneeweis, & Eneroth, 1999). In the hedge fund industry, alpha is a proxy for excess return to active management, adjusted for risk (Fama, Fisher, Jensen, & Roll, 1969). Alpha can also be interpreted as the abnormal rate of return on a security or portfolio in excess of what would be predicted by an equilibrium model similar to the CAPM. In other words, alpha is the return on an investment that is not due to general movement in the economic market. For example, an alpha of zero would indicate that the portfolio or fund is tracking perfectly aligned with the benchmark index and that the manager has not added or lost any value.

Even though alpha is very popular among investors, there is some consideration one should account for. Alpha is used in the analysis of a broad variety of fund and portfolio types, but comparing alpha values is only useful when investments contain assets in the same asset class. Next to this, because alpha is calculated relative to a benchmark deemed appropriate for the fund or portfolio, it is important that much consideration goes into the choosing process of an appropriate benchmark.

Over the years, researchers have attempted to find the source for alpha and what the reason could be for this excess of return when market efficiency is assumed. Two popular concepts are mispricing and risk factors. The efficient market hypothesis (EMH) states that all public information is correctly impounded into prices, whereas mispricing would mean that the intrinsic value of a security, good or service does not match the price and so, goes against the EMH (Hirschleifer, Hou, & Teoh, 2012). Another explanation, for when market efficiency is assumed, would be the rise of a risk factor. The rate of return of an asset is then assumed to be due to an irregular variable whose realization in any time period is a linear combination of other random variables plus an error term (Cochrane, 2009). In practice, this combination of observed factors could be included in a linear asset pricing model, for example, the Fama and French three-factor model.

As technical analysis is based on historical stock prices, it attempts to find (temporary) mispricing. In general, technical investors assume stock prices reflect all available market information regarding a stock's characteristics. Technical analysis can roughly determine the number of market participants willing to buy or sell a stock at various price levels, by using historical prices and trading volume (Wang

& Chan, 2007). Without considerable changes to fundamentals, the entry or exit price targets for participants should be relatively constant, so technical analysis can detect situations in which supply and demand imbalances at the current price. When such an imbalance occurs, it can be considered as mispricing.

2.6 Long/short strategy

As technical analysis tries to detect situations in which mispricing occurs, a strategy can be set up to exploit these market inefficiencies. Long/short strategies are designed to do so, generating alpha through both stock selection and market timing (Alexander & Dimitriu, 2002). This investing strategy takes positions in stocks that are expected to appreciate and shorts positions in stocks that are expected to decline. This strategy is assumed to be profitable on a net basis, as long as the long positions generate higher profits than the short positions, although this is not always the case.

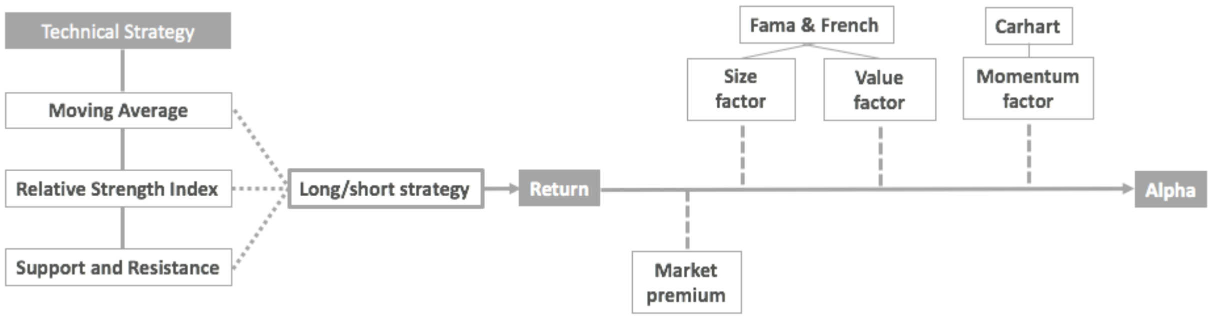
The long/short strategy is popular among hedge fund managers, many of whom employ a market-neutral strategy. This applies to the situation in which the dollar amounts of the long and short positions are equal. The undervalued stocks are expected to grow more or decrease less than the overvalued stocks, and so, the price difference between them is expected to decrease. However, this does not imply by any means market neutrality, as there is no proven relationship between the two individual equity groups to ensure that this will be eventually the case (Alexander & Dimitriu, 2002).

On the contrary of long/short strategies, market neutral strategies involve only equities or securities with proved interdependencies. Such interdependencies, ensure that over a given time period, the equities or securities will reach an expected pricing relation. Examples of such market neutral strategies are convertible securities arbitrage, futures/index arbitrage, fixed income, currency and options arbitrage. Long/short strategies ensure a more efficient use of information than long only strategies; this is the result of not restraining the weights of the undervalued assets to zero. By allowing portfolio returns to be created by both the short selling of underperforming stocks and the buying of overperforming stocks in the market, the strategy generates what is called a ‘double alpha.'

Nonetheless, there are several concerns that have limited the more comprehensive use of the long/short investment strategy. For example, it should be noted that double alpha usually means double transaction costs. Next to this, in the case of extreme market events, low volatility and low correlation with market returns in normal circumstances may disappear (Alexander & Dimitriu, 2002).

2.7 Framework

When connecting all concepts and theories together, one could create a flowchart like the one below in graph 4. At first, the different types of technical strategies are discussed. Since the focus of this research will be on the outcome of these strategies, this part has been elaborately discussed. All of these strategies trigger either buy- or sell-signals, which are combined with the long/short strategy. This strategy generates returns, however, these returns could simply be due to market movements or common risk-factors. To correct for this, a regression analysis will be implemented to see how much of these factors already explain the returns. Any return that remains after correcting for this, can be seen as risk-adjusted return or the alpha. This could be seen as the true excess return due to technical strategies.



Graph 4: Flowchart of all concepts combined that have been discussed in the theoretical framework. This methodology will be implemented in this research on daily data of four different markets in the timeperiod 1999-2015. The robustness check will consist of testing on subperiods and different timeframes for the strategies (either 12-, 14- or 26-day).

3. Hypothesis development

Now that all relative concepts and literature is discussed, the hypotheses that follow from this is elaborated upon. These hypotheses will help provide conclusions, to answer the research question:

> *To what extent will technical analysis be able to generate significant risk-adjusted portfolio returns on European equities?*

The purpose of this research is to find a possible answer to this question. The answer is elaborated upon in section 6, conclusions. To answer this question, three different types technical analyses will be tested on a Western-European market in the time-period 1999-2015. The three analyses are chosen based upon previous literature, in which these turned out to be the most popular and relatively easy to implement. This research will look at the moving-average-strategy (MA), the Relative Strength Index (RSI) strategy and the Support and Resistance (SR) strategy. Based on this information, several hypotheses have been stated.

H1. Technical analysis will generate significant positive risk-adjusted portfolio returns.

Technical analysis is a topic that has relatively not much research done upon. The majority of the papers state the advantage of using technical analysis (for example Han, Yang & Zhou (2013) or Han, Huang & Zhou (2015)), but there are also some papers that state the opposite (Cowles 3rd, 1933). In a paper by Menkhoff and Taylor (2007), the authors set up an overview of previous literature on technical analysis based on the foreign exchange markets. They find that the majority of the papers find excess returns of technical analysis, based on periods of 5 years or more. There has not been an overall conclusive result, which is mostly due to the majority of the different types of technical strategies. However, technical analysis should, in theory, be able to detect mispricing in the market, upon which an investor can act in time. Based on this and the fact that several types of strategies will be used, it is hypothesized that technical analysis will generate significant positive risk-adjusted portfolio returns.

H2. MA-strategy will generate higher significant results than the RSI-strategy or SR-strategy.

Based on the literature discussed above, it can be stated that it is likely that the MA-strategy will generate more/higher significant results than the RSI-strategy or SR-strategy. In Chong & Ng (2008), the MA-strategy was compared to the RSI-strategy on the same database. Both strategies turned out to generate significant positive returns, but the MA-strategy generated higher returns as well (0,021% on average using the long/short strategy, whereas the RSI-strategy generated 0,009% on average). Additionally, the MA-strategy also generated more significant results, where 83% of the results turned out to be significant on a 5% level, compared to 25% for the RSI-strategy.

Next to this, in Brock, Lakonishok & LeBaron (1992), the authors compared the MA-strategy to the SR-strategy. Their results turned out to favor the MA-strategy, as it generated more significant results than the SR-strategy. The authors used different timeframes as a robustness check for both strategies, of which it appeared that 60% of the MA-results were significant at a 1% level, versus 8% of the SR-results. Next to this, 80% of the MA-results were significant at a 5% level, whereas 33% of the SR-results showed to be significant at this level. Even though the long/short strategy using the SR-rule did generate higher returns (0,87% on average versus 0,067% on average for MA-strategy), the returns turned out to be less significant.

H3. A combination of the different types of technical strategies will generate higher significant results than these strategies separately.

Most of the known papers on technical analysis performed the strategies separately. However, there have been a few papers in which a combined strategy was compared to the single strategies. In a paper by Lento and Gradojevic (2007), it turned out that a combined signal approach can outperform the buy-and-hold strategy, even after adjusting for transaction costs. The results are especially remarkable because each rule alone is not able to consistently generate excess returns. In another paper, the authors combine the MA-strategy with the SR-strategy and find out that this combination outperforms all of the component rules in the testing period (Wang, Yu, & Cheung, 2014). They apply bootstrapping methodology to test three popular null models of stock return. The results show that the combined strategy is not consistent with the null models and has good predictive ability. Based on this, it is assumed that a combination of different types of technical strategies will perform better than these strategies separately.

Next to this, there have been papers in which a technical strategy was used to enhance other anomalies. For example, in a paper by Han, Huang & Zhou (2015), the MA-strategy is combined with other anomalies to enhance them. In this paper, it turned out that that the performance of eight fundamental anomalies is greatly enhanced, in which the returns rise from 0,64% to 1,47%. This is more than twice of the normal anomaly, and the performance improvement is even greater if measured by risk-adjusted abnormal returns, leading to returns as high as 1,61%.

4. Research design

The data used in this research stems from TRW (Thomson Reuter Worldscope) and TRD (Thomson Reuter Datastream). The data is retrieved by applying the same approach as Ince and Porter (2006) and Schmidt et al. (2017). A major obstacle in international asset pricing has been the lack of reliable and publicly obtainable data on international common risk factors and portfolios. They addressed this by providing a step-by-step description of how properly screened data from TRD and TRW can be used to construct high-quality systematic international risk factors. TRD is used because it mainly covers stock market data such as prices and dividends and TRW is used because it mainly covers accounting data such as common equity. The risk-factors (size- and value-factor) will be constructed based upon accounting data, but the technical analysis will be done based upon the stock data, so both lists are needed.

4.1 TRD, TRW and Dead lists

The data retrieved in this research is based on TRD constituent lists, TRW lists and dead lists. The dead lists are included since these contain companies that cease to exist (due to mergers, bankruptcy or other reasons). This way there can be controlled for survivorship bias. The TWD lists are added to get a population as large as possible. The focus of this study will be on Western-Europe. For this reason, the countries that are included in this research are France, Germany, the Netherlands and the UK, since these countries are likely to be most representative. The lists conducted for these countries are the following:

Country	Companies	Risk-free Proxy	Market Index Proxy
France	WSCOPEFR, FFRA, DEADFR	FRTBL3M	CAC40
Germany	WSCOPEBD, FGER1, FGER2, DEADBD1, DEADBD2	FIBOR3M	FTSE
The Netherlands	WSCOPENL, FHOL, DEADNL	HOLIB3M	AEX
The United Kingdom	WSCOPEUK, FBRIT, DEADUK	UKTBTND	FTSE

Table 1: TRD and TRW lists of companies, risk-free proxies and market index proxies.

When choosing the appropriate proxy for the risk-free interest rate, one important characteristic to account for is choosing an instrument that has no default risk (Damodaran, 2008). It is common for asset pricing studies to use a one- or three-month Treasury bill (for example Fama and French, 1993 or Dimson and Marsh, 2001). However, a one- or three-month Treasury bill is not available for every country in this study. Other possible proxies could be the three-month overnight indexed swap (OIS), as well as the one- or three-month interbank rate (IBR). The risk-free proxies in this study are based upon the 3-month Treasury bill, the OIS and the IBR.

4.2 Data variables

To construct the appropriate dataset, the required variables had to be retrieved. In the table below one can find the variables used in this research. Static variables contain data that did not change over time, and dynamic variables contain data that does.

Items	Code	Static/Dynamic
Major Security Flag	MAJOR	Static
Type of Instrument	TYPE	Static
Common equity	WC03501 (=CE)	Dynamic
Market Value	MV	Dynamic
Price	P	Dynamic
Price Index	PI	Dynamic
Total Return Index	RI	Dynamic
Date Of Fiscal Year End	WC05350 (=FY-E)	Dynamic
Number of shares	NOSH	Dynamic

Table 2: variables used from TRW and TRD. Variables are either static or dynamic.

The variable major shows which companies are the most significant regarding the market value and liquidity of the primary quotation of that country. Type indicates the type of instrument that is requested. Both of these variables are static and do not change over time. The variable common equity represents the common shareholders' investment in a company. The market value is calculated by multiplying the share price by the number of ordinary shares in issue. The amount in issue is renewed whenever new tranches of stock are issued or after capital change. The value is stated in millions.

The price represents the official closing price. The “current” price on Datastream’s equity programs is the latest price available from the appropriate market. It is the previous day's closing price from the default exchange except where more recent or real-time price is available. The prices are adjusted for subsequent capital actions, and this adjusted figure then becomes the default price offered on all research programs. The price index displays the price of an equity as a percentage of its value on the base date, adjusted for capital changes (P). The total return index shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested in the company. This variable is calculated as follows: $RI_t = RI_{t-1} * \frac{P_t}{P_{t-1}}$. Adjusted closing prices (P) are used throughout to determine the price index and hence return index. The date of fiscal year represents the year, month and day the company closes its books at the end of its fiscal period. Lastly, the number of shares outstanding is the total number of ordinary shares that represent the capital of the company. The datatype is expressed in thousands. The amount is renewed whenever new tranches of stock are issued or after capital changes.

4.3 Data time period and currency

The data from TRD and TRW for the specific variables are available from 1980 onwards, but this research will use a later starting date since the coverage improves over time. Therefore, in a sample starting in 1980 big firms would be most likely overrepresented. Next to that, to be able to compare data between countries, it is crucial that all data is expressed in the same currency. Since the countries are located in West-Europe, most companies have their data filed in euro (EUR). All data that was not expressed in EUR is converted to EUR by using historical exchange rates, available from the Federal Reserve Bank in the WRDS database. Since the EUR was implemented in July 1999, it makes most sense to start from there. Therefore, the data used in this research starts at January 1st, 1999 until December 31st, 2015. Data from January till July 1999, is converted by using fixed exchange rates. Some data was also available for 2016, but not for all variables, making the dataset incomplete. This means that this research covers daily data of 17 years.

4.4 Data screenings

When preparing the data for research, several static and dynamic screens have been implemented, as suggested by Ince and Porter (2006) as well as Schmidt et al. (2017). An overview is given in the table below.

Screen identifier	Short description	Items involved
SS01	All firms which are not indicated as major listings are deleted.	Major Security Flag
SS02	All stocks which are not of equity type are deleted.	Type of instrument
DS01	All companies must have available CE, P and FY-E. Companies without will be deleted.	Common Equity, Price and Fiscal Year End
DS02	All constant prices from the end of the sample until the first non-constant price, are deleted.	Price
DS03	All zero returns (with returns calculated from the total return index) from the end of the sample until the first non-zero return are deleted.	Total Return Index
DS04	All so-called "Penny-stocks" are deleted, with prices less than the 5 per cent quantile of the price distribution over the whole sample period per country.	Price
DS05	All prices greater than 1.000.000 EUR will be set to missing.	Price
DS06	All returns greater than 990% and lower than -100% are set to missing.	Total Return Index

Table 3: screens performed on dataset to correct for normality.

The data is screened for both static and dynamic criteria. The static screens are based on the major security flag and the type of instrument. This dataset only includes stocks which have a major listing and are of the equity type. The dynamic screens are based on common equity, price, fiscal year end and total return index. The screens remove companies which do not have data available for all three variables named in DS01. Next to that, it removes constant prices and zero returns at the end of the sample period, truncates a certain proportion at the lower end of the price distribution ("Penny-stocks") and performs sanity checks whether some data makes sense. The removal of constant prices and zero returns at the end of the sample period is because TRD reports for delisted stocks the last valid price and total return index available. The removal of small (or penny) stocks is common in the literature.

4.5 Descriptive statistics

All variables have been collected and screened, and so now a description of the statistics will be given. Based on this it can be seen if there are some remarkable data points that we should keep into account when analysing the results. In the table below one can find the descriptive statistics of the returns on the equity market in France, Germany, the Netherlands and the UK. The descriptive statistics of the used market- and risk-free rate proxies can be found in Appendix C.

When looking at the table, one can see that the number of observations for returns is similar between France and Germany. The Netherlands has a significantly lower amount, but this was expected since the country itself is also a lot smaller. Next to that, the UK seems to have both the most amount of observations as the most amount of companies included in the sample. When looking at the average returns, it can be seen that all countries generated a positive average return over the past 17 years and that the Netherlands seem to have performed best. The return distribution in the Netherlands also seems to be the most volatile, with a standard deviation of 1,485%. Next to this it also has the most positively skewed distribution. Skewness measures asymmetry in which a normal distribution is symmetric around its mean. In this case, all countries experienced a positive skewness, meaning that the right tail (positive returns) is more pronounced than the left tail (negative returns).

	France	Germany	Netherlands	UK
Observations	4.488.875	5.082.152	637.130	6.432.820
Number of companies	1.794	1.738	235	3.378
Average	0,008%	0,007%	0,013%	0,004%
Std. Dev.	0,463%	0,551%	1,485%	0,435%
Skewness	0,317	0,260	0,568	0,282
Kurtosis	39,410	27,869	70,395	35,534
JB. P-value	0,000	0,000	0,000	0,000
Minimum	-100%	-100%	-100%	-100%
Q1	-0,547%	-1,058%	-0,868%	-0,239%
Median	0,000%	0,000%	0,000%	0,000%
Q3	0,485%	1,032%	0,830%	0,003%
Maximum	953%	984%	979%	902%
$\rho(1)$	0,500	0,263	0,089	0,496
$\rho(2)$	0,222	0,121	0,047	0,253
$\rho(3)$	0,124	0,076	0,012	0,195
$\rho(4)$	0,119	0,111	0,042	0,193
$\rho(5)$	0,082	0,038	0,001	0,149

Table 4: descriptive statistics of daily returns per country. One can see that most observations are collected for the UK market, followed by Germany and France. The UK market also counts the highest number of companies. The Dutch market seems to have generated the highest daily return, however all countries have generated on average a positive return. All markets seem to be positively skewed with quite a high peak and so "fat tails". None of the markets seem to be normally distributed, however this is quite common in high frequency data. Lastly, autocorrelation seems relatively low in all markets.

Kurtosis can also be used to analyse the distribution of the countries. Kurtosis is the degree of how peaked a distribution is, meaning that if the kurtosis is higher than 3 (the value of a normal distribution), the tails are fatter, giving much higher probabilities to extreme returns. This is typical of financial data, especially at higher frequencies. This implies that the observed high kurtosis values for each country are not something to be too concerned about. To test for normality, a Jarque-Bera test has been performed. The p-values of this test can be seen for each country. Since this value is zero for all countries, the null hypothesis for a normal distribution can be rejected, and it can be confirmed that none of the countries show a normal return distribution. However, this is very typical for a dataset with a high frequency over a long time period. Due to the screenings that are shown in table 3, the return distributions should be relatively normalized. Also when looking at the return frequency table in Appendix D, one can see that most of the returns lie between -100% and 100%. Germany has the highest number of positive outliers and also the highest number of NA's. Lastly, ρ(1) states the autocorrelation of the return with a 1-day lag. All autocorrelations are significant at a 1% significance level, except for the 5-day lag in the Dutch market which is significant at a 5% level. Overall the correlation seems to be relatively low, with only two values near the 0,5 benchmark, namely the 1-day lag for the French and UK market. Autocorrelation for the Dutch market seems to be very low.

The correlation matrices of all variables used per country in this research can be found in Appendix E. The most important correlations, the ones higher than 0.4, will be discussed. It should be noted that 'COMB' stands for the combination of technical strategies, and in particular combining the MA- and the RSI-strategy. Due to a limited amount of signals, the SR-strategy could not be included (more on this can be found in Results). When looking at the correlation table per country, one can see that the relatively high correlations are all in combination with COMB. In the countries Germany and the Netherlands, it is as expected quite high with MA and RSI, but this is obviously because COMB is a combination of them. However, in France and the UK, COMB seems to have quite a high correlation with the SR-strategy as well (0,471 and -0,553 respectively). What stands out more is that these correlations do not have the same signal (France positive correlation, UK negative). Nonetheless, this should not pose a problem for the empirical results. The regression analyses will be performed per technical strategy in which the returns will be tested for risk factors, meaning that the returns of two or more different technical strategies will not be regressed in the same model and so will not pose a problem for endogeneity.

5. Methodology

To find out whether the technical strategies will generate significant positive returns, several actions have to be undertaken. At first, the most common risk factors, the size-, value- and momentum-factor, will be constructed to capture its risk. After this, the factors of the three technical strategies that will be focused on (Moving Average, Relative Strength Index and Support and Resistance) will be constructed. Average returns can be calculated by implementing a strategy in which one goes long in the most profitable signal and short in the least profitable one. This will be calculated and rebalanced for every day in the sample. Once these factors have been constructed, a regression analysis will be performed to see whether the returns of technical strategies are partly due to the common risk factors and if an alpha can be generated. Next to this, as a robustness check, there will also be separate analyses in which both different timeframes for the strategies as well as overall time effects will be analysed.

5.1 Construction common risk factors

Fama and French (1993) were the first ones to introduce common risk factors based on individual stock characteristics. To obtain market-wide factors, they sorted stocks on these properties and used the variation in portfolio returns between high- and low rated stocks according to the characteristics. To be more specific, they introduced two different factors: the size- and value factor.

The size factor is based on the phenomenon that stocks with a small market capitalization make higher returns than stocks with a big market capitalization (small-minus-big – SMB). The value factor is based on the phenomenon that stocks with a high book-to-market (BTM) equity ratio generate higher returns than stocks with a low BTM equity ratio (high-minus-low – HML). Additionally, Carhart added a fourth factor to this model, called the momentum factor. This factor is based on the phenomenon that stocks that have performed well over the last 12 months will continue to do so, whereas stocks that have performed poorly will also continue to do so (winners-minus-losers – WML). The returns used in this dataset are based on total return indices and include dividends and account for stock splits. Book equity is common equity in this dataset. When sorting on book equity, only values greater than zero will be included. Book equity is updated on an annual or quarterly basis. Size is equal to the market value in this research. Market value is updated on a daily basis. When constructing both factors, the last observable book- and market value will be taken into account on day_{t-1} and returns on day_t. To create the WML factor, the average daily return (using the return index) has been calculated over the period: day_{t-201} to day_{t-1}.

The breakpoints for the risk factors are given in the table below. These breakpoints were found by Schmidt et al. (2017) and applied to the whole sample. When looking at the Size breakpoints, it seems like the Dutch market contains companies that are relatively higher in market value compared to the other countries. France and Germany are quite similar. When looking the BTM breakpoints, France and Germany are also quite similar, however the German market seems to be more diverse. The WML breakpoints show that France seems to contain the strongest “winners and losers”.

	Breakpoints	France	Germany	Netherlands	UK
Size (BP1)	0,60	165,4	167,4	939,8	45,0
Size (BP2)	0,70	443,2	425,8	2.345,1	91,9
Size (BP3)	0,80	1.731,7	1.436,4	5.989,7	229,2
Size (BP4)	0,90	12.391,2	10.765,1	16.766,8	1.012,7
BTM (BP1)	0,20	85,4	51,5	18,1	39,3
BTM (BP2)	0,40	509,5	469,0	233,6	350,8
BTM (BP3)	0,60	2.764,0	3.853,7	970,1	2.158,1
BTM (BP4)	0,80	51.167,9	60.788,6	17.771,5	20.016,4
WML (BP1)	0,30	-0,017%	-0,045%	-0,025%	-0,065%
WML (BP2)	0,70	0,140%	0,146%	0,129%	0,136%

Table 5: breakpoints for common risk factors by Fama & French. Corresponding values for Size are in million euro, for BTM are in ratios and for WML and in average daily return. Size breakpoints are constructed by using market values, the BTM breakpoints by the ratio of book value to market value and the WML breakpoints by the Return Index.

In the tables below one can find an overview of the returns when implementing the Fama & French and Carhart method in the sample of this research. Since the common factors are not the main focus of this research, the results will be discussed shortly. The returns for all risk factors are value-weighted.

SMB	Small	2	3	4	Big	SMB
France	0,002%**	-0,005%***	-0,002%	0,010%	0,005%***	-0,004%***
	(0,001%)	(0,001%)	(0,002%)	(0,009%)	(0,000%)	(0,000%)
Germany	0,002%*	0,008%***	-0,001%	0,003%**	0,005%	-0,003%
	(0,001%)	(0,002%)	(0,005%)	(0,002%)	(0,008%)	(0,008%)
Netherlands	0,001%	0,004%	0,008%	-0,008%	0,003%	-0,002%
	(0,001%)	(0,002%)	(0,045%)	(0,011%)	(0,007%)	(0,006%)
UK	-0,003%	0,002%***	0,005%***	-0,007%	0,002%	-0,005%
	(0,007%)	(0,001%)	(0,002%)	(0,007%)	(0,002%)	(0,007%)

Table 6: SMB factor in daily returns per quintile, std. err. is stated in brackets.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

It seems like the SMB has not been generating any significant positive returns over the past 17 years. It rather seems to be the opposite, as it looks like the big firms generate higher positive returns. However, none of these are significant, except for France. This outcome is consistent with the literature. For example, Schmidt et al. (2016) find no significant size effect for any of the countries that they cover. In another paper, the author researches the effect of corporate governance on average stock returns including SMB and HML and also finds an overall negative significant size effect (Bauer, Guenster, & Otten, 2004). Lastly, when looking at the regularly updated database of Kenneth French, the SMB factor is equal to -0,003% per day over all of Europe, which is quite similar to the results in table 6. It seems like ever since the news on the size-factor came out, investors have been immediately trading upon this, meaning that the factor is completely traded out of the market.

HML	Low	2	3	4	High	HML
France	0,002%	-0,007%**	-0,006%*	0,009%***	0,007%***	0,005%
	(0,001%)	(0,001%)	(0,001%)	(0,001%)	(0,001%)	(0,070%)
Germany	-0,010%	0,000%	0,004%	-0,002%	0,002%**	0,013%
	(0,042%)	(0,003%)	(0,008%)	(0,005%)	(0,001%)	(0,042%)
Netherlands	0,003%	0,002%	0,000%	-0,002%	0,008%**	0,006%
	(0,009%)	(0,002%)	(0,000%)	(0,003%)	(0,003%)	(0,009%)
UK	0,000%	-0,007%***	0,000%	0,004%	0,004%	0,004%
	(0,000%)	(0,002%)	(0,002%)	(0,005%)	(0,002%)	(0,002%)

Table 7: HML factor in daily returns per quintile, std. err. is stated in brackets.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

The value factor, on the other hand, does appear to be emerging in the European stock market, however insignificant, but especially in Germany with an effect of 0,013% return per day. The sign of this outcome is consistent with previous research in European markets, in which the value factor was estimated to generate a daily return of 0,047% on a 5% significance level (Nijman, Swinkels, & Verbeek, 2004). Additionally, in the database of Kenneth French, the HML factor in Europe is equal to 0,015% per day, which is a bit higher than the results found in table 7, but quite similar. Altogether the HML factor seems to be positive, but insignificant.

WML	Losers	2	Winners	WML
France	-0,002%	0,005%**	0,001%	0,003%
	(0,003%)	(0,002%)	(0,004%)	(0,005%)
Germany	0,007%	-0,010%	0,004%	-0,003%
	(0,009%)	(0,021%)	(0,015%)	(0,016%)
Netherlands	-0,001%	-0,002%**	0,001%	0,002%**
	(0,000%)	(0,001%)	(0,000%)	(0,001%)
UK	-0,001%	0,002%	0,001%	0,003%**
	(0,001%)	(0,001%)	(0,001%)	(0,001%)

Table 8: WML factor in average daily returns per quintile, std. err. is stated in brackets. The risk factor is based on an average of daily returns over time period day_{t-201} till day_{t-1}.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Lastly, the momentum factor will be discussed. This factor seems to have a positive and significant effect in Europe, particularly in the Netherlands and the UK. The returns are also positive in France, but negative in Germany and both are insignificant. When looking at Kenneth French's data, the WML factor is equal to 0,041% return on a daily basis. Also when looking at another paper by Nijman and Swinkels (2003), the average daily momentum returns lie around 0,035% per day and have significance for France and UK. The WML factor returns found in table 8 seem to be relatively low. However, this database represents only a part of Europe.

5.2 Construction technical strategy factors

To find out whether technical strategies generate significant positive returns, this research will construct three main technical strategies and analyse its outcome. The strategies that will be focused on are the Moving Average, the Relative Strength Index and the Support and Resistance strategy. Additionally, a combination of these strategies will also be created. In this section, it will be explained how these technical factors are constructed.

5.2.1. Moving Average

This strategy is based on the averages over a certain time-period in a time-series. With this technique, a moving average convergence divergence (MACD) can be set up. It is calculated by subtracting the longer exponential moving average (EMA) from the shorter EMA. This research will look at the 12- and 26-day EMA's, which are the most regularly used short and long-period EMA's respectively (Murphy, 1999). The EMA is defined as follows:

$$EMA_t = (\frac{2}{n} * (P_t - EMA_{t-1}) + EMA_{t-1} \tag{4}$$

Where EMA_t is the exponential moving average at time t, n is the number of periods for EMA and P_t is the value of the price index at time t. The initial EMA is the n-day simple moving average of the series. A buy signal is triggered when the MACD crosses the zero line from below (because it will most likely go up soon), while a sell signal is triggered when the MACD crosses the zero line from above (because it will most likely go down soon).

5.2.2. Relative Strength Index

This index shows the 'strength' of certain stocks. It is measured as follows:

$$RSI_t(n) = \frac{\sum_{i=0}^{n-1}(P_{t-1} - P_{t-i-1})1\{P_{t-1} > P_{t-i-1}\}}{\sum_{i=0}^{n-1}|P_{t-i} - P_{t-i-1}|} * 100 \tag{5}$$

Where RSI_t is the Relative Strength Index at time t, P_t is the value of the index at time t, n is the number of RSI period, $1\{\}$ is an indicator function which equals one when the statement inside the bracket is true and equals zero otherwise, $|x|$ is the absolute value of x. The RSI ranges from 0 to 100. A stock is deemed overbought when its RSI is above 70, while it is regarded as oversold when the RSI is below 30. When the RSI is above 50, it indicates a bullish signal, while the stock is considered bearish when the RSI is below 50. To implement the trading rule, a buy signal is triggered when the RSI crosses the 30 from above, while a sell signal is triggered when the RSI crosses the 70 from below. In this research, the focus will be on the 14-day RSI, which is a popular length used by traders. However, to check for robustness, other time periods will also be researched, namely the 12- and the 26-day period to be more in line with the MA strategy.

5.2.3. Support and Resistance rule

The third rule that will be implemented is the Support and Resistance rule. The underlying idea behind this rule is that prices of securities tend to stop and reverse at 'support' and 'resistance' levels. Support is a minimum price of a certain history at which buyers attempt to prevent the price from dropping further. Similarly, resistance is where sellers attempt to prevent the price from going higher. According to the rule, the price will continue to drop (rise) once a support (resistance) is broken. This rule is also known as "Channel rule" or "Trading range breakout." A buy signal is triggered when the price crosses the maximum from below, and a sell signal is triggered when the price crosses the minimum from above. It is measured as follows:

$$SR_t(buy)\ when\ P_t > \max\left(P_{t-1}, \dots, P_{t-n}\right) \tag{6}$$

$$SR_t(sell)\ when\ P_t < \min\left(P_{t-1}, \dots, P_{t-n}\right) \tag{7}$$

To comply with the other strategies and to make the outcomes comparable, the same time-periods will be applied: 12-day, 14-day and 26-day.

5.2.4. Combination of strategies

Lastly, a combination of all technical strategies will be implemented. This will be constructed by combining all sell- and buy-signals per strategy. This means that a buy-signal will show when all three strategies show a buy-signal and a sell-signal will show when all strategies show a sell-signal. The timeframe for the RSI- and SR-strategies will be 14 days. As will be shown in the result section of this paper, a number of signals generated by the SR-strategy turned out to be too low to combine with the other strategies and still get a significant result. For this reason, the combination strategy will solely consider the MA- and RSI-strategy.

5.2.5. Return

Now that the technical strategies have been explained, the return calculation will be discussed. Following the paper of (Brock, Lakonishok, & LeBaron, 1992), this research will focus on the average of the 10-day returns, which is defined as:

$$10 - day\ return\ (r_t^{10}) = \log(P_{t+10}) - \log\left(P_t\right) \tag{8}$$

Where P_t is the closing price on day t. Note that a negative return generated by the sell signal implies a positive profit. Whenever there is a buy/sell signal, all other signals during the next ten days are ignored. To compare the returns with the common risk factor returns, which are daily returns, the average of the 10-day return will be taken to construct a daily return for the technical factors as well.

5.2.6. T-statistics

When interpreting the results and their significance, the following formula will be used to calculate the t-statistics, following the notations in Brock et al. (1992):

$$t - statistic\ for\ buys\ (sells) = \frac{\mu_r - \mu}{\sqrt{\frac{\sigma^2}{N} + \frac{\sigma^2}{N_r}}} \tag{9}$$

where μ_r and N_r are the mean return and number of signals for the buys or sells and μ and N are the unconditional mean and number of observations. σ^2 is the estimated variance for the entire sample. For the buy-sell statistic, the following is defined:

$$t - statistic\ for\ buys - sell = \frac{\mu_b - \mu_s}{\sqrt{\frac{\sigma^2}{N_b} + \frac{\sigma^2}{N_s}}} \tag{10}$$

where μ_b and N_b are the mean return and number of signals for the buys and μ_s and N_s are the mean return and number of signals for the sells.

5.3 Regression analysis factors

Lastly, after all factors have been constructed (both common risk and technical factors), a regression analysis will be performed to see how much of the returns of the technical factors can be explained by the market and by the common risk factors. The variables included in the regression analysis are a market proxy, SMB, HML, WML, MA, RSI, SR and dummies for the four different time periods. The dummies are added as a robustness check to make sure the returns are not due to a specific event in time. The sample is divided in four subperiods: (1) 1999-2002, (2) 2003-2006, (3) 2007-2011 and (4) 2012-2015. The first period will be omitted in the analysis. Note: the technical factors RSI and SR will be regarding the 14-day timeframe. The regression analysis will look as follows:

$$\begin{aligned} Technical\ factor_{ix} = \ & \alpha + \beta_1 Mkt_i + \beta_2 SMB_i + \beta_3 HML_i + \beta_4 WML_i + \beta_5 D(2003-2006)_i + \\ & \beta_6 D(2007-2011)_i + \beta_7 D(2012-2015)_i + \varepsilon \end{aligned} \tag{11}$$

Where the technical factor is equal to either MA, RSI or SR, marked by x, Mkt_i is the market proxy for specific country i, SMB_i, HML_i and WML_i are the common risk factors and $D(\,)_i$ is the dummy for a certain time period. The ‘robust' option is used when performing the regressions, to correct for possible heteroscedasticity and non-normality.

6. Empirical results and analysis

In this chapter, the empirical results will be discussed and analysed. At first the results of the Moving Average strategy will be discussed, followed by the results of the Relative Strength Index, the Support and Resistance rule and the combination strategy. Not only will the results of the whole sample be discussed, but there will also be a focus on the returns in different subperiods. The sample is divided into four periods: 1999-2002, 2003-2006, 2007-2011 and 2012-2015. Next to this, there has also been a focus on different timeframes for the RSI- and SR-strategy to check for robustness. Lastly, the regression analyses results will be discussed per strategy, to see if the generated returns might be explained by the market- and risk-factors and if a significant alpha can be generated.

6.1 Results Moving Average

In the table below one can find the results for the Moving Average strategy. The first thing that stands out is the fact that this strategy does not always create positive returns; for France and the UK it is negative and for France even significant. When looking at the number of buy- and sell signals it can be seen that these are quite balanced. Additionally, about half of the buy- and sell signals are significant, mostly for France and Germany. So far it seems like this strategy only generates significant positive returns for Germany, which results in 0,065% return per day. However, when looking at France, the significant negative returns are almost as high, with 0,058% per day. The positive return for this strategy in the Netherlands is just slightly significant. Additionally, when comparing to the paper of Wang, Yu and Cheung (2014) who find an average return of 0,054% per day, the returns seem to be relatively the same for France and Germany, but low for the Netherlands and the UK. Overall, the results appear to be divided per country.

	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France	1.840.286 *(34,0%)*	1.834.667 *(33,8%)*	-0,031%*** (0,002%)	0,027%*** (0,002%)	-0,058%*** (0,001%)
Germany	1.924.118 *(33,4%)*	1.936.748 *(33,7%)*	0,012%*** (0,002%)	-0,053%*** (0,002%)	0,065%*** (0,001%)
Netherlands	350.446 *(41,0%)*	399.083 *(46,7%)*	0,008% (0,002%)	-0,021% (0,002%)	0,030%* (0,001%)
UK	2.049.157 *(26,7%)*	2.064.58 *(26,9%)*	-0,019% (0,002%)	-0,017% (0,002%)	-0,001% (0,001%)

Table 9: MA (long: 26-day, short: 12-day) outcome in daily returns, the percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. err. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

To check whether the returns might be due to a specific time period, the same strategy has been performed over different subperiods. The results can be found in Appendix F. One thing that stands out is that the second period (2003-2006) generates significant results for almost all countries. For the Netherlands and the UK, this is the only subperiod with significant returns, while for France and Germany almost all subperiods generate significant returns. Next to this, when looking at France specifically, we see that the returns were negative for all periods, so the overall negative average return is not due to one period with large outliers, but simply accounts for the whole sample. The same thing applies to Germany, but then with positive returns. Overall it can be said that the average returns seen in table 9 do not seem to be due to a specific subperiod, with the small exception of the UK where the return from 1999-2002 is relatively much lower (-0,019%) compared to the other periods (about -0,006%). When looking at previous papers that also used subperiods, this seems to overlap quite well. For example, Chong & Ng (2008) also did not find and substantial differences in their subperiods, however using a longer total time period of sixty years.

Now that these returns have been analysed, a regression analysis is performed to see how much of the technical strategy returns can be explained by the common risk factors. The results of this regression analysis can be found in the table below. When looking at the results, it can be seen that the returns of the MA strategy are neither significantly explained by the common risk factors nor by the market. Also when looking at the dummy variables, all subperiods seem to be equally significant. When comparing alphas between countries, they seem to match the results shown in table 9. A significant negative alpha is generated for France and a positive alpha for Germany, regardless of the risk factors added. Lastly, when comparing the R^2 of all models, the model seems to fit France best, with an R^2 of 0,0446, but Germany and UK have a relatively close R^2 of 0,0373 and 0,0404 respectively.

	MA-France			MA-Germany		
	I	II	III	IV	V	VI
Alpha	-0,001***	-0,001***	-0,001***	0,001***	0,001***	0,001***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	-0,040	-0,034	-0,047	-0,026	-0,027	-0,027
	(0,081)	(0,082)	(0,087)	(0,063)	(0,063)	(0,063)
SMB	-0,002	0,023	0,010	0,025	0,052	0,080
	(0,100)	(0,100)	(0,099)	(0,235)	(0,234)	(0,221)
HML	-0,708	-0,819	-0,978	0,005	0,002	0,001
	(0,155)	(0,160)	(0,159)	(0,029)	(0,030)	(0,026)
WML		-0,204	-0,186		0,152	0,154
		(0,194)	(0,204)		(0,114)	(0,107)
D_2003-2006			0,003***			0,001***
			(0,003)			(0,003)
D_2007-2011			0,003***			0,003***
			(0,003)			(0,004)
D_2012-2015			0,003***			0,002***
			(0,003)			(0,003)
Sample	4.398	4.185	4.185	4.398	4.185	4.185
R^2	0,0002	0,0004	0,0446	0,0001	0,0006	0,0373

	MA-Netherlands			MA-UK		
	VII	VIII	IX	X	XI	XII
Alpha	0,000***	0,000***	0,000**	0,000*	0,000	0,000***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	-0,099	-0,100	-0,103	0,013	0,017	0,016
	(0,081)	(0,082)	(0,083)	(0,034)	(0,035)	(0,032)
SMB	0,369	0,355	0,412	0,037	0,197	0,121
	(0,513)	(0,530)	(0,536)	(0,225)	(0,231)	(0,222)
HML	0,019	0,018	0,001	-0,389	-0,386	-0,377
	(0,164)	(0,164)	(0,154)	(0,398)	(0,407)	(0,427)
WML		-0,104	-0,103		0,327	0,267
		(0,559)	(0,545)		(0,128)	(0,129)
D_2003-2006			0,002***			0,001***
			(0,004)			(0,002)
D_2007-2011			0,003***			0,002***
			(0,004)			(0,002)
D_2012-2015			0,002***			0,002***
			(0,004)			(0,002)
Sample	4.398	4.185	4.185	4.398	4.185	4.185
R^2	0,0008	0,0008	0,0135	0,0002	0,0006	0,0404

Table 10: MA (long: 26-day, short: 12-day) regression analysis outcome, std. err. is stated in brackets. Results per variable or dummy is stated in coefficients, sample is stated in number of days.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

6.2 Results Relative Strength Index

In this part, the results of the RSI strategy will be discussed. The results can be found in table 11 below, per country and per timeframe (either 12-, 14- or 26-day) used in the strategy. The first thing that stands out is that this strategy again quite differs per country. In France and Germany, it seems to generate significant positive returns, in the UK significant negative returns and in the Netherlands no significant returns at all. The returns in Germany seem to be the highest, with almost double the returns of France in the 12- and 14-day strategy. On top of this, the 26-day strategy seems to generate the highest return for each country, regardless of significance and signal. When comparing the returns with previous literature, the outcome is quite overlapping. Levy (1967) also used the 26-day timeframe and found daily returns of 0,041% and Chong & Ng (2008) find an average daily return of 0,018%. The returns for each country is quite similar to this, except for Germany and the 26-day timeframe for France. Next to this, going against previous literature (Brock, Lakonishok, & LeBaron, 1992), the 14-day strategy seems to perform less well, compared to the 12- or 26-day strategy, generating fewer significant returns (especially in France). Next to that, most of the sell-signals seem to be significant, except for the Netherlands. The buy-signals only generate significant returns in Germany and the UK.

Overall, when comparing all returns per country and per timeframe, this strategy seems to generate the most significant returns for the UK, however negative. Next to this, the 26-day timeframe seems to work best, generating the most significant and highest returns among all countries. Like the MA-strategy, this strategy seems to work best for Germany as well.

To check whether the returns might be due to a specific time period, the same strategy has been performed on different subperiods. The results can be found in Appendix F. The timeframe used is 14-day, other timeframes can be found in Appendix G. When looking upon the table, it is immediately noticeable that rarely any return is significant due to a specific time period, except for Germany and the UK. The highest possible significant positive return is equal to 0,092% per day in the third subperiod in Germany. The next highest return is 0,055% in the fourth period in Germany. This could mean that the RSI-strategy worked specifically well during the credit crisis and its aftermath in Germany. This strategy also generates significant returns for the UK, however negative. Especially in the second period, right before the credit crisis, this strategy would generate 0,021% negative significant returns. The same accounts for the UK, but with the second period, right before the crisis.

Lastly, when looking at the returns per subperiod of the Netherlands, it can be seen that half of those generate negative returns. However, since the return in the third subperiod is relatively high (0,056% vs. -0,004%), the overall returns have been positive. Previous literature has found similar results (Chong & Ng, 2008), in which the RSI-strategy returns seemed to be due to a specific period as well (1975-1994), however only at a 10% significance level.

	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France					
12-day	714.934 *(13,2%)*	686.075 *(12,7%)*	0,002%	-0,027%**	0,029%**
			(0,001%)	(0,002%)	(0,001%)
14-day	690.843 *(12,7%)*	632.415 *(11,7%)*	0,002%	-0,014%	0,017%
			(0,001%)	(0,000%)	(0,001%)
26-day	546.930 *(10,1%)*	418.229 *(7,7%)*	0,006%	-0,043%***	0,049%***
			(0,001%)	(0,002%)	(0,002%)
Germany					
12-day	614.050 *(10,7%)*	596.749 *(10,4%)*	-0,003%*	-0,054%***	0,051%***
			(0,001%)	(0,002%)	(0,002%)
14-day	580.304 *(10,1%)*	538.078 *(9,4%)*	-0,002%*	-0,056%***	0,054%***
			(0,001%)	(0,002%)	(0,002%)
26-day	418.040 *(7,3%)*	320.059 *(5,6%)*	-0,001%	-0,062%**	0,060%***
			(0,001%)	(0,002%)	(0,002%)
Netherlands					
12-day	130.495 *(15,3%)*	102.433 *(12,0%)*	-0,007%	-0,017%	0,010%
			(0,001%)	(0,001%)	(0,002%)
14-day	100.930 *(11,8%)*	92.035 *(10,8%)*	-0,007%	-0,025%	0,018%
			(0,001%)	(0,003%)	(0,003%)
26-day	68.040 *(8,0%)*	52.802 *(6,2%)*	-0,007%	-0,032%	0,024%
			(0,001%)	(0,004%)	(0,004%)
UK					
12-day	1.010.490 *(13,2%)*	915.272 *(11,9%)*	-0,013%**	-0,004%**	-0,009%**
			(0,001%)	(0,002%)	(0,001%)
14-day	956.030 *(12,5%)*	875.961 *(11,4%)*	-0,013%**	-0,003%**	-0,010%**
			(0,001%)	(0,002%)	(0,001%)
26-day	823.339 *(10,7%)*	690.456 *(9,0%)*	-0,012%**	-0,002%**	-0,011%**
			(0,001%)	(0,001%)	(0,001%)

Table 11: RSI outcome in daily returns, the percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. err. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Also for this strategy, a regression analysis has been performed. Note that the results are based on the RSI 14-day strategy. When looking at the results, it can be seen that in this case, the SMB and HML might already explain the returns of the RSI strategy. Especially the SMB factor generates significant coefficients, except for the Netherlands. The signal, however, differs per country. The HML factor seems to partially explain the returns only in France on a 5% significance level. Additionally, the WML factor seems to play a small role in explaining the returns in Germany, but only on a 10% significance level. When looking at the subperiod dummies, it seems like especially 2007-2015 generated significant returns for most countries, but in France and Germany also 2003-2006. This seems to be quite comparable to what has been found in the table in Appendix F. In line with the results shown in table 11; a significant positive alpha seems to be generated in Germany, however not in France and neither a negative alpha in the UK. When comparing R^2 of all models, it seems to fit the UK the best, with an R^2 of 0,1056, followed by Germany with an R^2 of 0,0483.

	RSI-France			RSI-Germany		
	I	II	III	IV	V	VI
Alpha	0,000***	0,000***	0,000	0,001***	0,001***	0,001***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	-0,130*	-0,136	-0,145	0,049	0,042	0,055
	(0,091)	(0,092)	(0,090)	(0,123)	(0,122)	(0,117)
SMB	-0,253**	-0,282**	-0,274**	0,144**	0,147**	0,144**
	(0,141)	(0,142)	(0,140)	(0,619)	(0,619)	(0,599)
HML	0,197	0,257**	0,218**	0,062	0,059	0,056
	(0,989)	(0,105)	(0,994)	(0,053)	(0,054)	(0,047)
WML		-0,191	-0,183		0,521*	0,509*
		(0,120)	(0,122)		(0,292)	(0,285)
D_2003-2006			0,002***			-0,003***
			(0,004)			(0,001)
D_2007-2011			0,001			0,004***
			(0,000)			(0,001)
D_2012-2015			0,002***			0,001
			(0,000)			(0,001)
Sample	4.411	4.185	4.185	4.411	4.185	4.185
R^2	0,0030	0,0041	0,0267	0,0033	0,0051	0,0483

	RSI-Netherlands			RSI-UK		
	VII	VIII	IX	X	XI	XII
Alpha	0,000***	0,000***	0,000*	0,000***	0,000***	0,000***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	-0,417	-0,417	-0,419	0,017	0,029	0,031
	(0,497)	(0,500)	(0,504)	(0,048)	(0,047)	(0,046)
SMB	-0,115	-0,126	-0,120	-0,516***	-0,490***	-0,485***
	(0,108)	(0,112)	(0,110)	(0,372)	(0,368)	(0,368)
HML	-0,597	-0,618	-0,669	-0,960	-0,932	-0,104
	(0,571)	(0,572)	(0,537)	(0,904)	(0,944)	(0,950)
WML		-0,121	-0,123		-0,345	-0,298
		(0,996)	(0,973)		(0,212)	(0,210)
D_2003-2006			0,001			0,000
			(0,001)			(0,000)
D_2007-2011			0,001***			0,002***
			(0,001)			(0,003)
D_2012-2015			0,003***			0,001***
			(0,000)			(0,000)
Sample	4.411	4.185	4.185	4.411	4.185	4.185
R^2	0,0020	0,0025	0,0174	0,0950	0,0904	0,1056

Table 12: RSI regression analysis outcome, std. err. is stated in brackets. Results per variable or dummy is stated in coefficients, sample is stated in number of days.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

6.3 Results Support and Resistance rule

In the table below the results for the Support and Resistance rule can be found. What stands out is that this strategy generates consistent positive returns for all countries. In France and the UK, the returns are significant as well. The highest returns are made in France, followed by Germany and the UK. The relatively highest amount of both buy- and sell-signals can be found in the Netherlands, followed by France and Germany. With this strategy, mostly the buy-signals seem to generate significant returns. The buy-signals in Germany would give negative returns. However, these appear to be insignificant. When comparing the different timeframes, the 12-day timeframe seems to generate the most significant returns, even though the significance level in Germany is only 10%. The highest returns, however, are created by the 26-day timeframe. Again, comparing to the RSI-strategy, the 14-day timeframe does not seem to outperform the other timeframes. Overall, this strategy generates the highest returns in the French market, but the most significant returns in the UK market. When comparing these results with previous literature, the returns seem quite high. Brock et al. (1992) find an average daily return of 0,010%, whereas the average return in this sample seems to be around 0,030%., which is relatively higher.

	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France					
12-day	406.446 *(7,5%)*	393.961 *(7,3%)*	0,024%**	-0,007%	0,031%**
			(0,002%)	(0,002%)	(0,002%)
14-day	373.881 *(6,9%)*	366.034 *(6,8%)*	0,025%**	-0,007%	0,032%**
			(0,002%)	(0,002%)	(0,002%)
26-day	266.658 *(4,9%)*	271.070 *(5,0%)*	0,032%***	-0,006%	0,037%**
			(0,003%)	(0,002%)	(0,002%)
Germany					
12-day	424.898 *(7,4%)*	416.866 *(7,2%)*	-0,002%	-0,034%*	0,032%*
			(0,003%)	(0,002%)	(0,002%)
14-day	296.423 *(5,2%)*	386.732 *(6,7%)*	-0,028%	-0,035%	0,007%
			(0,002%)	(0,003%)	(0,002%)
26-day	281.531 *(4,9%)*	285.670 *(5,0%)*	-0,001%	-0,032%	0,032%
			(0,003%)	(0,003%)	(0,003%)
Netherlands					
12-day	72.849 *(8,5%)*	75.574 *(8,8%)*	0,011%	-0,017%	0,029%
			(0,004%)	(0,003%)	(0,004%)
14-day	66.967 *(7,8%)*	70.215 *(8,2%)*	0,013%	-0,018%	0,030%
			(0,004%)	(0,003%)	(0,004%)
26-day	47.795 *(5,6%)*	52.267 *(6,1%)*	0,016%	-0,016%	0,031%
			(0,006%)	(0,004%)	(0,007%)
UK					
12-day	397.168 *(5,2%)*	438.324 *(5,7%)*	0,001%**	-0,020%**	0,021%**
			(0,002%)	(0,002%)	(0,002%)
14-day	371.476 *(4,8%)*	407.231 *(5,3%)*	0,001%**	-0,020%**	0,022%**
			(0,002%)	(0,002%)	(0,002%)
26-day	280.993 *(3,7%)*	300.893 *(3,9%)*	0,001%*	-0,022%*	0,023%*
			(0,002%)	(0,002%)	(0,002%)

Table 13: SR outcome in daily returns, the percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. err. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

The table with the 14-day SR-strategy divided into subperiods can be found in Appendix F, other timeframes divided into subperiods can be found in Appendix H. One remarkable return is the 0,055% daily return on a 5% significance level for French buy-signals using the 14-day timeframe in 2003-2006, the period right before the credit crisis. This return could have contributed to the relatively high overall return for France of 0,032% on a 5% significance level. Additionally, there is the 0,049% daily (insignificant) return for the UK in the period 1999-2002 for the buy-sell strategy. This is relatively high compared to the other subperiods which show an average daily return of 0,013%. Lastly, the German market seemed to have generated a relatively high return using the long/short strategy, generating 0,027% per day during 2007-2011. Since the other subperiods generated around 0,002% per day, one could say the overall high return of Germany might be due to this specific period. However, the returns are insignificant for the subperiods.

Also for this strategy, a regression analysis has been performed. The results can be seen in the table below. Note that the results are based on the SR 14-day strategy. When looking at the table, it can be seen that the common risk factors do not seem to explain the technical factor returns at all, except for the UK market. Here the SMB factor seems to explain the returns quite well, with a significant negative coefficient of -0,364 in the four-factor model. The WML factor seems to play a smaller role, with a less significant positive coefficient of 0,195 in the four-factor model. When looking at the alphas, this strategy seems to generate none, meaning that the returns are nearly completely explained by the market and risk factors. Looking at subperiod dummies, the period 2003-2006 seems to play a significant role in all markets, which is quite comparable to the table in Appendix F. When comparing the R^2 of all models, the model seems to fit the UK market best with an R^2 of 0,0293, followed by the German market with an R^2 of 0,0133.

	SR-France			SR-Germany		
	I	II	III	IV	V	VI
Alpha	0,000***	0,000***	0,000***	0,000***	0,000***	0,000
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	0,008	0,018	-0,001	-0,103	-0,096	-0,099
	(0,155)	(0,158)	(0,158)	(0,086)	(0,085)	(0,083)
SMB	-0,130	-0,078	-0,096	-0,025	-0,025	-0,065
	(0,303)	(0,306)	(0,307)	(0,414)	(0,415)	(0,411)
HML	0,146	0,155	0,175	0,024	0,031	0,029
	(0,234)	(0,238)	(0,240)	(0,025)	(0,024)	(0,024)
WML		-0,343	-0,385		0,084	0,076
		(0,412)	(0,405)		(0,140)	(0,136)
D_2003-2006			0,002***			0,001**
			(0,001)			(0,000)
D_2007-2011			0,002***			0,003***
			(0,001)			(0,001)
D_2012-2015			0,000			0,000
			(0,001)			(0,000)
Sample	4.410	4.185	4.185	4.410	4.185	4.185
R^2	0,0001	0,0001	0,0072	0,0004	0,0004	0,0133

	SR-Netherlands			SR-UK		
	VII	VIII	IX	X	XI	XII
Alpha	0,000***	0,000***	0,000***	0,000***	0,000***	0,000***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	0,319	0,337	0,403	-0,040	-0,066	-0,056
	(0,865)	(0,878)	(0,882)	(0,094)	(0,102)	(0,098)
SMB	-0,127	-0,195	-0,187	-0,314***	-0,364***	-0,342***
	(0,467)	(0,478)	(0,479)	(0,514)	(0,519)	(0,514)
HML	0,782	0,812	0,699	0,200*	0,195*	0,189
	(0,189)	(0,189)	(0,186)	(0,112)	(0,115)	(0,117)
WML		0,162	0,144		0,243	0,241
		(0,584)	(0,584)		(0,329)	(0,329)
D_2003-2006			-0,001*			-0,004***
			(0,001)			(0,001)
D_2007-2011			0,001			-0,004***
			(0,001)			(0,001)
D_2012-2015			0,001			0,000***
			(0,001)			(0,000)
Sample	4.410	4.185	4.185	4.410	4.185	4.185
R^2	0,0001	0,0001	0,0030	0,0127	0,0170	0,0293

Table 14: SR regression analysis outcome, std. err. is stated in brackets. Results per variable or dummy is stated in coefficients, sample is stated in number of days.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

6.4 Results Combination Strategy

Lastly, the combination strategy will be discussed. As all results have been shown above, it might be interesting to see what the effect is when one combines them. This can be done by taking the same market per country and implement a strategy in which a buy-signal will be given on a specific day when all three strategies give a buy-signal on that day, and a sell-signal in the same way. Unfortunately, when combining all signals per strategy, it turned out that there are too few signals to give a result because the SR-strategy gave relatively fewer signals off than the other strategies. Based on this, the MA-strategy and the RSI-strategy are combined and the results can be seen in the table below.

Looking at the results, the returns quite differ per country. In most countries this strategy generates a (significant) positive return, however, for the UK these returns turn out to be negative and significant. The highest return can be produced in France, giving a daily return of 0,081% on a significance level of 1%. The returns for the Netherlands are nearly the same, with a daily return of 0,079% on the same significance level. The negative return for the UK is slightly less significant and the positive return for France seems to be insignificant at all. Overall, the buy-signals seem to generate a positive return (except for the UK, which might be the cause of the buy-sell negative return) and the sell-signals negative returns (however this can be seen as positive returns since these stocks will be shorted). Overall, this strategy seems to work best for Germany and the Netherlands.

	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France	317.242 *(1,4%)*	297.628 *(1,5%)*	0,014%	-0,026%	0,040%
			(0,278%)	(0,284%)	(0,361%)
Germany	362.145 *(5,5%)*	357.766 *(5,2%)*	0,046%***	-0,035%	0,081%***
			(0,156%)	(0,150%)	(0,165%)
Netherlands	77.179 *(9,0%)*	82.061 *(9,6%)*	0,006%	-0,073%***	0,079%***
			(0,206%)	(0,201%)	(0,222%)
UK	619.064 *(8,1%)*	508.477 *(6,6%)*	-0,031%	-0,003%*	-0,028%**
			(0,159%)	(0,132%)	(0,111%)

Table 15: Combined strategy outcome in daily returns, the percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. err. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

For this strategy, the returns are also tested in subperiods and the results can be found in Appendix F. When looking at these results, it can be seen that the different subperiods affected France and Germany. Especially the subperiod 2007-2011 had significant effects on the returns, leading to 0,112% daily return for France and 0,125% for Germany, both on an 1% significance level. Especially in Germany, the last three subperiods generate relatively high returns, meaning this could be the cause for the overall high return. However, this is not consistent over all periods. For the Netherlands however, there seems to be no specific period that contributes to this.

When looking at the regression analysis results below, one can see that the risk factors seem to play a relatively small role. In France, the HML factor seems to contribute to the returns, but only on a 10% significance level, whereas in the UK, the SMB factor seems to play a large role with its 1% significance. This could be due to the RSI-strategy where the same occurs. Upon comparing the subperiods, one could say that almost all subperiods are equally significant for each country. When looking at the alphas, this strategy seems to be particularly profitable for France and Germany on a 1% significance level. Lastly, when comparing R^2, it seems like this model fits best in the UK market with an R^2 of 0,0410, followed by the German market with an R^2 of 0,0227.

	COMB-France			COMB-Germany		
	I	II	III	IV	V	VI
Alpha	0,001***	0,001***	0,001***	0,001***	0,001***	0,001***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	-0,128	-0,114	-0,143	0,023	0,014	0,020
	(0,202)	(0,206)	(0,200)	(0,160)	(0,160)	(0,157)
SMB	-0,381	-0,259	-0,306	0,174	0,222	0,256
	(0,360)	(0,361)	(0,352)	(0,970)	(0,970)	(0,955)
HML	0,672*	0,689*	0,767*	0,038	0,042	0,039
	(0,359)	(0,365)	(0,374)	(0,065)	(0,067)	(0,058)
WML		-0,120*	-0,128*		0,832***	0,831***
		(0,728)	(0,678)		(0,315)	(0,296)
D_2003-2006			0,002**			0,000
			(0,001)			(0,001)
D_2007-2011			0,005***			0,001***
			(0,001)			(0,001)
D_2012-2015			-0,001			0,004***
			(0,000)			(0,001)
Sample	4.398	4.185	4.185	4.398	4.185	4.185
R^2	0,0012	0,0014	0,0193	0,0000	0,0015	0,0227

	COMB-Netherlands			COMB-UK		
	VII	VIII	IX	X	XI	XII
Alpha	0,000***	0,000***	0,000***	0,000***	0,000***	0,000***
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Mkt	-0,590	-0,541	-0,499	0,026	0,044	0,038
	(0,111)	(0,114)	(0,113)	(0,093)	(0,099)	(0,097)
SMB	-0,386	-0,401	-0,350	0,405***	0,466***	0,453***
	(0,478)	(0,491)	(0,495)	(0,469)	(0,459)	(0,463)
HML	-0,415	-0,349	-0,595	-0,129	-0,128	-0,124
	(0,156)	(0,158)	(0,152)	(0,118)	(0,119)	(0,120)
WML		-0,125	-0,142		0,907	0,925
		(0,560)	(0,557)		(0,297)	(0,299)
D_2003-2006			0,001***			0,002***
			(0,001)			(0,000)
D_2007-2011			0,000***			0,002***
			(0,001)			(0,001)
D_2012-2015			0,000***			0,002***
			(0,001)			(0,000)
Sample	4.398	4.185	4.185	4.398	4.185	4.185
R^2	0,0002	0,0002	0,0084	0,0260	0,0353	0,0410

Table 16: COMB regression analysis outcome, std. err. is stated in brackets. Results per variable or dummy is stated in coefficients, sample is stated in number of days.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

6.5 General results

Now that all results have been discussed elaborately per strategy, an overview will be given in the table below. The table will be discussed per column. The first column tells us the average daily returns per strategy over the entire market. Looking at this, we can see that the combination strategy which combines the MA- and the RSI-strategy generates the highest returns, with 0,043% per day. Secondly would be either the RSI- or SR-strategy using a 26-day timeframe, which generates around the same return of 0,03% per day. The "worst" performing strategy, generating the lowest average returns seems to be the MA-strategy, generating 0,009% per day.

Strategy		**Average returns**	**Highest returns**	**Lowest returns**	**Risk-factor**	**Alpha**
MA-strategy		0,0090%	Germany: 0,065%***	France: -0,058%***	No	Germany and negative alpha in France
RSI-strategy	12-day 14-day 26-day	0,0203% 0,0198% 0,0305%	Germany: 0,060%***	UK: -0,0110%**	Mostly SMB	Germany
SR-strategy	12-day 14-day 26-day	0,0283% 0,0228% 0,0308%	France: 0,0370%**	Netherlands: 0,007%	SMB only in UK	No
COMB-strategy		0,0430%	Germany: 0,0810%***	UK: -0,0280%**	HML in France and SMB in UK	France and Germany

Table 17: overview of results per technical strategy. Percentage values are daily returns.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Looking at the second result column, one can compare the highest daily return generated per strategy. It looks like the highest return can be generated by using the combined strategy, which will give 0,0810% return per day in Germany on a 1% significance level. This is higher than the two strategies (MA and RSI) separately, which have generated maximum return between 0,060% and 0,065% per day, also in Germany. The SR-strategy seems to perform relatively the worst, generating 0,037% per day as the highest return in France. One thing that stands out is that all these best returns have been found in the German market.

Moving on to the next column we can see the lowest returns generated per strategy. Based on this it seems like the MA-strategy generated the lowest returns in France with -0,058% per day on a 1% significance level. The next "worst" strategy would be the combination strategy, generating -0,028% daily return in the UK. The least "worst" strategy seems to be the SR-strategy, generating a positive return of 0,007% per day in the Netherlands, however insignificant. This is quite interesting since it looks like the SR-strategy generates the lowest positive returns, but also the lowest negative returns, making it quite a ‘safe' strategy. As opposed to the more popularly known phrase "high risk, high return," this seems to be "low risk, low return."

When looking at which strategy generates the most significant returns (regardless of the absolute value), one can look at the third performance column. For each strategy, there have been at least two countries in which it created significant returns. Almost all strategies seem to generate significant returns in Germany, except the SR-strategy. This strategy generates significant returns for France and the UK. Lastly, only the combined strategy generates significant returns for the Netherlands, none of the other strategies do so.

Average returns can be generated by the strategies, but they could also be due to common risk-factors and the market. This has been tested by the regression analyses. Looking at this, it seems like mostly the SMB and HML factors have played a role in some strategies. The MA-strategy is the only strategy that had no relation to these factors. The RSI-strategy seems to be partially explained by the SMB factors in nearly all countries and the SR- and COMB-strategy partially by SMB and HML but only in a few countries.

Lastly, when looking if the strategies can generate any significant alpha, we look at the last column. This seems to mostly be the case for Germany for nearly all strategies, except SR-strategy, which is in line with the rest of the results. Next to this, the SR-strategy seems to be incapable of generating an alpha for either country. What is also noticeable is the fact that the MA-strategy generates both positive and negative alpha for Germany and France respectively.

Additionally, for each of the strategies the Sharpe ratio has been calculated. An overview can be found in Appendix I. A consistent pattern that can be found among all strategies is that Germany seems to have the highest Sharpe ratio. Next to that, the UK market mostly generates negative Sharpe ratios, except for the SR-strategy. The highest average Sharpe ratio using a buy-sell strategy is equal to 0,92 in the German market with an MA-strategy. However, this strategy also generated the lowest Sharpe ratio of -1,18 in France. This overlaps with previous results in which the MA-strategy seems to be quite volatile. Also only the SR-strategy generates all positive ratios, which is in line with the results mentioned above.

Overall it seems like the technical strategies perform better in the German market, regardless of timeframe, subperiod or strategy. It appears that some characteristic of this market makes technical analysis perform well. In a paper by Dustmann et al. (2014), the authors find that the German market has been performing exceptionally well compared to other European countries. They find that the specific governance structure of the German labor market institutions allowed them to react flexibly in a time of extraordinary economic circumstances and that this distinctive characteristic has been the main reason for Germany's economic success over the last decade. Perhaps this flexibility smoothed out the stock market performance as well, making it more fitting for technical strategies, which are solely based on historical stock price performance.

Now that all results have been analysed and discussed, the hypotheses which were stated in chapter 3 will be discussed. The first hypothesis states the following: "Technical analysis will generate significant positive risk-adjusted portfolio returns." Looking at table 17, we can see that all strategies indeed generated a significant positive return, dependent on the country. The highest positive return generated was done by using the combination strategy of both the MA- and RSI-strategy, and resulted in an average 0,0430% per day over all countries, and 0,081% per day in Germany. However, once we adjust for the market- and risk-factors, there are not always positive returns. For example, especially the RSI-strategy is heavily influenced by the SMB factor. When looking at the alphas, we can see that most strategies only generate positive significant risk-adjusted returns in the German market or the French market. This means that the hypothesis is not rejected, but that one has to consider this return might heavily dependent on the market.

The second hypothesis states the following: "MA-strategy will generate higher significant results than the RSI-strategy or SR-strategy." When looking at the results stated above, we can see that the MA-strategy generates the lowest average returns, compared to the RSI- or SR-strategy. The MA-strategy generates 0,0090% daily return, whereas the RSI- and SR-strategy (dependent of which timeframe is chosen) generate around 0,0250% daily return. Next to this, when adjusted for the market- and risk factors, the MA-strategy even results in a negative alpha in some markets. However, the SR-strategy generates no significant alpha at all, whereas the MA- and RSI-strategy do for the German market. Compared to previous literature, it has been quite odd that this seems to be the case. Brock et al. (1992) compared the MA-strategy with the SR-strategy and found that on a daily basis, the MA-strategy and the SR-strategy generate 0,0093% and 0,0087% return respectively. Another paper by Chong & Ng (2008) compared the MA-strategy with the RSI-strategy and found that the MA-strategy generates 0,0205% return, whereas RSI-strategy generates 0,0091% daily return. However, both of these researches looked at the U.S. market and took different timeframes for the MA-strategy. Overall, the MA-returns are relatively lower compared to other strategies, meaning that this hypothesis is rejected.

The third and last hypothesis states the following: “A combination of the different types of technical strategies will generate higher significant results than these strategies separately." When looking at the results above we can see that the combination of the MA- and RSI-strategy generates higher average returns compared to the other strategies separately, generating 0,0430% compared to around 0,023% average for other strategies separately. Also when correcting for the market- and risk factors, the combination strategy can generate a significant positive alpha for both France and Germany, whereas the other strategies can either only generate this for the German market, generate a negative alpha or even generate no alpha at all. Based on this, the third hypothesis is not rejected.

7. Conclusions

Technical trading strategies have been around in the finance world for quite a long time. These strategies have shown that they can generate a significant positive return; however, it is not sure how these came to exist. Technical strategies usually look at historical stock prices only, meaning that if the EMH is true, the prices should already reflect all possible information. This would mean that there should not be any arbitrage opportunities, however since this happens to be the case because technical strategies can generate positive returns, technical analysis must be correcting for some form of mispricing. Since most research based on technical strategies have been showing inconclusive results or only looked at one specific technical strategy, this research attempts to find out if several different technical strategies can generate positive returns in a different setting, the European market. The countries that have been researched are France, Germany, the Netherlands and the UK, forming most of the Western-Europe. The data used in this research contains financial information on all domestic markets for the past seventeen years (1999-2015). The technical strategies that have been tested are the Moving Average strategy, the Relative Strength Index strategy, the Support and Resistance strategy (also known as Trading Range Break analysis) and a combination of these strategies. The research question of this thesis is the following: "To what extent will technical analysis be able to generate significant risk-adjusted portfolio return on Western-European equities?". With the results mentioned above, an answer elaborate as possible will be given.

First of all, when looking at the general results, it turns out that all strategies indeed generate an average positive return. The results, however, differ per country. For most strategies, the returns turned out to be significant and positive for the German market, but less significant or not as high in other countries. The Netherlands usually generated no significant returns at all. Out of the three strategies separately, the SR-strategy generated the highest returns on average, but the highest return was found using the MA-strategy. However, the lowest found return was also found using the MA-strategy, whereas the SR-strategy generated the least "worse" returns. Concluding, we could say that the MA-strategy is more volatile than the SR-strategy and so the SR-strategy can be seen as more "safe" strategy. Initially the three strategies were supposed to be combined, but due to the relatively low amount of signals generated by the SR-strategy, only the MA- and RSI-strategy were combined. This strategy generated higher average significant returns than the strategies separated, but also the lowest average returns compared to all three other strategies.

As these strategies have been analysed, there were also several robustness checks. For the RSI- and SR-strategy, the most popular timeframe is 14-days, but the MA-strategy was tested using the 12- and 26-day timeframes, so these were also checked for the RSI- and SR-strategy. Upon doing this, it turned out that the 26-day timeframe is more favourable compared to the 14-day timeframe, for both strategies. Next to this, since the time period chosen for the sample (1999-2015) might contain certain time effects, the sample has also been divided into four subperiods, to check whether specific subperiods might contribute to the overall average return. Upon analysing these results, there have been several instances in which a certain subperiod (mostly the 2007-2011 period) showed relatively different returns (either much higher or much lower), but this does not seem to be consistent for all countries or all strategies.

Lastly, the returns have been controlled for several markets- and risk factors. To do so, the market return, the risk-free rate, the Fama & French size- and value factors and Carhart's momentum factor have been constructed for each country. A regression analysis has been performed for each strategy and each country. When looking at the risk factors, the MA-strategy seems to be the only one unaffected by them. The RSI-strategy is mostly influenced by the SMB factor and the SR-strategy a little less but influenced by SMB in the UK market. The combination strategy of MA- and RSI-strategy is partly influenced by HML in the French market (but only on a 10% significance level) and partly by the

SMB factor in the UK. So overall, except for the RSI-strategy, the technical strategy returns do not seem to be consistently influenced by the risk-factors. When correcting for both risk- and market factors, we can see if a significant positive alpha can be generated. This seems to be the case for almost all strategies, but only in the German market. The combination strategy also generates a significant positive alpha for the French market. Additionally, the SR-strategy generates no significant alpha at all.

Overall it looks like the "best" strategy would be to combine the MA- and RSI-strategy in the German market. This would on average generate significant positive returns. However, these have also generated quite low returns at points. If one would want a safer strategy, one could implement the SR-strategy, which generates less high returns, but also less low returns. When one also corrects for the risk factors, one could best use the combination strategy in both French and German markets, since this will generate a significant positive alpha.

7.1 Limitations and suggestions for further research

This paper has shown some new insights into technical trading analysis. These insights, however, are limited to the assumptions this research has made. For instance, there could a type of selection bias, since this research looked at Western-European markets. Most previous literature used the U.S. market, making this research more notable, however, it might also be interesting to look at other markets, such as the upcoming Asian or South-American markets. Next to this, the time period used is 1999-2015. This covers seventeen years of daily data, but other earlier periods also could have been considered. If information available, the data could have gone back to even the 1930's, since the primarily needed information is historical stock prices. When looking into this, one must consider that data improves over time and that such early data might be incomplete or biased by major firms only.

When analysing technical strategies, three of the most popular ones have been chosen and researched. Even though quite some interesting results came out of this, it might be interesting to consider other less popular technical strategies as well, as mentioned in chapter 2. Next to this, the risk-adjusted returns have been constructed by looking at the popular Fama & French size- and value factor and Carhart's momentum factor. In recent studies, however, Fama & French added two new risk factor called the profitability and investment factors. In future research, one could add these two factors to see if technical strategy returns might be partially explained by these. Lastly, this research did not take transaction costs into account. Since certain strategies might lead to relatively a lot of buy- or sell signals, these costs should be carefully considered before these strategies are implemented. Naturally, there could be cases where the marginal transaction costs are equal to zero, such as for pension funds that must reinvest dividends and funds contributed by sponsors. Opportunities also might exist in the future markets where transaction costs are minimal (Brock, Lakonishok, & LeBaron, 1992).

Overall, this paper shows that in certain conditions, a significant risk-adjusted return can be generated using technical strategies. However, this appears to be dependent on which specific country is chosen and which strategy, meaning that it is still a complicated matter. It seems to be possible that technical strategies respond to certain hidden patterns. However, this research only focused on three of the most popular strategies. Future research that focuses on more elaborate strategies may generate even larger and more significant results. In the end, why exactly these strategies seem to work, is still a challenging matter for future research.

8. Reference list

Alexander, C., & Dimitriu, A. (2002). The Cointegration Alpha: Enhanced Index Trcking and Long-Short Equity Market Neutral Strategies. *ISMA Discussion Papers in Finance*.

Bauer, R., Guenster, N., & Otten, R. (2004). Empirical evidence on corporate governance in Europe: The effect on stock returns, firm value and performance. *Journal of Asset Management*, 91-104.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, 1731-1764.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 57-82.

Chong, T. T., & Ng, W. K. (2008). Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30. *Applied Economics Letters*, 1111-1114.

Chung, S. Y., Schneeweis, T., & Eneroth, K. (1999). Corporate reputation and investment performance: the UK and US experience.

Cochrane, J. H. (2009). In J. H. Cochrane, *Asset pricing:(Revised Edition).* Princeton university press.

Conrad, J., & Kaul, G. (1998). An anatomy of trading strategies. *Review of Financial studies*, 489-519.

Cowles 3rd, A. (1933). Can stock market forecasters forecast? *Econometrica: Journal of the Econometric Society*, 309-324.

Dustmann, C., Fitzenberger, B., Schönberg, U., & Spitz-Oener, A. (2014). From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy. *Journal of Economic Perspectives*, 167-188.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 3-56.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 457-472.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 69-103.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International economic review*, 1-21.

Fernández-Rodríguez, 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. *Economics of Letters*, 89-94.

Goh, J., Jiang, F., Tu, J., & Zhou, G. (2013). Forecasting government bond risk premia using technical indicators. *Working Paper, Singapore Management University and Washington University*. St. Louis.

Han, Y., Huang, D., & Zhou, G. (2015). Anomalies enhanced: the value of higher frequency information. *Available at SSRN 2704106*.

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: the cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, 1433-1461.

Hirschleifer, D., Hou, K., & Teoh, S. H. (2012). The accrual anomlay: risk or mispricing? *Management Science*, 320-335.

Lento, C., & Gradojevic, N. (2007). The Profitability of Technical Trading Rules: A Combined Signal Approach. *Journal of Applied Business Research*.

Lettau, M., & Ludvigson, S. (2001). Consumption, aggregate wealth and expected stock returns. *Journal of Finance*, 815-849.

Levich, R. M., & Thomas, L. R. (1991). The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach. *NBER Working Paper Series*.

Levy, R. A. (1967). Relative Strength as a Criterion for Investmens Selection. *The Journal of Finance*, 595-610.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: computational algorithms, statistical inference and empirical implementation. *The journal of finance*, 1705-1770.

Malkiel, B. G. (1981). A random walk down Wall Street. In B. G. Malkiel. WW Norton & Company.

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance*, 2573-2586.

Menkhoff, L., & Taylor, M. P. (2007). The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis. *Journal of Economic Literature*, 936-972.

Ming-Ming, L., & Siok-Hwa, L. (2006). The profitability of the simple moving averages and trading range breakout in the Asian stock markets. *Journal of Asian Economics*, 144-170.

Murphy, J. J. (1999). Technical Analysis of the Financial Markets. *New York Institute of Finance*.

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2013). Forecasting the equity risk premium: the role of technical indicators. *Management Science*.

Neely, C., Weller, P., & Dittmar, R. (1997). Is technical analysis in the foreign exchange market profitable? A genetic programming approach. *Journal of Financial and Quantitative Analysis*, 405-426.

Nijman, T., Swinkels, L., & Verbeek, M. (2004). Do countries or industries explain momentum in Europe? *Journal of Empirical Finance*, 461-481.

Oberlechner, T. (2001). Importance of technical and fundamental analysis in the european foreign exchange market. *International Journal of Finance and Economics*, 81-93.

Osler, C. L., & Chang, P. H. (1995). *Head and Shoulders: Not Just a Flaky Pattern.*

Salaber, J. M. (2007). The Determinants of Sin Stock Returns: Evidence on the European Market. *Finance International Meeting AFFI-EUROFIDAI*.

Schmidt, P. S., Von Arx, U., Schrimpf, A., Wagner, A. F., & Ziegler, A. (2016). On the construction of common size, value and momentum factors in international stock markets: A guide with applications.

Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance*, 939-974.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, 1903-1948.

ValueWalk. (2015, May 20). *The Five-Factor Fama-French Model: International Evidence*. Retrieved from ValueWalk: http://www.valuewalk.com/2015/05/the-five-factor-fama-french-model-international-evidence/

Van Bergen, J. (2016, Sep 27). *Introduction to Types of Trading*. Retrieved from Investopedia: http://www.investopedia.com/articles/trading/02/100102.asp

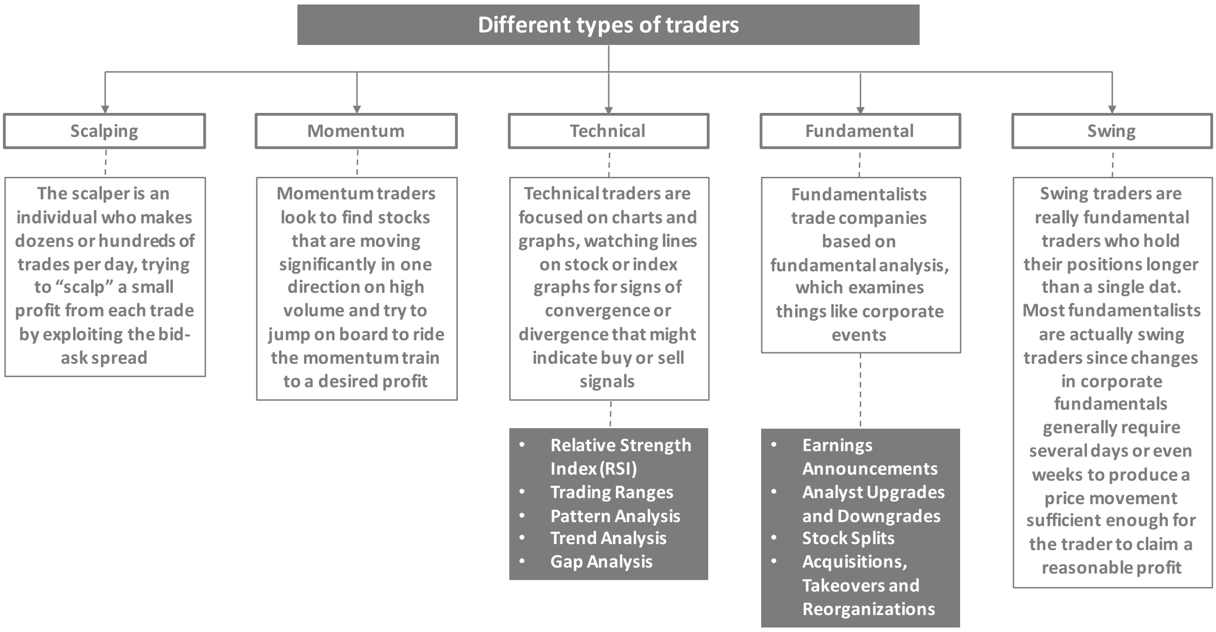
Wang, F., Yu, P. L., & Cheung, D. W. (2014). Combining technical trading rules using particle swarm optimization. *Expert Systems with Applications*, 3016-3026.

Wang, J. L., & Chan, S. H. (2007). Stock market trading rule discovery using pattern recognition and technical analysis. *Expert Systems with Applications*, 304-315.

Zhu, Y., & Zhou, G. (2009). Technical analysis: an asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, 519-544.

9. Appendices

Appendix A: detailed breakdown of different types of traders



Appendix B: detailed overview of different types of fundamental and technical strategies

Name strategy	**Type of strategy**	**By whom**	**Entails**
Book-to-Market (BM) *aka Value, HML*	Fundamental	Fama & French (1996, 2008)	Higher B/M, higher future returns
Size (S) *SMB*	Fundamental	Fama & French (1996, 2008)	Smaller capitalization, higher future returns
Gross profitability (GP)	Fundamental	Novy & Marx (2013)	Higher gross profit, higher future returns
Operating profit (OP)	Fundamental	Fama & French (2015)	Higher operating profit, higher future returns
Asset growth (AG)	Fundamental	Cooper et al. (2008), Hou et al. (2015) and Fama & French (2015)	Higher asset growth rates, lower future returns
Investment growth (IG)	Fundamental	Xing (2008)	Higher investment, lower future returns
Net Stock issue (NS)	Fundamental	Ritter (1991), Loughran & Ritter (1995) and Fama & French (2008)	Larger net stock issue, lower future returns
Accrual (AC)	Fundamental	Sloan (1996) and Fama & French (2008)	Larger accrual, lower future returns
Net Operating Assets (NOA)	Fundamental	Hirshleifer et al. (2004)	Larger operating assets, lower future returns
Financial Distress	Fundamental	Campbell, Hilscher & Szilagyi (2008)	Larger financial distress, lower future returns. Poor profits, poor sales growth could be indicators
Return on assets	Fundamental	Fama & French (2006), Chen, Novy-Marx & Zhang (2010)	Higher returns on assets, higher future returns. Earnings divided by (lagged) assets
Volatility	Fundamental	Haugen & Heins (1972)	Lower variance in monthly returns, larger future returns
MA – crossover, MACD	Technical	Yule (1909), Wold (1938)	Buy/sell signal when short-term crosses long-term (double or triple)
MA - ribbon	Technical	Zoicas-Lenciu (2016)	Many moving averages are placed onto the same chart and are used to judge the strength of the current trend
Head and shoulder pattern	Technical	Osler & Chang (1995)	Locate neckline, wait till pattern is complete, when neckline is broken, invest
Inverted hammer candlestick	Technical	Quintairos et al (2013)	Acts as warning for potential reversal upwards
Relative Strength index	Technical	Chong & Ng (2008)	Relative evaluation of the strength of a security's recent price performance, making it a momentum indicator. Above 80, overbought, below 20, oversold
Bollinger band	Technical	John Bollinger (1980's)	Can be used to measure the 'highness' or 'lowness' of the price relative to previous trades → volatility indicator. Combination of MA and a std. dev.

Appendix C: descriptive statistics market- and risk-free rate proxies

	Mkt-CAC40-F	Mkt-FTSE-G	Mkt-AEX-NL	Mkt-FTSE-UK	Rf-F	Rf-G	Rf-NL	Rf-UK
Average	0,009%	0,005%	0,014%	0,005%	0,002%	0,002%	0,002%	0,003%
Median	0,039%	0,043%	0,041%	0,043%	0,002%	0,002%	0,002%	0,003%
Std. Dev.	1,222%	1,464%	1,484%	1,464%	0,001%	0,001%	0,001%	0,002%
Minimum	-8,848%	-9,145%	-9,037%	-9,145%	0,000%	0,000%	0,000%	0,000%
Maximum	9,839%	10,548%	11,176%	10,548%	0,004%	0,005%	0,005%	0,005%
Obs.	4291	4345	4344	4345	4433	4433	4433	4433
Skewness	-0,013	0,067	0,143	0,067	0,127	0,127	0,122	-0,156
Kurtosis	5,985	6,253	4,839	6,253	-1,338	-1,295	-1,301	-1,758

Appendix D: frequency table return distributions per country

	France	Germany	Netherlands	UK
NA	1.204.654	1.752.702	163.548	3.076.247
(100%)<=X<=0%	2.254.583	2.593.788	321.843	3.313.047
0%<X<=100%	2.237.915	2.491.256	319.461	3.123.373
100%<X<=200%	645	691	205	650
200%<X<=300%	93	133	28	98
300%<X<=400%	36	89	7	33
400%<X<=500%	7	46	7	20
500%<X<=600%	13	25	2	14
600%<X<=700%	7	13	2	6
700%<X<=800%	4	13	2	6
800%<X<=900%	3	10	5	4
900%<X<=990%	3	16	3	1
Total	4.493.309	5.086.080	641.565	6.437.252

Appendix E: correlation matrix of all used variables

France	Mkt-Rf	SMB	HML	WML	MA	RSI	SR	COMB
Mkt-Rf	1,00							
SMB	-0,100***	1,00						
HML	-0,007	-0,036**	1,00					
WML	0,017	-0,020	0,000	1,00				
MA	-0,031**	0,000	-0,009	-0,012	1,00			
RSI	-0,103***	-0,038**	0,024	-0,001	0,000***	1,00		
SR	-0,019	-0,010	0,007	-0,007	0,206***	0,331***	1,00	
COMB	-0,005	-0,021	0,026*	-0,021	0,240***	0,320***	**0,471*** **	1,00

Germany	Mkt-Rf	SMB	HML	WML	MA	RSI	SR	COMB
Mkt-Rf	1,00							
SMB	0,013	1,00						
HML	0,000	-0,007	1,00					
WML	0,005	-0,008	0,009	1,00				
MA	0,024	0,002	0,002	0,023	1,00			
RSI	0,074***	0,055***	0,013	0,041***	0,310***	1,00		
SR	-0,012	-0,001	0,006	0,007	0,212***	0,247***	1,00	
COMB	0,017	0,004	0,005	0,038**	**0,459*** **	**0,655*** **	0,288***	1,00

NL	Mkt-Rf	SMB	HML	WML	MA	RSI	SR	COMB
Mkt-Rf	1,00							
SMB	-0,023	1,00						
HML	-0,002	-0,009	1,00					
WML	0,029*	-0,020	-0,030*	1,00				
MA	-0,038**	0,019	0,0010	-0,004	1,00			
RSI	0,027*	-0,018	-0,017	-0,018	0,179***	1,00		
SR	0,023	-0,005	0,004	0,004	0,287***	0,180***	1,00	
COMB	0,028*	-0,012	-0,002	-0,003	0,337***	**0,412*** **	0,295***	1,00

UK	Mkt-Rf	SMB	HML	WML	MA	RSI	SR	COMB
Mkt-Rf	1,00							
SMB	-0,046***	1,00						
HML	-0,002	0,060***	1,00					
WML	-0,004	0,075***	0,016	1,00				
MA	0,022	0,003	-0,013	0,006	1,00			
RSI	0,065***	-0,308***	-0,039**	-0,026*	0,175***	1,00		
SR	-0,004	-0,109***	0,0193	0,004	-0,358***	-0,205***	1,00	
COMB	0,008	0,160***	-0,009	0,0192	**0,450*** **	0,345***	**-0,553*** **	1,00

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Appendix F: results subperiods for all strategies

MA	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France					
1999-2002	458.905 *(33,9%)*	419.576 *(31,0%)*	-0,053%***	0,022%**	-0,076%***
			(0,004%)	(0,004%)	(0,002%)
2003-2006	472.330 *(34,9%)*	449.903 *(33,2%)*	-0,002%	0,051%***	-0,053%***
			(0,002%)	(0,003%)	(0,001%)
2007-2011	390.889 *(28,8%)*	499.283 *(36,8%)*	-0,045%***	0,009%	-0,054%***
			(0,004%)	(0,004%)	(0,001%)
2012-2015	518.162 *(38,2%)*	465.905 *(34,4%)*	-0,018%	0,031%***	-0,050%***
			(0,002%)	(0,002%)	(0,001%)
Germany					
1999-2003	488.040 *(33,9%)*	488.302 *(33,9%)*	-0,014%	-0,061%***	0,047%***
			(0,005%)	(0,004%)	(0,002%)
2003-2006	390.039 *(27,1%)*	443.899 *(30,9%)*	0,041%***	-0,015%	0,056%***
			(0,003%)	(0,003%)	(0,001%)
2007-2011	544.246 *(37,8%)*	501.203 *(34,8%)*	0,004%**	-0,078%***	0,082%***
			(0,005%)	(0,005%)	(0,002%)
2012-2015	501.793 *(34,9%)*	503.344 *(35,0%)*	0,018%***	-0,052%**	0,071%***
			(0,003%)	(0,003%)	(0,002%)
Netherlands					
1999-2002	86.713 *(40,6%)*	98.344 *(46,0%)*	-0,027%	-0,041%	0,014%
			(0,005%)	(0,004%)	(0,003%)
2003-2006	80.994 *(37,9%)*	99.001 *(46,3%)*	0,038%*	0,007%	0,031%
			(0,003%)	(0,003%)	(0,002%)
2007-2011	88.901 *(41,6%)*	101.203 *(47,3%)*	0,001%	-0,037%	0,038%
			(0,005%)	(0,003%)	(0,003%)
2012-2015	93.838 *(43,9%)*	100.535 *(47,0%)*	0,022%	-0,012%	0,033%
			(0,001%)	(0,001%)	(0,001%)
UK					
1999-2002	501.440 *(26,1%)*	510.093 *(26,6%)*	-0,037%	-0,018%	-0,019%
			(0,001%)	(0,001%)	(0,000%)
2003-2006	490.204 *(25,6%)*	534.030 *(27,8%)*	0,006%***	0,009%***	-0,003%
			(0,003%)	(0,003%)	(0,001%)
2007-2011	502.304 *(26,2%)*	500.330 *(26,1%)*	-0,033%	-0,039%	0,006%
			(0,004%)	(0,004%)	(0,001%)
2012-2015	555.209 *(28,9%)*	520.132 *(27,1%)*	-0,008%	-0,016%	0,008%
			(0,003%)	(0,003%)	(0,001%)

MA outcome in daily returns per time period, percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. dev. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

RSI-14day	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France					
1999-2002	170.499 *(12,6%)*	155.940 *(11,5%)*	-0,001%	-0,014%	0,013%
			(0,003%)	(0,000%)	(0,003%)
2003-2006	175.030 *(12,9%)*	160.847 *(11,9%)*	0,013%	-0,013%	0,026%
			(0,001%)	(0,000%)	(0,001%)
2007-2011	171.040 *(12,6%)*	161.059 *(11,9%)*	-0,002%	-0,012%	0,010%
			(0,001%)	(0,000%)	(0,001%)
2012-2015	174.274 *(12,9%)*	154.569 *(11,4%)*	0,001%	-0,019%	0,020%
			(0,001%)	(0,001%)	(0,001%)
Germany					
1999-2002	145.939 *(7,6%)*	132.948 *(6,9%)*	-0,012%	-0,055%	0,043%
			(0,003%)	(0,004%)	(0,004%)
2003-2006	147.920 *(7,7%)*	139.843 *(7,3%)*	0,011%	-0,006%	0,017%
			(0,001%)	(0,003%)	(0,002%)
2007-2011	142.040 *(7,4%)*	129.430 *(6,7%)*	-0,007%	-0,099%***	0,092%***
			(0,002%)	(0,005%)	(0,005%)
2012-2015	144.405 *(7,5%)*	135.857 *(7,1%)*	0,001%	-0,054%	0,055%*
			(0,001%)	(0,003%)	(0,003%)
Netherlands					
1999-2002	24.940 *(11,7%)*	20.439 *(9,6%)*	-0,025%	-0,021%	-0,004%
			(0,004%)	(0,006%)	(0,006%)
2003-2006	27.830 *(13,0%)*	21.438 *(10,0%)*	0,004%	0,011%	-0,006%
			(0,003%)	(0,005%)	(0,005%)
2007-2011	25.030 *(11,7%)*	25.934 *(12,1%)*	-0,008%	-0,065%	0,056%
			(0,002%)	(0,008%)	(0,007%)
2012-2015	23.130 *(10,8%)*	24.224 *(11,3%)*	0,002%	-0,014%	0,016%
			(0,001%)	(0,006%)	(0,006%)
UK					
1999-2002	238.040 *(12,4%)*	204.902 *(10,7%)*	-0,025%	-0,003%	-0,021%
			(0,003%)	(0,004%)	(0,002%)
2003-2006	241.477 *(12,6%)*	194.309 *(10,1%)*	-0,003%	0,018%**	-0,021%**
			(0,001%)	(0,003%)	(0,002%)
2007-2011	230.994 *(12,0%)*	228.943 *(11,9%)*	-0,018%	-0,022%	0,003%
			(0,001%)	(0,003%)	(0,003%)
2012-2015	245.519 *(12,8%)*	247.807 *(12,9%)*	-0,005%*	0,001%*	-0,005%*
			(0,000%)	(0,002%)	(0,002%)

RSI outcome in daily returns, percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. dev. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

SR-14day	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France					
1999-2002	92.002 *(6,8%)*	90.328 *(6,7%)*	0,013% (0,007%)	-0,013% (0,004%)	0,026% (0,006%)
2003-2006	91.032 *(6,7%)*	89.320 *(6,6%)*	0,055%** (0,003%)	0,018% (0,003%)	0,037% (0,003%)
2007-2011	95.020 *(7,0%)*	94.029 *(6,9%)*	0,013% (0,005%)	-0,033% (0,004%)	0,045% (0,004%)
2012-2015	95.827 *(7,1%)*	92.357 *(6,8%)*	0,025% (0,003%)	0,006% (0,003%)	0,019% (0,003%)
Germany					
1999-2002	73.040 *(3,8%)*	91.032 *(4,7%)*	-0,042% (0,004%)	-0,037% (0,005%)	-0,005% (0,003%)
2003-2006	72.043 *(3,8%)*	99.320 *(5,2%)*	0,006% (0,003%)	0,002% (0,003%)	0,004% (0,002%)
2007-2011	79.382 *(4,1%)*	96.023 *(5,0%)*	-0,046% (0,005%)	-0,073%* (0,007%)	0,027% (0,005%)
2012-2015	71.958 *(3,8%)*	100.357 *(5,2%)*	-0,026% (0,003%)	-0,021% (0,004%)	-0,004% (0,003%)
Netherlands					
1999-2002	14.932 *(7,0%)*	17.039 *(8,0%)*	-0,029% (0,008%)	-0,039% (0,006%)	0,010% (0,008%)
2003-2006	18.932 *(8,9%)*	16.329 *(7,6%)*	0,042% (0,005%)	0,020% (0,005%)	0,024% (0,006%)
2007-2011	15.039 *(7,0%)*	19.832 *(9,3%)*	0,009% (0,010%)	-0,036% (0,008%)	0,043% (0,011%)
2012-2015	18.064 *(8,4%)*	17.015 *(8,0%)*	0,029% (0,008%)	-0,013% (0,005%)	0,042% (0,009%)
UK					
1999-2002	91.030 *(4,7%)*	100.393 *(5,2%)*	0,004% (0,004%)	-0,045% (0,005%)	0,049% (0,004%)
2003-2006	90.320 *(4,7%)*	98.023 *(5,1%)*	0,021%* (0,003%)	0,014% (0,004%)	0,008% (0,003%)
2007-2011	93.040 *(4,9%)*	101.304 *(5,3%)*	-0,022% (0,005%)	-0,035% (0,005%)	0,013% (0,004%)
2012-2015	97.086 *(5,1%)*	107.511 *(5,6%)*	0,008% (0,004%)	-0,010% (0,004%)	0,018% (0,004%)

SR outcome in daily returns, percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. dev. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

COMB	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
France					
1999-2002	84.050 *(1,6%)*	73.491 *(1,4%)*	0,021%	-0,042%	0,063%*
			(0,180%)	(0,175%)	(0,196%)
2003-2006	76.920 *(1,4%)*	76.993 *(1,4%)*	0,084%***	0,000%	0,084%**
			(0,132%)	(0,112%)	(0,133%)
2007-2011	78.388 *(1,4%)*	75.020 *(1,4%)*	0,039%*	-0,074%**	0,112%***
			(0,170%)	(0,175%)	(0,178%)
2012-2015	77.884 *(1,4%)*	72.124 *(1,3%)*	0,041%*	-0,015%	0,056%
			(0,127%)	(0,104%)	(0,136%)
Germany					
1999-2003	89.663 *(1,6%)*	88.302 *(1,5%)*	-0,022%	-0,063%	0,041%
			(0,212%)	(0,174%)	(0,214%)
2003-2006	94.221 *(1,6%)*	87.553 *(1,5%)*	0,039%**	-0,010%	0,049%**
			(0,155%)	(0,114%)	(0,144%)
2007-2011	90.133 *(1,6%)*	91.033 *(1,6%)*	-0,008%	-0,133%***	0,126%***
			(0,236%)	(0,279%)	(0,275%)
2012-2015	88.128 *(1,5%)*	90.878 *(1,6%)*	0,017%	-0,070%*	0,087%**
			(0,201%)	(0,145%)	(0,210%)
Netherlands					
1999-2002	18.044 *(2,1%)*	19.994 *(2,3%)*	-0,049%	-0,016%	-0,032%
			(0,258%)	(0,310%)	(0,363%)
2003-2006	19.033 *(2,2%)*	21.331 *(2,5%)*	0,059%	0,015%	0,044%
			(0,207%)	(0,182%)	(0,236%)
2007-2011	20.344 *(2,4%)*	20.440 *(2,4%)*	-0,004%	-0,075%	0,070%
			(0,337%)	(0,355%)	(0,443%)
2012-2015	19.758 *(2,3%)*	20.296 *(2,4%)*	0,053%	-0,015%	0,067%
			(0,262%)	(0,229%)	(0,337%)
UK					
1999-2002	153.449 *(2,0%)*	127.758 *(1,7%)*	-0,050%	-0,003%	-0,046%
			(0,175%)	(0,148%)	(0,112%)
2003-2006	155.820 *(2,0%)*	130.775 *(1,7%)*	0,003%	0,020%**	-0,017%
			(0,123%)	(0,100%)	(0,080%)
2007-2011	151.884 *(2,0%)*	129.502 *(1,7%)*	-0,051%	-0,026%	-0,025%
			(0,192%)	(0,162%)	(0,134%)
2012-2015	157.911 *(2,1%)*	120.442 *(1,6%)*	-0,024%	0,001%	-0,025%
			(0,115%)	(0,094%)	(0,099%)

Combined strategy outcome in daily returns, percentage of total observations is stated in brackets in columns N(Buy) and N(Sell), std. dev. is stated in brackets in columns Buy, Sell and Buy-Sell.

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Appendix G: results Relative Strength Index

France	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	176.040 *(13,0%)*	170.939 *(12,6%)*	-0,003%	-0,032%	0,029%
			(0,003%)	(0,004%)	(0,004%)
2003-2006	180.405 *(13,3%)*	159.860 *(11,8%)*	0,013%	-0,001%	0,014%
			(0,001%)	(0,002%)	(0,002%)
2007-2011	177.940 *(13,1%)*	179.049 *(13,2%)*	-0,003%	-0,054%***	0,051%**
			(0,001%)	(0,003%)	(0,003%)
2012-2015	180.549 *(13,3%)*	176.228 *(13,0%)*	0,001%	-0,014%	0,015%
			(0,001%)	(0,002%)	(0,002%)
14-day					
1999-2002	170.499 *(12,6%)*	155.940 *(11,5%)*	-0,001%	-0,014%	0,013%
			(0,003%)	(0,000%)	(0,003%)
2003-2006	175.030 *(12,9%)*	160.847 *(11,9%)*	0,013%	-0,013%	0,026%
			(0,001%)	(0,000%)	(0,001%)
2007-2011	171.040 *(12,6%)*	161.059 *(11,9%)*	-0,002%	-0,012%	0,010%
			(0,001%)	(0,000%)	(0,001%)
2012-2015	174.274 *(12,9%)*	154.569 *(11,4%)*	0,001%	-0,019%	0,020%
			(0,001%)	(0,001%)	(0,001%)
26-day					
1999-2002	130.589 *(9,6%)*	109.595 *(8,1%)*	0,010%	-0,052%**	0,062%**
			(0,003%)	(0,005%)	(0,005%)
2003-2006	135.030 *(10,0%)*	90.420 *(6,7%)*	0,012%	-0,021%	0,033%
			(0,001%)	(0,003%)	(0,003%)
2007-2011	133.040 *(9,8%)*	110.439 *(8,2%)*	0,000%	-0,067%***	0,068%***
			(0,001%)	(0,003%)	(0,003%)
2012-2015	148.271 *(10,9%)*	107.765 *(8,0%)*	0,002%	-0,026%	0,028%
			(0,000%)	(0,002%)	(0,002%)

Germany	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	150.399 *(7,8%)*	148.039 *(7,7%)*	-0,015%	-0,050	0,035%
			(0,003%)	(0,004%)	(0,004%)
2003-2006	154.029 *(8,0%)*	151.043 *(7,9%)*	0,012%	-0,006%	0,018%
			(0,001%)	(0,003%)	(0,002%)
2007-2011	153.040 *(8,0%)*	150.932 *(7,9%)*	-0,007%	-0,096%***	0,088%***
			(0,002%)	(0,005%)	(0,005%)
2012-2015	156.852 *(8,2%)*	146.735 *(7,6%)*	0,000%	-0,052%	0,053%*
			(0,001%)	(0,003%)	(0,003%)
14-day					
1999-2002	145.939 *(7,6%)*	132.948 *(6,9%)*	-0,012%	-0,055%	0,043%
			(0,003%)	(0,004%)	(0,004%)
2003-2006	147.920 *(7,7%)*	139.843 *(7,3%)*	0,011%	-0,006%	0,017%
			(0,001%)	(0,003%)	(0,002%)
2007-2011	142.040 *(7,4%)*	129.430 *(6,7%)*	-0,007%	-0,099%***	0,092%***
			(0,002%)	(0,005%)	(0,005%)
2012-2015	144.405 *(7,5%)*	135.857 *(7,1%)*	0,001%	-0,054%	0,055%*
			(0,001%)	(0,003%)	(0,003%)
26-day					
1999-2002	103.040 *(5,4%)*	80.103 *(4,2%)*	-0,007%	-0,062%	0,056%
			(0,003%)	(0,005%)	(0,005%)
2003-2006	109.988 *(5,7%)*	79.320 *(4,1%)*	0,008%	-0,004%	0,012%
			(0,001%)	(0,003%)	(0,003%)
2007-2011	105.560 *(5,5%)*	81.043 *(4,2%)*	-0,007%	-0,108%***	0,101%**
			(0,001%)	(0,006%)	(0,006%)
2012-2015	99.452 *(5,2%)*	79.593 *(4,1%)*	0,001%	-0,061%	0,062%
			(0,001%)	(0,004%)	(0,004%)

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Netherlands	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	31.044 *(14,5%)*	23.843 *(11,2%)*	-0,026%	-0,007%	-0,018%
			(0,004%)	(0,000%)	(0,004%)
2003-2006	30.593 *(14,3%)*	27.439 *(12,8%)*	0,006%	-0,012%	0,017%
			(0,003%)	(0,000%)	(0,003%)
2007-2011	35.003 *(16,4%)*	25.392 *(11,9%)*	-0,009%	-0,016%	0,007%
			(0,002%)	(0,000%)	(0,002%)
2012-2015	33.855 *(15,8%)*	25.759 *(12,0%)*	0,002%	-0,032%	0,034%
			(0,001%)	(0,003%)	(0,004%)
14-day					
1999-2002	24.940 *(11,7%)*	20.439 *(9,6%)*	-0,025%	-0,021%	-0,004%
			(0,004%)	(0,006%)	(0,006%)
2003-2006	27.830 *(13,0%)*	21.438 *(10,0%)*	0,004%	0,011%	-0,006%
			(0,003%)	(0,005%)	(0,005%)
2007-2011	25.030 *(11,7%)*	25.934 *(12,1%)*	-0,008%	-0,065%	0,056%
			(0,002%)	(0,008%)	(0,007%)
2012-2015	23.130 *(10,8%)*	24.224 *(11,3%)*	0,002%	-0,014%	0,016%
			(0,001%)	(0,006%)	(0,006%)
26-day					
1999-2002	15.969 *(7,5%)*	10.284 *(4,8%)*	-0,020%	-0,027%	0,006%
			(0,004%)	(0,008%)	(0,008%)
2003-2006	19.483 *(9,1%)*	12.043 *(5,6%)*	-0,001%	-0,003%	0,001%
			(0,003%)	(0,006%)	(0,007%)
2007-2011	15.030 *(7,0%)*	14.053 *(6,6%)*	-0,008%	-0,066%	0,054%
			(0,002%)	(0,010%)	(0,009%)
2012-2015	17.558 *(8,2%)*	16.422 *(7,7%)*	0,000%	-0,027%	0,027%
			(0,001%)	(0,009%)	(0,008%)

UK	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	250.302 *(13,0%)*	214.389 *(11,2%)*	-0,025%	-0,003%	-0,022%
			(0,003%)	(0,004%)	(0,002%)
2003-2006	253.099 *(13,2%)*	263.439 *(13,7%)*	-0,003%	0,017%***	-0,020%***
			(0,001%)	(0,003%)	(0,002%)
2007-2011	253.040 *(13,2%)*	203.894 *(10,6%)*	-0,019%	-0,023%	0,004%
			(0,001%)	(0,003%)	(0,003%)
2012-2015	254.049 *(13,2%)*	233.550 *(12,2%)*	-0,005%	-0,002%	-0,003%
			(0,000%)	(0,002%)	(0,002%)
14-day					
1999-2002	238.040 *(12,4%)*	204.902 *(10,7%)*	-0,025%	-0,003%	-0,021%
			(0,003%)	(0,004%)	(0,002%)
2003-2006	241.477 *(12,6%)*	194.309 *(10,1%)*	-0,003%	0,018%**	-0,021%**
			(0,001%)	(0,003%)	(0,002%)
2007-2011	230.994 *(12,0%)*	228.943 *(11,9%)*	-0,018%	-0,022%	0,003%
			(0,001%)	(0,003%)	(0,003%)
2012-2015	245.519 *(12,8%)*	247.807 *(12,9%)*	-0,005%*	0,001%*	-0,005%*
			(0,000%)	(0,002%)	(0,002%)
26-day					
1999-2002	200.593 *(10,5%)*	169.832 *(8,9%)*	-0,023%	-0,003%	-0,020%
			(0,002%)	(0,004%)	(0,002%)
2003-2006	207.889 *(10,8%)*	159.023 *(8,3%)*	-0,005%	0,020%**	-0,025%**
			(0,001%)	(0,002%)	(0,002%)
2007-2011	206.344 *(10,8%)*	194.309 *(10,1%)*	-0,017%	-0,023%	0,006%
			(0,001%)	(0,003%)	(0,002%)
2012-2015	208.513 *(10,9%)*	167.292 *(8,7%)*	-0,004%	0,004%	-0,008%
			(0,000%)	(0,002%)	(0,002%)

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Appendix H: Results Support and Resistance rule

France	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	100.394 *(7,4%)*	97.930 *(7,2%)*	0,009%	-0,014%	0,023%
			(0,006%)	(0,004%)	(0,005%)
2003-2006	99.843 *(7,4%)*	98.032 *(7,2%)*	0,053%**	0,019%	0,034%
			(0,003%)	(0,003%)	(0,003%)
2007-2011	101.829 *(7,5%)*	99.200 *(7,3%)*	0,012%	-0,033%	0,045%
			(0,005%)	(0,004%)	(0,004%)
2012-2015	104.380 *(7,7%)*	98.799 *(7,3%)*	0,024%	0,005%	0,019%
			(0,003%)	(0,003%)	(0,003%)
14-day					
1999-2002	92.002 *(6,8%)*	90.328 *(6,7%)*	0,013%	-0,013%	0,026%
			(0,007%)	(0,004%)	(0,006%)
2003-2006	91.032 *(6,7%)*	89.320 *(6,6%)*	0,055%**	0,018%	0,037%
			(0,003%)	(0,003%)	(0,003%)
2007-2011	95.020 *(7,0%)*	94.029 *(6,9%)*	0,013%	-0,033%	0,045%
			(0,005%)	(0,004%)	(0,004%)
2012-2015	95.827 *(7,1%)*	92.357 *(6,8%)*	0,025%	0,006%	0,019%
			(0,003%)	(0,003%)	(0,003%)
26-day					
1999-2002	65.029 *(4,8%)*	65.932 *(4,9%)*	0,022%	-0,012%	0,034%
			(0,007%)	(0,005%)	(0,007%)
2003-2006	63.400 *(4,7%)*	69.328 *(5,1%)*	0,064%**	0,021%	0,043%
			(0,004%)	(0,003%)	(0,004%)
2007-2011	67.932 *(5,0%)*	70.829 *(5,2%)*	0,018%	-0,033%	0,049%
			(0,005%)	(0,004%)	(0,004%)
2012-2015	70.297 *(5,2%)*	64.981 *(4,8%)*	0,028%	0,009%	0,019%
			(0,004%)	(0,003%)	(0,003%)

Germany	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	105.932 *(5,5%)*	99.230 *(5,2%)*	-0,029%	-0,038%	0,010%
			(0,006%)	(0,005%)	(0,005%)
2003-2006	101.832 *(5,3%)*	107.930 *(5,6%)*	0,032%**	0,001%	0,031%
			(0,004%)	(0,003%)	(0,003%)
2007-2011	108.229 *(5,6%)*	108.439 *(5,7%)*	-0,011%	-0,068%*	0,057%
			(0,006%)	(0,006%)	(0,005%)
2012-2015	108.905 *(5,7%)*	101.267 *(5,3%)*	-0,001%	-0,022%	0,022%
			(0,004%)	(0,004%)	(0,004%)
14-day					
1999-2002	73.040 *(3,8%)*	91.032 *(4,7%)*	-0,042%	-0,037%	-0,005%
			(0,004%)	(0,005%)	(0,003%)
2003-2006	72.043 *(3,8%)*	99.320 *(5,2%)*	0,006%	0,002%	0,004%
			(0,003%)	(0,003%)	(0,002%)
2007-2011	79.382 *(4,1%)*	96.023 *(5,0%)*	-0,046%	-0,073%*	0,027%
			(0,005%)	(0,007%)	(0,005%)
2012-2015	71.958 *(3,8%)*	100.357 *(5,2%)*	-0,026%	-0,021%	-0,004%
			(0,003%)	(0,004%)	(0,003%)
26-day					
1999-2002	69.038 *(3,6%)*	70.329 *(3,7%)*	-0,026%	-0,030%	0,005%
			(0,007%)	(0,005%)	(0,007%)
2003-2006	72.032 *(3,8%)*	69.327 *(3,6%)*	0,034%*	0,007%	0,027%
			(0,005%)	(0,003%)	(0,004%)
2007-2011	70.329 *(3,7%)*	68.328 *(3,6%)*	-0,008%	-0,075%	0,067%
			(0,006%)	(0,009%)	(0,009%)
2012-2015	70.132 *(3,7%)*	77.686 *(4,0%)*	-0,001%	-0,019%	0,018%
			(0,005%)	(0,004%)	(0,005%)

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Netherlands	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	17.930 *(8,4%)*	17.930 *(8,4%)*	-0,029%	-0,042%	0,012%
			(0,007%)	(0,006%)	(0,008%)
2003-2006	19.380 *(9,1%)*	16.329 *(7,6%)*	0,043%	0,020%	0,024%
			(0,005%)	(0,005%)	(0,005%)
2007-2011	18.393 *(8,6%)*	19.203 *(9,0%)*	0,007%	-0,029%	0,036%
			(0,009%)	(0,008%)	(0,010%)
2012-2015	17.146 *(8,0%)*	22.112 *(10,3%)*	0,026%	-0,015%	0,040%
			(0,008%)	(0,005%)	(0,008%)
14-day					
1999-2002	14.932 *(7,0%)*	17.039 *(8,0%)*	-0,029%	-0,039%	0,010%
			(0,008%)	(0,006%)	(0,008%)
2003-2006	18.932 *(8,9%)*	16.329 *(7,6%)*	0,042%	0,020%	0,024%
			(0,005%)	(0,005%)	(0,006%)
2007-2011	15.039 *(7,0%)*	19.832 *(9,3%)*	0,009%	-0,036%	0,043%
			(0,010%)	(0,008%)	(0,011%)
2012-2015	18.064 *(8,4%)*	17.015 *(8,0%)*	0,029%	-0,013%	0,042%
			(0,008%)	(0,005%)	(0,009%)
26-day					
1999-2002	10.483 *(4,9%)*	13.049 *(6,1%)*	-0,035%	-0,036%	-0,001%
			(0,009%)	(0,007%)	(0,009%)
2003-2006	9.043 *(4,2%)*	12.943 *(6,1%)*	0,048%	0,019%	0,030%
			(0,007%)	(0,005%)	(0,008%)
2007-2011	11.039 *(5,2%)*	15.920 *(7,4%)*	0,018%	-0,032%	0,048%
			(0,017%)	(0,009%)	(0,018%)
2012-2015	17.230 *(8,1%)*	10.355 *(4,8%)*	0,030%	-0,011%	0,041%
			(0,011%)	(0,006%)	(0,012%)

UK	N (Buy)	N (Sell)	Buy	Sell	Buy - Sell
12-day					
1999-2002	98.430 *(5,1%)*	103.940 *(5,4%)*	0,004%	-0,044%	0,048%
			(0,004%)	(0,005%)	(0,004%)
2003-2006	100.329 *(5,2%)*	108.320 *(5,6%)*	0,021%*	0,014%*	0,007%
			(0,003%)	(0,003%)	(0,003%)
2007-2011	98.039 *(5,1%)*	120.430 *(6,3%)*	-0,022%	-0,034%	0,012%
			(0,005%)	(0,005%)	(0,004%)
2012-2015	100.370 *(5,2%)*	105.634 *(5,5%)*	0,006%	-0,011%	0,017%
			(0,004%)	(0,004%)	(0,004%)
14-day					
1999-2002	91.030 *(4,7%)*	100.393 *(5,2%)*	0,004%	-0,045%	0,049%
			(0,004%)	(0,005%)	(0,004%)
2003-2006	90.320 *(4,7%)*	98.023 *(5,1%)*	0,021%*	0,014%	0,008%
			(0,003%)	(0,004%)	(0,003%)
2007-2011	93.040 *(4,9%)*	101.304 *(5,3%)*	-0,022%	-0,035%	0,013%
			(0,005%)	(0,005%)	(0,004%)
2012-2015	97.086 *(5,1%)*	107.511 *(5,6%)*	0,008%	-0,010%	0,018%
			(0,004%)	(0,004%)	(0,004%)
26-day					
1999-2002	69.320 *(3,6%)*	74.029 *(3,9%)*	0,004%	-0,049%	0,053%
			(0,005%)	(0,006%)	(0,005%)
2003-2006	71.039 *(3,7%)*	73.049 *(3,8%)*	0,023%*	0,015%	0,008%
			(0,003%)	(0,004%)	(0,003%)
2007-2011	72.304 *(3,8%)*	79.238 *(4,1%)*	-0,025%	-0,037%	0,013%
			(0,005%)	(0,005%)	(0,005%)
2012-2015	68.330 *(3,6%)*	74.577 *(3,9%)*	0,008%	-0,012%	0,020%
			(0,004%)	(0,004%)	(0,005%)

***. Coefficient is significant at the 0,01 level (2-tailed)
**. Coefficient is significant at the 0,05 level (2-tailed)
*. Coefficient is significant at the 0,10 level (2-tailed)

Appendix I: Sharpe ratios per technical strategy

MA	France	Germany	Netherlands	UK
Buy	-0,29	0,07	0,05	-0,18
Sell	0,23	-0,40	-0,21	-0,17
Buy-Sell	-1,18	0,92	0,31	-0,09

MA-time	France			Germany			Netherlands			UK		
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
1999-2002	-0,42	0,16	-1,21	-0,11	-0,44	0,62	-0,18	-0,32	0,12	-0,29	-0,16	-0,45
2003-2006	-0,05	0,60	-1,43	0,43	-0,18	1,14	0,33	0,05	0,42	0,04	0,08	-0,17
2007-2011	-0,35	0,06	-1,08	0,01	-0,44	0,97	0,00	-0,31	0,33	-0,24	-0,28	0,07
2012-2015	-0,25	0,38	-1,29	0,17	-0,58	1,24	0,22	-0,21	0,44	-0,12	-0,23	0,15

RSI	France	Germany	Netherlands	UK
Buy	0,01	-0,06	-0,10	-0,30
Sell	-1,87	-0,39	-0,12	0,05
Buy-Sell	0,28	0,40	0,07	-0,17

RSI-time	France			Germany			Netherlands			UK		
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
1999-2002	-0,03	-8,29	0,13	-0,13	-0,41	0,31	-0,22	-0,11	-0,03	-0,33	-0,05	-0,35
2003-2006	0,34	-5,04	0,74	0,21	-0,09	0,19	0,03	0,06	-0,05	-0,17	0,19	-0,40
2007-2011	-0,08	-3,55	0,19	-0,16	-0,51	0,53	-0,13	-0,24	0,20	-0,44	-0,20	0,01
2012-2015	-0,06	-1,31	0,73	-0,03	-0,51	0,52	-0,01	-0,08	0,07	-0,50	-0,02	-0,12

SR	France	Germany	Netherlands	UK
Buy	0,40	0,44	0,62	-0,07
Sell	-0,09	-1,01	-0,06	-0,25
Buy-Sell	0,33	0,56	0,32	0,24

SR-time	France			Germany			Netherlands			UK		
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
1999-2002	0,05	-0,10	0,13	-0,32	-0,26	-0,07	-0,13	-0,20	0,03	0,01	-0,27	0,36
2003-2006	0,50	0,17	0,38	0,04	0,00	0,03	0,23	0,11	0,12	0,19	0,10	0,05
2007-2011	0,06	-0,24	0,29	-0,27	-0,31	0,15	0,02	-0,13	0,11	-0,15	-0,20	0,08
2012-2015	0,21	0,05	0,19	-0,31	-0,20	-0,08	0,10	-0,08	0,14	0,04	-0,11	0,12

COMB	France	Germany	Netherlands	UK
Buy	0,04	0,28	0,02	-0,21
Sell	-0,10	-0,25	-0,37	-0,05
Buy-Sell	0,11	0,48	0,35	-0,28

COMB-time	France			Germany			Netherlands			UK		
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
1999-2002	0,11	-0,25	0,31	-0,11	-0,37	0,18	-0,20	-0,06	-0,09	-0,29	-0,02	-0,41
2003-2006	0,62	-0,01	0,62	0,24	-0,10	0,32	0,27	0,07	0,18	0,03	0,20	-0,21
2007-2011	0,22	-0,43	0,62	-0,04	-0,48	0,45	-0,02	-0,22	0,15	-0,27	-0,16	-0,18
2012-2015	0,31	-0,16	0,40	0,07	-0,50	0,41	0,19	-0,07	0,19	-0,20	0,02	-0,25