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On market efficiencies on the German stock market

- Evidence via the implementation of momentum strategies -

By
Christian Naber

Supervisor:
Hossein Asgharian

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Abstract

This paper investigates whether the German Stock is efficient or not, i.e. whether there is a way to systematically beat the market. Within this framework momentum strategies with formation and holding periods over 3- to 12-month horizons are applied on the CDAX.

The results do not show clear signs of market inefficiencies. While momentum strategies were successful in 67% of the cases, the winner portfolio outperformed the loser portfolio over all strategies in 53% of the cases. Moreover, the results lack statistical significance in 50% of the cases meaning that these results could have occurred by chance.

What remains puzzling, however, is the robustness, with which some of these strategies exhibit momentum. Firstly, the momentum returns are existent throughout every month and different sub-periods. Secondly, even controlling for risk, industry- and index-related factors could not explain the sources of momentum.

Keywords: Market efficiency, momentum, winner and loser portfolio, risk-neutral portfolio, industry-neutral portfolio, index-neutral portfolio.

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II List of abbreviations

BAFIN	Bundesanstalt f r Finanzdienstleistungsaufsicht (= German Federal Agency for Financial Market Supervision)
BLUE	Best Linear Unbiased Estimator
B rsZulV	B rsenzulassungsverordnung (Stock Exchange Admission Regulation)
CAPM	Capital Asset Pricing Model
DW	Durbin-Watson
e.g.	exempli gratia (= for example)
EMH	Efficient Market Hypothesis
i.e.	id est (= that is)
JB	Jarque-Bera
L	Loser Portfolio
OLS	Ordinary Least Squares
RW	Random Walk
W	Winner Portfolio
WpHG	Wertpapierhandelsgesetz (= German Securities Trading Act)

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1 Introduction

"The trend is your friend"

This saying is an old and well-known stock market wisdom within the trader community and means that an existing trend is set to continue. If a stock moves within an upward tendency the most likely scenario is that the stock price further increases. In this case investors should not over-hastily sell but hold their stakes to gain from further price increases. Similarly, those who have not yet invested could likewise profit from an investment in that stock. If, however, a downward tendency is apparent the stock price will most likely decrease further. In this context, an investor can earn some money (and does not lose so much money respectively) by selling stocks or by buying products that bet on further stock price decreases. This is just one strategy amongst many others, for instance the O'Higgens-strategy[1] and the growth-strategy[2] just to name a few of them.

However, is it possible at all in these times to gain abnormal returns in the long run via the implementation of such strategies? It can be expected that if such a strategy is successful, market participants begin to imitate this strategy. As a result, the market incorporates these expectations and the abnormal returns will fade away. This should be even truer in countries where economies and financial systems are well developed, e.g. Germany. In those countries laws, regulators, high numbers of active traders and a high analyst coverage ensure a smooth settlement of security trading.

The analysis of such strategies, with which an investor can constantly beat the market, and in particular momentum and contrarian strategies enjoyed great popularity in the past. A momentum strategy recommends buying stocks that performed best over a certain period in the past while selling those stocks that performed most poorly in the same period, i.e. buying past winners and selling past losers. The contrarian strategy follows the opposite way. Via buying prior losers and selling prior winners the investors bet on past losers turning into winners and past winners turning into losers.

In this context two main tendencies can be presented. Firstly, a mean-reversion tendency stating that past winners turn into future losers while past losers turn into future winners. This is particularly true for stocks that performed poorly over a period from 3 to 5 years and are then hold for 3 to 5 years (DeBondt and Thaler, 1985). A similar strategy can be applied

[1] The O'Higgins strategy goes back to the American author Michael O'Higgens. In a first step the ten stocks with the highest dividend yield are identified. In a second step the five with the lowest price are added to the portfolio.

[2] Every year the investors sort the stock according to companies' turnover. The stocks from those companies with the highest percentage sales growth are then added to the investor's portfolio.

to short-term periods. Jegadeesh (1990) and Lehman (1990) showed that contrarian strategies selecting stocks based on the previous week's and month's performance generate abnormal returns.

The second tendency is a return continuation tendency. Their statements are based on so called momentum-strategies of taking a long position in stocks that performed best in the past, i.e. buying winners, and taking a short position in stocks that performed poorest in the past, i.e. selling losers. Via this strategy significant abnormal returns can be achieved over a horizon of 3 to 12 months (Jegadeesh and Titman, 1993).

These two tendencies are approved by Schiereck, DeBondt and Weber (1999) when analysing the German stock market (357 companies listed in the top segment of the Frankfurt Stock Exchange) between 1961 and 1991. They apply the momentum strategy for periods of 1 to 12 months and a contrarian strategy for periods of 12 up to 60 months.

Additionally, there are those who claim that the findings mentioned above are market anomalies that disappear as time goes by and are therefore no proof against market efficiency. The contrary is true: "In an efficient market, apparent underreaction will be as frequent as overreaction." (Fama, 1998).

Nevertheless, the findings towards market inefficiencies put a great challenge to the efficient market theory. In this context many papers have been written so far with the intention of explaining those anomalies. However, as traditional asset pricing models could not explain these phenomena behavioural finance, i.e. the study of social, cognitive and emotional factors and their influence on human behaviour, gained more and more popularity. In the context of behavioural finance the anomalies mentioned above can be attributed to bounded rationality.

The aim of this paper is to analyse whether the German stock market meets the requirements in the sense of market efficiency or not. Efficiency in this context means that there is no way of systematically beating the market. This is be done by applying momentum strategies on the CDAX – representing the German stock market – within the time period of January 2000 - February 2012. Past performance is measured over the past J months (J = 3, 6, 9 and 12) and according to this performance the portfolios are held for K months (K = 3, 6, 9 and 12). Via this, in total 16 strategies are analyzed. Similar to the "The trend is your friend"-strategy the past performance of different stocks is observed and according to this performance a momentum strategy is applied, i.e. past well-performing stocks are bought while past poorly-performing stocks are sold.

By doing this previous empirical results can be cross-checked. Even though some research already exists – both in German and in other markets - empirical results are often charged with data mining. Therefore, empirical studies with different data, i.e. from different countries and different time periods, will contribute to draw a clearer picture whether the results happened by chance or whether they are systematic. This is also true for the possible sources of momentum strategies' success, especially whether the industry composition could be attributed for the momentum or contrarian anomaly. This work enhances the research and goes even further: Via controlling for index effects it should be checked whether the index decomposition can be accounted as a potential source for the anomaly.

The results in this paper do not draw a black and white picture. In 67% of the cases the results show return continuation tendencies, while the remaining 33% indicate toward contrarian strategies. However, just 50% of the results are statistically significant suggesting that these results are occurred by chance and are therefore no proof of market inefficiencies. Instead, this rather indicates towards market efficiency. However, when analyzing the J6K6-strategy, which exhibits significant momentum returns, the momentum effect seems quite strong. Even controlling for CAPM risk, industries and indices, does not sufficiently explain the appearance of that anomaly.

The remainder of this paper is organized as follows: Chapter 2 provides the theoretical framework. Chapter 3 deals with the previous research and should provide a quick overview about the studies that already dealt with momentum strategies. In chapter 4, the methodology applied is presented. Chapter 5 shows the results of the analysis. This includes both the pure results, i.e. whether the momentum strategy was successful or not, and also an in-depth analysis like tests for statistical significance and potential sources for the success of this momentum strategy. This paper ends with a conclusion in chapter 6.

2 Theoretical Framework

2.1 The Efficient Market Hypothesis

The efficient market approach followed in this paper is that a market is efficient when there is no opportunity of implementing a strategy with which an investor can systematically outperform the market. Whether the market and the prices respectively are efficient in the rational sense as mentioned in Statman (1999)[3] goes beyond the scope of this analysis and is not a focus of this paper.

Nevertheless, to provide a common understanding the theoretical framework of the efficient market concept is introduced. Fama stated already in 1970 the probably most used definition of an efficient market: *„A market in which prices always fully reflect available information is called efficient."* Within the framework of this concept it is impossible to gain abnormal risk adjusted returns as all information will be processed and incorporated into the stock prices as soon as the information becomes available. Hence, information efficiency refers to the market's talent to process and incorporate information relevant for the value of those securities that are traded on that stock exchange.

However, what is meant by "available information"? According to Fama (1970) three different versions of the efficient market hypothesis can be distinguished:

1. Weak form efficiency
2. Semi strong form efficiency
3. Strong from efficiency

2.1.1 Weak form efficiency

The weakest form of the Efficient Market Hypothesis (EMH) is the weak form efficiency, which states that current market prices reflect all information contained in past market prices.

What does this mean for investors? Under the concept of the weak form efficiency trading strategies based on technical stock price analysis are useless. With technical analysis a chartist "seeks to predict future movements by seeking to interpret past patterns on the assumption that "history tends to repeat itself" (Keane, 1983). As stock

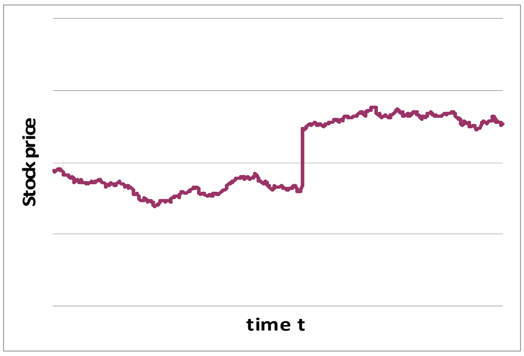
[3] Market efficiency in the sense of rationality goes back to Fama (1991) stating that „market efficiency per se is not testable. It must be tested jointly with some model of equilibrium, an asset pricing model." According to this theory there should not be any divergence from the stock's real value at all.

prices under the weak form efficiency already reflect all historical information available, only new information can cause share price movements. This, in turn, implies independent stock prices movements, i.e. they follow a random walk. Thus, the application of chart analysis is useless.

2.1.2 Semi strong form efficiency

The semi strong form of the EMH demands that current market prices contain besides historical information all publicly available information. This implies that all the historical and public information is processed correctly and instantaneously into the stock prices (see Figure 1). For example, if a company releases its annual report the market participants evaluate and process the published information and the stock price reacts accordingly.

Figure 1: Correct and instantaneous price reactions



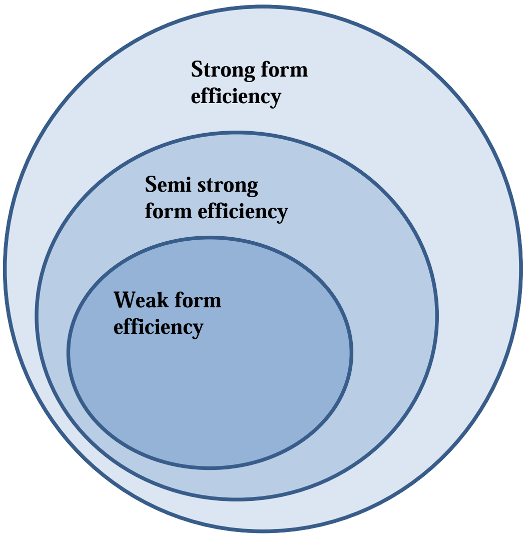
This is guaranteed by the existence of some professional analysts and institutional investors (Fama, 1995). These professional players support the market to become (more) efficient as they understand the accounting policies and can handle the information. Moreover, it is not important where the public information is disclosed, e.g. annual report, management report or press releases as long as information is publicly available. These professional players guarantee “price protection” as not every market participant has to understand financial theory to its single details. Some professional players are sufficient for public information being mirrored in stock prices correctly. Therefore it is not possible for investors to gain excess returns via technical or fundamental analysis.

This goes even so far that manager have no chance to influence the companies stock price via accounting measures because the professional analysts would anticipate these measures.

2.1.3 Strong form efficiency

The strongest version of the EMH is the strong form efficiency. It states that stock prices contain all information, regardless of whether they are available publicly or privately. Figure 2 clarifies the connection between the different forms of the EMH.

Figure 2: Various forms of information efficiency (Haugen, 2000)



Under this concept insider-trading, i.e. trading by individuals that have access to non-public information is useless as all the information is already incorporated into the stock prices. However, this seems not to be a sound concept due to two reasons. Firstly, insider trading is forbidden by law in most of the industrial countries and secondly, and most important: Grossmann and Stiglitz (1980) showed that the strong version of the EMH leads to a so called information paradox. Individuals gathering information for other capital market participants claim compensation for their efforts. However, "when the efficient market hypothesis is true and information is costly, competitive markets break down". The reason for this is that the prices fully reflect all available information, i.e. the private information as well. In this case the informed investors have no incentive anymore to buy costly information when uninformed investors profit by that without paying. Hence, private information will not be gathered anymore. On the other hand, with no investor being informed there would not be a stable equilibrium as investors anticipate that profits can be made by getting private information.

Even though the strong form is not an exact image of the reality, it is nevertheless useful as it serves as a benchmarkt against which deviations from other models regarding market efficiency can be judged (Fama, 1995).

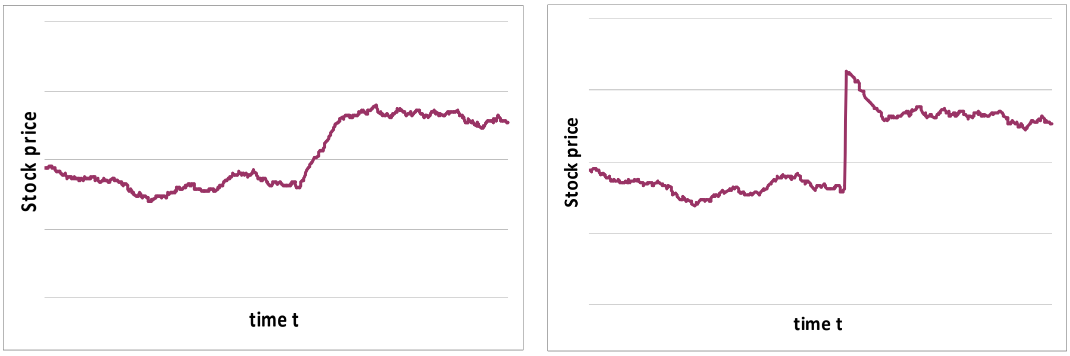
2.1.4 Limitations of Information efficiency

Again, information efficiency states that the current market prices fully reflect the available information. In this context, however, it is important to note that information efficiency does not make any statement about the information's influence on the price formation, i.e. it cannot be predicted how the information will be processed and thus how the stock price will react on that information. Therefore, no reliable conclusions about its welfare effects can be drawn. This makes it difficult to detect information inefficiencies directly. To measure it directly, the expected price movement is compared with the real price movement. This might sometimes lead to complications when several pieces of information interfere with each other.

Figure 3 illustrates the problematic with the interference of information and shows some examples of violations of instantaneous price reactions.

Figure 3: Violations of instantaneous and correct price reactions

Violation of instantaneous price reaction **Violation of correct price reation**



This interference problematic can be avoided by the implementation of indirect efficiency tests. Here, trading strategies are applied, which are not supposed to be successful in the presence of information efficiency.

Where the information comes from, is also not of interest. Usually the corporate reporting serves as a large source of information, but it is just one source. Other examples are ad-hoc releases, interviews, corporate publicity activities and analyst reports.

2.2 Random Walk

Closely related to the efficient market hypothesis is the random walk theory stating that stock prices follow a random walk, i.e. successive price changes are independent from each other. "Most simply, the theory of random walks implies that a series of stock price changes has no memory – the past history of the series cannot be used to predict the future in any meaningful way" (Fama, 1995).

In an efficient market the current stock price reflects all the information available, i.e. the current stock price is equal its intrinsic value. In the real world, however, it is unlikely that every market participant evaluates the information in the same way. Hence, the current stock will be in some cases higher and in some cases lower than the intrinsic value, hence the different opinions of the market participants make the price wander randomly about its intrinsic value (Fama, 1995). It can be argued that this might lead to a status where the current stock price is systematically higher than its real value. In this case, however, some smart players might take advantage of this systematic error. As a consequence this signals other market participants to imitate the strategy and the systematic error will fade away. The above mentioned shows that the theory of random walk is diametrically opposed to the momentum strategy which is based on finding a strategy that constantly exploits the market's underreaction.

Three different forms of random walk hypothesis can be distinguished (Asgharian, 2008):

1. The strongest version of the random walk hypothesis (Random Walk 1) assumes that price changes are independent and identically distributed (IID).
2. The second version of the random walk hypothesis relaxes the assumptions of identically distributed returns. According to Random Walk 2 the distribution of the returns can change over time, so that prices changes are independent and not-identically distributed.
3. In its weakest form (Random Walk 3) the assumptions of both the independence and identically distributed returns are softened, such that the price changes can be dependent, but uncorrelated, and not identically distributed.

2.3 Behavioural Finance

So far this work deals with the financial (normative) theory and its assumptions of efficient markets and rational market participants. For sufficiently simple problems, these assumptions might be appropriate (Thaler, 1979). The real world, however, is a complex entity. *"The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behaviour in the real world -- or even for a reasonable approximation to such objective rationality."* (Simon, 1957). Therefore, decisions are often affected by irrational behaviour or "bounded rationality". One example out of the real world is about depreciations and its accounting effects on the hand side and its psychological effects on the other side. As depreciations reduce the taxable income and the reported profits (or increase reported losses), many firms tend to report high depreciations to benefit from those tax treatments. Rational investors take those considerations into account. Practical experience, however, tells a different story both true for professionals and laymen (Arrow, 1982).

The above stated goes in hand with Beaver (1981) claiming that the heterogeneity of believes may lead to different decisions even though all individuals posses the same set of information. The reason for this is rooted in several aspects: The training to obtain the specific knowledge is costly and hence not available for everyone. Even under the same set of information it is possible to evaluate the same facts in different ways as long as the management's motivation is not known. Behavioural finance examines the decisions and the influence of psychology, i.e. of social, cognitive, emotional and moral factors, on the decision behaviour of individuals and on the market efficiency.

One of the maybe most popular papers in this context is the Prospect Theory: An Analysis of Decision under Risk by Kahneman and Tversky in 1979. They showed that the expected utility theory, formulated by von Neumann and Morgenstern in 1944, and the axioms, it is based upon, is violated in several decision problems.

According to normative theory it should not matter whether costs are opportunity costs or out-of-pocket costs. One interesting finding, however, is that opportunity costs and out-of-pocket expenses are treated in different ways. In this context opportunity costs can also be viewed as foregone gains and out-of-pocket expenses as losses (Thaler, 1979). Following this logic, it certainly makes a difference for the individuals whether they buy (sell) an increasing stock too late (early) or if they suffer a real loss by selling a stock under its purchase price.

An additional finding is that sunk costs (=costs, that have already been incurred and that cannot be recovered) are relevant for future decisions, while normative theory postulates that only incremental costs and benefits should be taken into account. Though hard to prove due to selectivity biases, evidence exists that individuals take past costs into account (amongst others Thaler, 1979, Kahnemann/Tversky, 1979 and Aronson/Mills, 1959). In this context, the reference point with which the individuals view the problem is of great importance. This means that the changes of wealth have more influence on the individual's utility than the final asset position.

3 Previous Research

3.1 Return continuation and momentum strategies

Momentum strategies are applied to exploit return continuation tendencies. The investors buy past well performing stocks with the hope of further stock price increases.

In the context of evidence for momentum strategies one has to name Jegadeesh and Titman and their work form 1993. They show that by taking long positions in past winners (=stocks that performed well in the previous 3 to 12 months) and short positions in past losers (=stocks that performed poorly in the previous 3 to 12 months) significant abnormal returns can be achieved. The returns of this winner-loser-strategy are positive for all formation and holding periods, i.e. 16 strategies, and show in almost all cases significant test statistics. Further analysis suggests that the abnormal returns cannot be attributed to systematic risk effects.

Rouwenhorst's work (1998) supports these findings, even in different stock markets. By analyzing the stocks of 12 European countries and constructing winner- and loser-portfolios in the same way as Jegadeesh and Titman (1993), Rouwenhorst observes for each of the formation and holding period that past winners outperformed previous losers by around 1% per month. Further analysis shows additionally that momentum persists even after creating industry-neutral portfolios[4]. While Grundy and Martin (2000) support these findings, Moskowitz and Grinblatt (1999) find evidence that after controlling industry effects, momentum profits turn in significantly weaker and are statistical insignificant.

Schiereck, DeBondt and Weber (1999) find similar results when applying a momentum strategy for ranking periods of 1 month up to 12 months and holding periods of 3 months up to 12 months. They analyze 357 companies listed in the top segment of the Frankfurt Stock Exchange between 1961 and 1991. To make comparisons with the Jegadeesh/Titman-study possible the 1965-1989-period is also analyzed. Even though the returns are constantly smaller than those reported from Jegadeesh/Titman the returns increase in almost every case as the holding period gets longer.

[4] Industry-neutral takes the industry decomposition into account. By creating industy-neutral portfolios it should be avoid that the momentum is driven by some anomalies in specific industries.

3.2 Return reversals and contrarian strategies

So far, empirical evidence presented medium term price continuation tendencies. For shorter and longer time frames, however, different results are obtained.

One of the most influential papers on the field of contrarian strategies was written by DeBondt and Thaler (1985). They documented that companies with a poor three to five year past performance significantly outperform well-performing companies in the consecutive three to five years. The authors attribute this anomaly to overreaction, i.e. "most people "overreact" to unexpected and dramatic news events" (DeBondt and Thaler, 1985). The overreaction hypothesis could not, however, explain the January anomaly meaning that most of the abnormal returns are earned in January, while other months hardly contribute to contrarian returns.

These results are approved by Schiereck, DeBondt and Weber (1999), who applied a contrarian strategy for long term holding periods (12, 24, 36, 48 and 60 months). Via this the authors showed that the anomalies – momentum returns on the medium term (see 3.1. Return continuation and momentum strategies) and contrarian returns on the long term – work simultaneously in the German stock market. Even controlling for several factors such as beta, risk, firm size the anomalies does not entirely explain these observations.

Jegadeesh (1990) and Lehman (1990) provide evidence of the success of contrarian strategies for shorter time periods. By forming portfolios on the basis of prior month's performance Jegadeesh (1990) documents that winner's average monthly returns is almost 2% higher than those of the losers. Lehman (1999) found evidence that stocks "that had positive returns in one week typically had negative returns in the next week (-0.35% to -0.55% per week on average), while those with negative returns in one week typically had positive returns in the next week (0.86% to 1.24% per week on average)."

3.3 Behavioural Finance

The traditional theories failed to explain the above mentioned findings. This in turn has led to models dealing with human behaviour. In this context the financial players do not act as a homo economicus[5], but with bounded rationality.

[5] Under the concept of homo economicus, a human being is considered as a self-interested and rational actor, who seeks to maximize his benefits according to his preferences, while being fully informed and taking constraints into account (Franz, 2004).

Barberis, Shleifer and Vishny (1998) propose a model of investor sentiment. In their model earnings follow a random walk. The investor, however, is not aware of that and believes in the existence of two states, firstly a mean-reverting state and secondly a return-continuation state. In every period the investor observes earnings and adjusts his beliefs about which state he is in. When, for example, positive earnings information arrive the investor raises the probability of being in a bull market, while he adjusts the probability towards a bearish market, when receiving negative earnings information. Their model especially takes into account, that investors - when adjusting their forecasts - "pay too much attention to the strength of the evidence they are presented with and too little attention to its statistical weight"(Barberis, Shleifer and Vishny, 1998).

Daniel, Hirshleifer, and Subrahmanyam (1998) find that stock prices tend to overreact to private information and tend to underreact to public information. Their model is based on the so-called overconfidence and attribution bias. Let us assume that an investor gets private information. On the basis of this information the investor buys the stock causing its price to rise over it intrinsic value. Then, public information enters the market. As public information does suggest a rather broad range of the stock's fair price the stock price will be gradually adjusted. Not before more and more public information becomes available, the stock prices will tend towards its real value step by step.

Hong and Stein (1999) show that "if there is ever any short-run underreaction [...], there must eventually be overreaction in the longer run as well." They propose a model with only two types of financial players, i.e. "newswatchers" and "momentum traders". Newswatchers forecast the stock prices just according to their own private information (which spreads gradually to other newswatchers) while momentum traders evaluate an investment just according to past price changes. Let us assume positive information comes to the market. The newswatchers process the information and make the stock price rise. However, the stock price is still below its fundamental value. Then, momentum traders appear, who just observe the price increase – not knowing whether the increases are based upon fundamental information or just momentum - which makes them buy more stocks. Hence, the stock price increase is followed by another stock prices increase and a process is initiated making the stock price rise further. Then at some point the stock price exceeds its fundamental value and when new information flows to the market causing the stock price to fall a downward process is initiated.

3.4 (Further) Explanations for Momentum and Contrarian Profits

The behavioural models mentioned above name overreaction as cause for abnormal returns over medium-term horizons. These models predict that market participants realize these overreactions and that the stock price quotes over its fundamental value. When the stocks tend to their real values in the following periods the stocks that reacted too strong on the information (=winners) are outperformed by those that reacted less sensitive (=losers). This is line with the finding, that momentum returns are positive in the first 12 months and negative in the months 12 to 60 (Jegadeesh and Titman, 2001).

Conrad and Kaul (1998), however, provide an alternative explanation. When analyzing the American stock market between 1926 and 1989 they documented patterns that match with those from DeBondt and Thaler (1985) and Jegadeesh and Titman (1993), i.e. mainly significant momentum returns over a medium horizon and partly significant contrarian returns. However, they attribute those anomalies not with investor's behaviour but to some sort of risk. To be more concrete, they emphasize that profits to both momentum and contrarian strategies are based on two components: time-series predictability in stock-returns and cross-sectional variation in mean returns of individual stocks comprising the portfolios. Their findings suggest "that cross-sectional differences in mean returns play a nontrivial role in determining the profitability of momentum strategies." (Conrad and Kaul, 1998)[6].

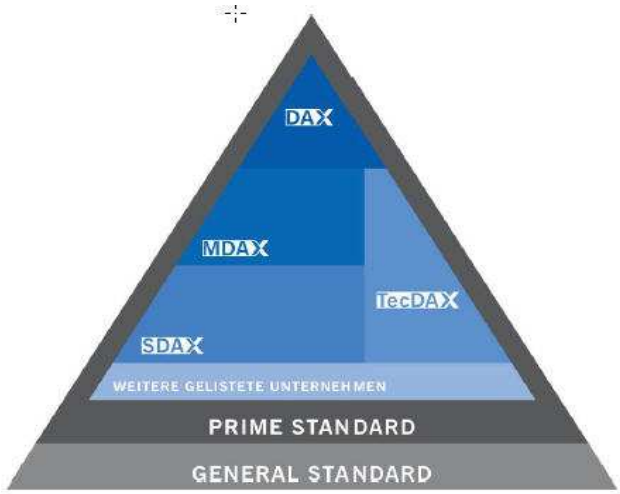
[6] Even though this shows that momentum does not necessarily have to be tantamount to overreaction these words are used synonymously in this paper.

4 Methodology

4.1 Data

The sample considers all stocks listed on the German CDAX in the period from 2000-01-01 to 2012-01-31. The CDAX covers all German stocks across Prime and General Standard. Thus, the CDAX measures the performance of the German stock market and is therefore very suitable for analysis purposes (Deutsche B rse AG, 2011).

Figure 4: Overview of the CDAX composition (Deutsche B rse AG, 2011)



As can be seen by Figure 4 the CDAX can be separated into different sub indices, i.e. DAX, MDAX, SDAX, TecDAX and further listed companies. The DAX displays the blue chip segment and contains the 30 largest German companies in terms of order book volume and market capitalization. The MDAX index portfolio consists of 50 midcap companies that follow the blue chips. The SDAX-index consists of 50 companies ranking directly below the MDAX. The TecDAX represents the 30 largest companies coming from the technology sector.[7]

The analysis covers in total 1,012 companies that have been listed in the CDAX at some point. During that time, however, some companies enter the index while others exit. This can occur for a variety of reasons: A company goes out of business, declares bankruptcy or is involved in a merger and acquisition transaction. Another reason might be that the company is no longer able or willing to satisfy the listing requirements (see Appendix 1). The number of stocks being listed in the CDAX at the same time ranges from 834 to 611 companies during the sample period. In this context it is important to

[7] On March 24^{th}, 2003 the MDAX and the SDAX were restructured. With the introduction of the TecDAX the MDAX and the SDAX were reduced from 70 and 100 companies respectively to 50 companies (Deutsche B rse, 2011a).

note that companies that are delisted within the sample period are included into the analysis. This is done to avoid the so called survivorship bias. Excluding delisted companies from the sample might lead to excessively positive results as just "successful" ones are considered (Elton et al., 1996).

To be listed on the Prime and General Standard companies have to fulfil at least the requirements set up by the European Union (for requirements of the Regulated Market see Appendix 1) in order to guarantee high market efficiency, to protect investors and to ensure a fair competition. Additionally, the companies have to comply with the German WpHG and are regulated by the Bafin. These laws and regulations are set up to ensure a smooth and proper settlement of transactions. Therefore, biases and distortions due to imperfect market organizations and regulations are minimized and cannot be invoked as causes for market inefficiencies.

The data is extracted from Bloomberg. Bloomberg is an information service company that is well accepted under capital market participants. One facet for Bloomberg considered as a highly reliable source is that even pricings, e.g. for bond issuances and buybacks, is based on information obtained from Bloomberg. Therefore, biases which can be traced back to data generation problems can be minimized.

4.2 Portfolio construction

The portfolios are constructed in the same way as presented in Jegadeesh and Titman (1993). Every month the companies being listed in the CDAX at that time are ranked into deciles according to their past performance. The past performance is measured through the average returns over time horizons of 3, 6, 9 and 12 months (formation period J). To calculate the returns the following formulae is applied:

$$R_t^i = \frac{P_t^i + D_t^i - P_{t-1}^i}{P_{t-1}^i}$$

with:

R_t^i = Return of Stock i in month t

P_t^i = Price of Stock i in month t

D_t^i = Dividend of Stock i in month t

Based on these rankings, portfolios for the different deciles are constructed with every company being incorporated with equal weights. The companies having performed best in the formation period form the "winner portfolio", while the companies having performed worst form the "loser portfolio". In the next step a zero-investment strategy is created by taking a long position in the winner portfolio and a short position in the loser portfolio. Both portfolios are then held for the subsequent 3, 6, 9 and 12 months (holding period K). The aim of this strategy is that the winner portfolio will show a better performance over the holding period than the loser portfolio does. If this is the case a positive yield can be earned.

During the holding period the portfolios are not rebalanced. Hence, a situation might arise in which some companies already being included in either the winner or the loser portfolio are delisted during the holding period. In this case simply nothing is done. It can be argued to invest the liquidating proceeds in a market index or in risk free assets (e.g. German Federal bonds). This however, might also affect the statistical results.

This procedure is repeated in every single month. As the holding period, however, is always longer than one month, i.e. 3, 6, 9 and 12 months, overlapping portfolios can be included to increase the power of the statistical analysis (Jegadeesh and Titman, 1993). To be more specific one imagines the case where both the formation and the holding period are three months. In this case, the winner portfolio consists of six equal weighted parts: Firstly, a position resulting from the investment in the winner portfolio at the end of month t and secondly from positions resulting from investments in the corresponding winner portfolios at the end of month t-1 and t-2. Via this procedure 1/K of each portfolio is rebalanced every month, while the remaining portion (K-1)/K is carried over to the following months.

Blume and Stambough (1983) show that stock returns computed with closing prices are upward biased, mainly due to a bid-ask affect. The closing price is the price at which the last transaction occurred prior to the close of trading. However, it is not taken into account whether the last transaction was executed at bid price, ask price or within bid-ask-spread. If, for example, the last transaction on the previous day was at bid (ask) price, the stock appears more profitable than it really is (Lehmann, 1990). Therefore the results might be biased. For monthly returns as used in this paper, however, the extent of the bias can be assumed as very small (Jegadeesh, 1990) and is therefore neglected in the further considerations.

4.3 Statistical tests

Now, that the returns of different strategies have been calculated, it is not possible to declare with certainty if the results are significant or not, i.e. if a reasoned statement can be derived from the analysed data or if the results just occurred by chance. Therefore, a test of significance is conducted. To test whether the returns of the zero-investment strategy are significantly different from zero or not, so that the null and the alternative hypothesis can be stated as followed:

H_0: Returns are not significantly different from zero.

H_1: Returns are significantly different from zero.

The corresponding t-test is applied via the following formulae:

$$t = \frac{\bar{X} - \mu}{\sigma} * \sqrt{N} \sim t_{n-1,\alpha}$$

with:

$$\begin{aligned} &\bar{\mathrm{X}} = \text{mean of the zero - investment portfolio} \\ &\mu = \text{expected mean under the null hypothesis} \\ &\delta = \text{standard deviation of the zero - investment portfolio} \\ &\mathrm{N} = \text{number of observations} \end{aligned}$$

The hypothesis is tested at a significance level of 5%. If the calculated value exceeds the critical value this will lead to the rejection of the null hypothesis, i.e. the return of the zero-investment strategy is significantly different from zero. This means that the CDAX is not efficient, but strategies can be implemented to exploit these inefficiencies.

4.4 Further analysis of profits

4.4.1 Riskiness of portfolio

It can be argued that the abnormal returns earned by this momentum strategy are attributable to higher riskiness, i.e. the winner portfolio exhibits a higher risk and the higher return is simply a compensation for that risk.

To estimate the riskiness of the portfolios the Capital Asset Pricing Model (CAPM) will be applied. The core idea of the CAPM is about a linear relationship between a stock's expected return and its systematic risk. This systematic risk is expressed via the so called beta factor β, which measures how a stock behaves when compared with a market portfolio. The CAPM is characterized via the following formulae:

$$\underbrace{(R_{it} - r_{ft})}_{\substack{\text{excess return of Stock i} \\ \text{in month t}}} = \alpha + \beta * \underbrace{(R_{mt} - r_{ft})}_{\substack{\text{excess return of market} \\ \text{portflio in month t}}} + \varepsilon_{it}$$

with:

R_{it} = Return of stock i in month t
r_{ft} = Risk free rate of return in month t
R_{mt} = Return of market portfolio in month t
α, β = Regression parameters
ε_{it} = Residual of stock i in month t

As the risk free rate of return the 1-month-Euribor is chosen. As proxy for the market portfolio the MSCI Europe Index is taken. The MSCI Europe Index has the advantage when compared to a German Index, that it is not biased towards some industries that dominate the German market (Koller et. al., 2010).[8]

In order to make a statement whether the higher return of this strategy can be traced back to a higher riskiness the excess returns of the Winner/Loser-Portfolio is regressed against the excess returns of the market portfolio. If the β is higher than 1, it means that the Winner/Loser-Portfolio has a higher volatility and thus a higher risk than the market portfolio. In this case one can conclude that the higher returns are a compensation for the higher risks. A beta of lower than 1 would indicate that if the market portfolio rises by 1% the stock would increase by less than 1%. This in turn means that the stock is not that vulnerable against market volatility.

4.4.2 Test of Robustness

One can argue that the success of the zero-investment strategy is just temporarily. It can be imagined the case with one sub-period, in which the market exhibits many anomalies and is highly inefficient, while the other sub-periods are efficient. If the "inefficient" sub-period dominates it could influence the whole statistics in that way that the entire time period can be falsely assumed to be inefficient. To take these considerations into account the time period is split into three sub-periods, i.e. from 2001-01-01 to 2004-03-31, from 2004-04-01 to 2007-06-31 and from 2007-07-01 to 2010-12-31.

4.4.3 Industry-related factors

Table 1 shows a detailed picture of the industry decomposition. With a portion of 14.8% the capital goods sector accounts for the highest portion. Following with the second highest portion of 13.9% is software & services. Ranking third is the financial sector

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[8] Before applying the CAPM-formulae several tests have to performed. First and foremost it is important to test for stationarity. Additionally, the five OLS-assumptions have to be checked. Appendix 2 and Appendix 3 provide more information and the corresponding the test results.

accounting for 6.6%. The remaining 64.7% are distributed to the remaining 21 sectors meaning an average portion of around 3%.

Table 1: Industry decomposition according to Bloomberg[9]

		Number of stocks [abs.]	Number of stocks [%]
1	Automobiles & Components	26	2,6%
2	Banks	26	2,6%
3	Capital Goods	150	14,8%
4	Commercial & Professional Serv	39	3,9%
5	Consumer Durables & Apparel	58	5,7%
6	Consumer Services	10	1,0%
7	Diversified Financials	67	6,6%
8	Energy	9	0,9%
9	Food & Staples Retailing	9	0,9%
10	Food Beverage & Tobacco	27	2,7%
11	Health Care Equipment & Servic	39	3,9%
12	Household & Personal Products	8	0,8%
13	Insurance	19	1,9%
14	Materials	48	4,7%
15	Media	66	6,5%
16	Pharmaceuticals, Biotechnology	34	3,4%
17	Real Estate	60	5,9%
18	Retailing	36	3,6%
19	Semiconductors & Semiconductor	28	2,8%
20	Software & Services	141	13,9%
21	Technology Hardware & Equipmen	50	4,9%
22	Telecommunication Services	21	2,1%
23	Transportation	18	1,8%
24	Utilities	23	2,3%
	Total	**1012**	**100%**

The industry of a nation can be classified into different sub-industries. Every sub-industry is coined by its specific characteristics. The same is true for the performance during the economic cycle. There are some industries that are affected by economic changes while others are not. During economics upturns and boom phases, for example, cyclical industry sectors like the automotive or the building industry, show generally better performances than stocks in rather non-cyclical or defensive industries like utilities or consumer staples that are more immune against economic changes. Birmingham (1965) indicates the same and refers to a not-published correlation-analysis suggesting “that the majority of individual stock price changes are controlled by more dominant “general market” and industry tendencies.” To be more concrete, successive stock price movements in a stock might be independent of previous changes of that

[9] According to Bloomberg, there are 25 sub-industries. However, the sub-industry “unclassified” is reassigned manually.

particular stock, but they are not independent of simultaneous stock price movements of other stocks, especially from stocks belonging to the same industry.

Considering this the momentum effect can be industry driven, i.e. certain industries outperform the remaining industries and could therefore be the momentum driver. Hence, industry-neutral portfolios are introduced, which are constructed in a similar way as before. However, instead of ranking the companies listed in the CDAX the companies are first assigned to a certain industry sector and then ranked according to their past performance. Again, the top decile of each industry will form the winner portfolio and the bottom decile the loser portfolio. Via this both the winner and the loser portfolios contain companies from every industry sector. Here, every industry is considered with the same weight.

If the momentum effect is still observable in the same degree as before the industry performance is not the driver of momentum. If, however, no momentum can be observed and in a lesser degree respectively, this indicates that the momentum effect can be at least partly reduced by industry diversification.

4.4.4 Index-related factors

The elaboration regarding industries is also true for indices. As mentioned before, the CDAX reflects the price development of all German shares across the Prime and General Standard (Deutsche B rse, 2011). In this respect it is important to note that it is a composite index, i.e. CDAX consists of several sub-indices: DAX, TecDAX, MDAX, SDAX and further listed shares.

Hence, it might be interesting to analyze whether the momentum can be observed through different sub-indices or if just one sub-index drives the momentum. Therefore, index neutral portfolios are created. To construct index-neutral portfolios the stocks within the particular sub-indices are ranked according to their past performance. It is important to note that the composition of the corresponding indices is checked regularly, i.e. the index composition is not constant, but might change from time to time. Therefore, every month the indices have to be adjusted for relevant changes. In the next step, the top and bottom decile of each sub-index is taken with equal weights to form the winner and the loser portfolio respectively. Thereby, index-neutral portfolios will be created. If the momentum effect is still observable, this is an indication that particular indices are the momentum driver. If, however, the momentum will fade away this indicates towards momentum being driven by sub-indices.

5 Results

5.1 Profitability of momentum strategies

Table 2 presents the results of the momentum strategies. It can be seen that the results are not a black and white picture. All in all the momentum strategies are successful in 67% of the cases. The remaining 33% indicate towards contrarian strategies. When coming to the average success rate of all strategies, the winner portfolio outperforms the loser portfolio in 53% of the cases. Additionally, just 50% show statistical significance meaning that those results are not really robust, but could have occurred by chance. Hence, these findings are no clear sign of market inefficiencies, but are in line with Fama who states that in efficient markets "chance generates apparent anomalies that split randomly between overreaction and underreaction." (Fama, 1998).

Table 2: Returns of relative strength portfolios

Formation period (J)		Return in Ranking Period	Holding Period (K): 3 months	6 months	9 months	12 months
3 months	Loser (L)	-15,77%	2,91%	2,26%	2,27%	2,32%
	Winner (W)	24,53%	1,50%	1,82%	1,92%	2,03%
	W-L	**40,29%**	**-1,41%**	**-0,44%**	**-0,34%**	**-0,29%**
	(t-stat)		-3,79	-2,22	-1,78	-1,66
	Sucess rate		39%	42%	41%	42%
6 months	Loser (L)	-11,47%	1,59%	1,34%	1,57%	1,88%
	Winner (W)	17,18%	2,07%	2,37%	2,32%	2,17%
	W-L	**28,65%**	**0,48%**	**1,03%**	**0,75%**	**0,30%**
	(t-stat)		1,44	5,10	4,23	1,93
	Sucess rate		61%	63%	64%	55%
9 months	Loser (L)	-9,73%	1,55%	1,42%	1,84%	2,06%
	Winner (W)	13,71%	2,33%	2,44%	2,29%	2,20%
	W-L	**23,44%**	**0,78%**	**1,02%**	**0,45%**	**0,14%**
	(t-stat)		1,90	4,06	2,21	0,79
	Sucess rate		61%	60%	54%	55%
12 months	Loser (L)	-8,38%	1,73%	1,80%	2,14%	2,28%
	Winner (W)	12,11%	2,27%	2,23%	2,10%	2,12%
	W-L	**20,50%**	**0,54%**	**0,43%**	**-0,04%**	**-0,15%**
	(t-stat)		1,23	1,56	-0,19	-0,83
	Sucess rate		60%	58%	49%	47%

= Insignificant at a 5%-confidence level

The success rate shows the rate in per cent, how many times the winner outperformed the loser

Column 1 shows the average monthly returns of the portfolios in the ranking period. It attracts attention that the returns of the Winner-loser-portfolio (W-L) in the ranking period decrease as the formation period increases. Over a formation period of 3 months, for example, the top decile of the winners outperforms the top loser decile by 40%, while it is 21% over a formation period of 12 months.

For formation periods of 3 months losers outperform the winner portfolios 59% of the time on average. This is equivalent to an average success rate of 41% for strategies with a formation period of 3 months. As a result the loser portfolios constantly beat the winner portfolios when taking the entire sample period into account. However, just two strategies show statistical significance, i.e. the J3K3 and the J3K6 strategy with 1.41% and 0.44% respectively. The two other strategies gain negative results as well, but lack statistical significance.

In contrast to the J3-strategies, the formation periods of 6 and 9 months show opposite results. Here, the winner portfolios outperform the loser portfolios 61% and 58% out of the time resulting that winners constantly outperform the loser portfolio over the entire sample period suggesting a successful momentum strategy. The J6K6-strategy offered the highest returns (1.03%), while the lowest return was gained via the J9K12 strategy (0.14%). However, these results lack statistical significance in 50% of the cases, suggesting that they occurred by chance.

With the focus on the J12-strategy all strategies lack statistical significance. However, it is interesting to see that by increasing the holding period the average monthly returns of the W-L-portfolio constantly decreases. While J12K3 and J12K6 exhibit positive returns (0.54% and 0.43%) longer holding periods show negative returns (J12K9 with -0.04% and J12K12 -0.15%). This affects the success rates as well. For the two shorter holding periods they are around 60%. With an increase of the holding period up to 9 and 12 months respectively, the winner portfolio outperforms the loser portfolio in just 48% of the time.

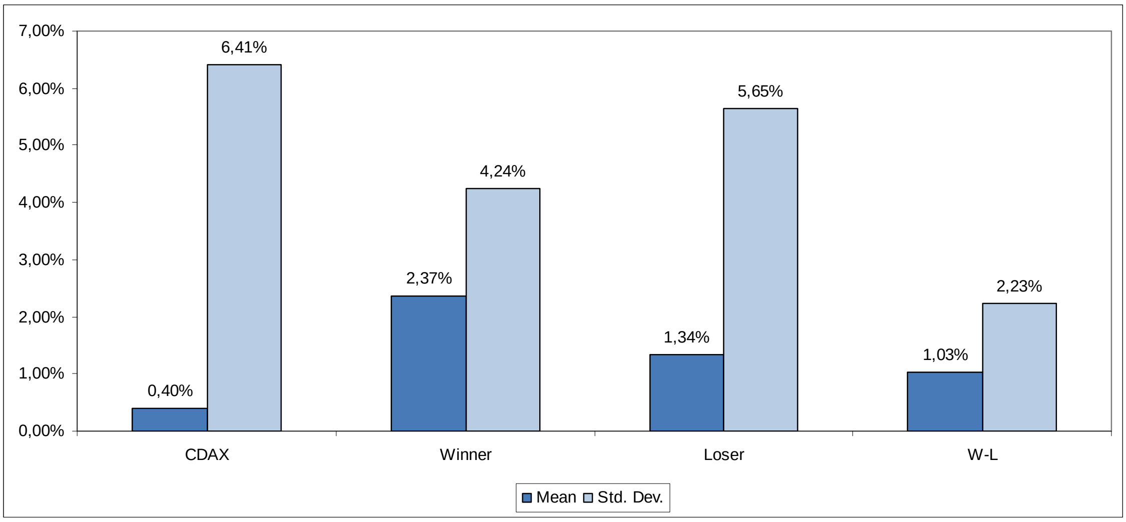
So far, the results do not show a clear picture of momentum. Instead they rather recommend market efficiency due to two reasons. Firstly, neither overreaction (as a sign for return reversals) nor underreaction (as a sign for return continuation) is constantly observable. Secondly, 50% of those returns lack statistical significance.

However, taking a look at the J6K6-strategy alone, which shows the highest average monthly return (1.03%) and is highly significant, indicates towards an inefficient market. Therefore, it might be interesting to see how the results behave when doing further analysis. This has the further advantage of comparing these results with other works supporting momentum strategies.

5.2 Explanation of profits

5.2.1 Riskiness of portfolio

Figure 5: Mean and Standard Deviation



In a first step, the riskiness of the portfolios is examined in more detail. Figure 5 compares the mean and standard deviation of different portfolios, i.e. the CDAX as the reference portfolio and the winner and loser portfolio respectively. It attracts attention that the CDAX is dominated by all others portfolios. On the one hand it earns the lowest returns (0.40%). On the other hand it shows the highest standard deviation (6.41%). The same is true when comparing the winner portfolio with the loser portfolio. The winner earns higher returns (2.37% vs. 4.24%) with being exposed to a lower risk (4.24% vs. 5.65%) at the same time. This proves that the higher returns of the winner portfolio cannot be attributed to higher volatility and higher risk respectively. This is supported when analyzing the CAPM riskiness of the portfolios. The regression analysis yields the following results:

Table 3: CAPM regression parameters

	α	t(α)	β	t(β)
Loser	-0,0006	-0,1049	0,5606	6,6593
Winner	0,0075	1,6817	0,4821	7,9379
W-L	**0,0081**	**3,5671**	**-0,0785**	**-1,8815**

=Insignificant at a 5%-confidence level (critical value: ±1.98)

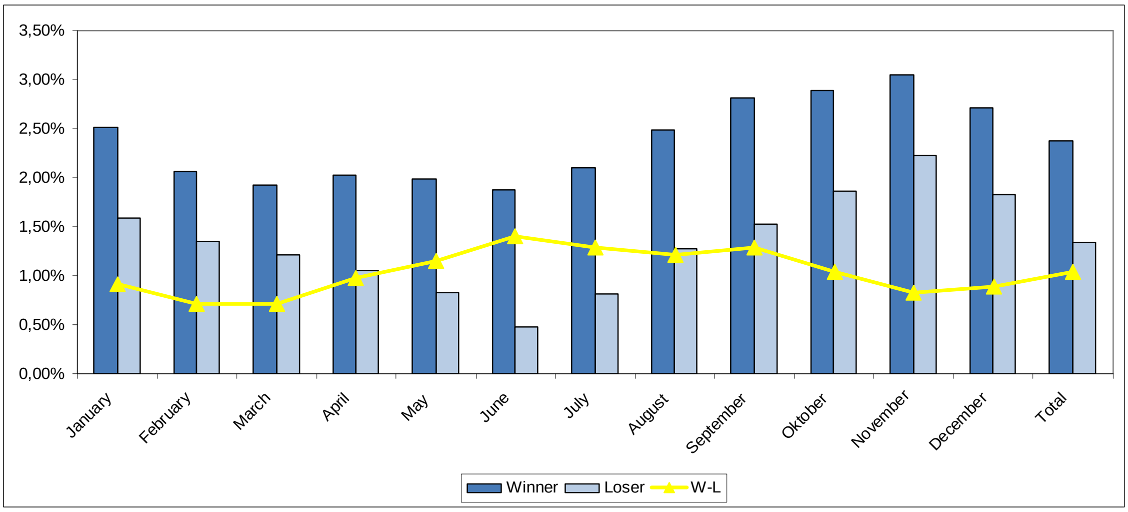
The intercepts, i.e. the alpha-coefficients, can be considered as the abnormal returns of the corresponding portfolios over the expected returns as predicted by the CAPM. Following this logic the winner-loser portfolio yields a significant excess return of 0.81%. Compared to the unrestricted winner-loser portfolio the return slightly decreases from 1.03%. Both, the winner- and the loser-portfolio exhibit positive beta-values with the beta-value of the loser-portfolio being slightly higher (0.5606) than the beta-value of the winner-portfolio. If, however, the success of the momentum strategy is attributed to higher riskiness, a beta value higher than one should be obtained. This is obviously not the case. Hence, risk in the sense of the CAPM is not the momentum driver.

These findings are in line with those of Jegadeesh & Titman (1993) and Rouwenhorst (1998). Both reported that beta-risk could not be named as the cause for the success of the momentum strategy.

5.2.2 Test of Robustness

In the next step, the average monthly returns are analysed for each calendar month. Via Figure 6 it can be seen that the J6K6-momentum strategy is not driven by particular months. Instead, the winner portfolios constantly outperform the loser portfolios in every calendar month on average with 1%, which is an indication towards momentum. This contradicts the findings of both DeBondt and Thaler (1985) and Jegadeesh and Titman (1993). In both papers it is reported that loser portfolios achieve positive abnormal returns on average in each January.

Figure 6: Average monthly returns for each calendar month



To check the persistency of momentum of the J6K6-strategy the sample period is divided into three sub-periods, i.e. 2002-12-01 – 2004-03-01, 2004-04-01 – 2007-06-31 and 2007-07-01 – 2010-12-31. The results can be seen in Table 4.

Table 4: Results of Robustness test

	Full sample		2000-12-01 - 2004-03-31		2004-04-01 - 2007-06-31		2007-07-01 - 2010-12-31	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Loser	1,34%	5,65%	-0,89%	6,40%	2,21%	3,33%	2,43%	6,05%
Winner	2,37%	4,24%	1,17%	4,93%	2,83%	2,36%	2,95%	4,66%
W-L	**1,03%**	**2,23%**	**2,05%**	**2,52%**	**0,61%**	**1,33%**	**0,52%**	**2,28%**
(t-stat)	5,10		5,08		2,63		1,49	

= Insignificant at a 5%-confidence level

From the results, it can be seen that every sub-period exhibits momentum tendencies. However, the magnitude differs substantially. In the first sub-period, the momentum strategy yields highly statistical abnormal returns of 2.05%, which is almost twice as high as for the full sample. In the following sub-periods both returns and significances decrease. In the last sub-period (2007-07-01 – 2010-12-31) the strategy exhibits once again positive returns, but is twice as low as in the full sample (0.52%) and lacks statistical significance. The high returns (2.05% vs. 0.61%) in the first sub-period can partly be explained by higher volatility (2.52% vs. 1.33%) when compared to the second sub-period. Regarding standard deviation it is also interesting to note, that the standard deviation of the loser portfolios always exhibits higher volatility for the full sample when compared to the winner portfolios which underpins again that the momentum cannot be attributed to higher risk (see also 5.2.1).

5.2.3 Industry-related factors

Table 5: Returns of industry relative strength portfolios

		Mean	Std. Dev.	t-stat (mean)
1	Automobiles & Components	-0,30%	8,99%	-0,37
2	Banks	3,49%	10,94%	3,52
3	Capital Goods	0,26%	3,79%	0,75
4	Commercial & Professional Services	4,46%	11,68%	4,22
5	Consumer Durables & Apparel	0,91%	4,59%	2,18
6	Consumer Services	3,62%	8,69%	4,60
7	Diversified Financials	1,28%	6,67%	2,12
8	Energy	-0,11%	8,12%	-0,50
9	Food & Staples Retailing	0,17%	2,46%	0,74
10	Food Beverage & Tobacco	0,76%	3,36%	2,50
11	Health Care Equipment & Services	1,84%	7,09%	2,87
12	Household & Personal Products	-3,04%	6,58%	-5,10
13	Insurance	1,35%	2,86%	5,20
14	Materials	1,98%	7,08%	3,09
15	Media	-2,92%	5,10%	-6,32
16	Pharmaceuticals, Biotechnology	0,36%	5,76%	0,69
17	Real Estate	0,48%	5,40%	0,99
18	Retailing	4,54%	13,58%	3,69
19	Semiconductors & Semiconductor	4,74%	11,96%	4,38
20	Software & Services	-0,46%	4,66%	-1,09
21	Technology Hardware & Equipment	-0,60%	5,91%	-1,12
22	Telecommunication Services	-5,10%	11,40%	-4,94
23	Transportation	-3,02%	6,85%	-4,87
24	Utilities	2,76%	5,95%	5,12
		0,73%	**1,88%**	**4,01**

= Insignificant at a 5%-confidence level

Table 5 reports the results of constructing industry-neutral portfolios. Via this strategy the average monthly return decreases from 1.03% to 0.73%, but still exhibits statistical significance. Hence, the strategy's profitability can just be partly attributed to industry related factors, but not entirely. The return reductions can be regarded as cost for the decreased standard deviation. Via industry diversification the standard deviation of the strategy's returns could be reduced from 2.23% to 1.88%, which is almost four times lower than the average standard deviation of the corresponding individual industries (7.04%).

A closer look at the particular industries shows that 16 out of the 24 industries exhibit positive returns, thereof 12 with statistical significance. The momentum strategies are especially successful in the sectors of Semiconductors & Semi. Equipment (4.74%), Retailing (4.54%) and Commercial & Professional Services (4.46%). The industry sectors of Capital goods, Food & Staples Retailing, Pharmaceuticals & Biotechnologies and Real Estate lack significance.

On the contrary, the momentum strategy produces negative returns for eight industries. Especially, the sectors of Telecommunication Services (-5.10%), Household & Personal Products (-3.04%) and Transportation (-3.02) exhibit statistical significance pointing out that it quite unlikely that the results happened by coincidence.

It is also interesting to take a look at the average monthly-returns of industry-neutral portfolios in each calendar month (Figure 7). Even though the winner portfolio outperformed the loser portfolio in almost every month (with the exception of February), the picture is not that clear. From February until April the returns of the winner and the loser portfolio are almost the same, so that the momentum strategy yields no significant returns in that time period. In the following half year the returns of that strategy almost constantly increase with gaining a yield of over 1.00% between August and November and having its peak in October (1.50%).

Figure 7: Average monthly returns of industry-neutral portfolios for each calender month

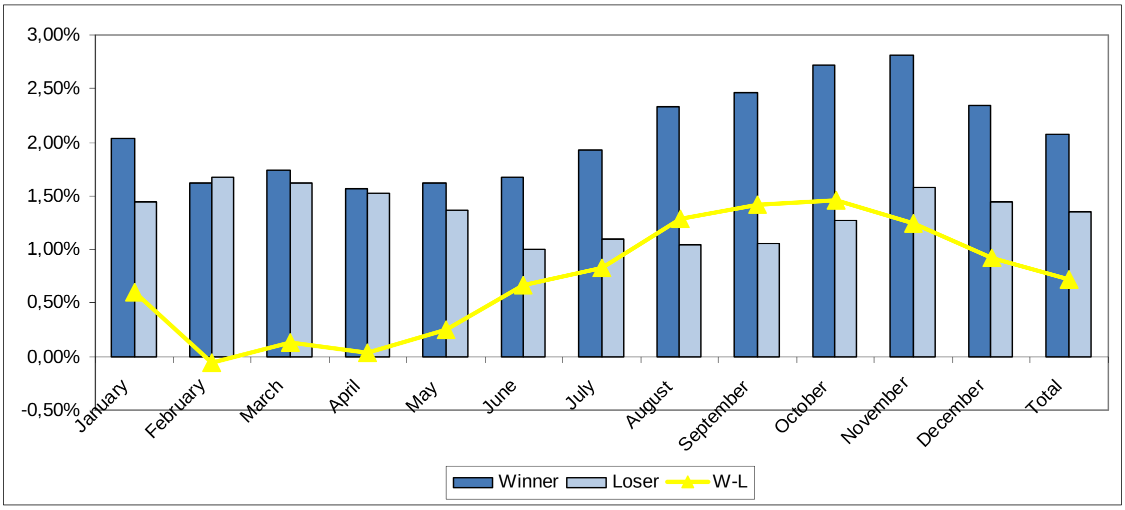


Table 6 shows the CAPM regression analysis. This is in line with the mentioned above. It can be seen that the winner-loser portfolio yields an excess return of 0.46% over the predicted expected return. Hence, adjusting the industry-neutral portfolios for CAPM market risk makes the return further decrease from 0.73% by 0.26%. The beta-values of the loser (0.5187) and the winner portfolio (0.4428) are smaller than 1 again, indicating that risk cannot be mentioned as momentum driver.

Table 6: CAPM regression parameters for industry-neutral portfolios

	α	t(α)	β	t(β)
Loser	-0,0022	-0,4710	0,5187	7,9495
Winner	0,0024	0,6446	0,4423	8,4280
W-L	**0,0046**	**2,4550**	**-0,0764**	**-2,9856**

=Insignificant at a 5%-confidence level (critical value: ±1.98)

These findings indicate toward momentum tendencies as the return of the "Buy winners, sell losers"-strategy slightly decreased when controlling for industry effects, but still are significantly positive and could be attributed to a decreased standard deviation. This is in accordance with the findings of Grundy and Martin (2001) and Nijman, Swinkels & Verbeek (2004) both reporting that the success of momentum strategies cannot be explained by industry factors. A closer look, however, does not confirm this clear picture. Firstly, the momentum effect cannot be observed throughout all industries and secondly, the momentum effect is not constant throughout the year, but exhibits up- and downturns.

5.2.4 Index-related factors

Table 7: Average monthly returns of index-neutral portfolios for each calendar month

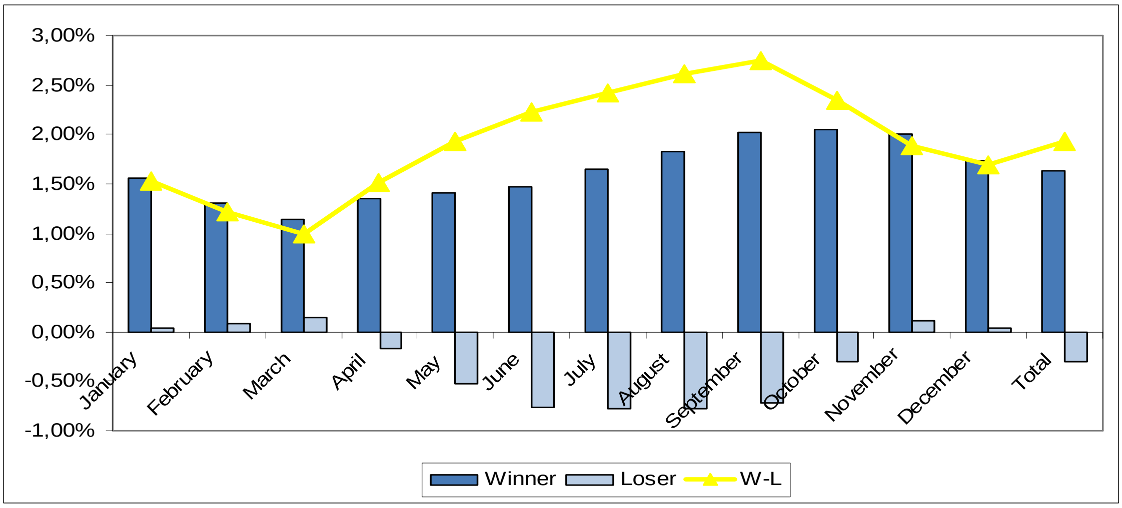
		Mean	Std. Dev.	t-stat (mean)
1	DAX	0,42%	8,99%	1,48
2	MDAX	2,21%	10,94%	7,50
3	SDAX	2,86%	3,79%	9,03
4	TecDAX	3,61%	11,68%	12,50
5	Remaining stocks	0,51%	4,59%	2,30
		1,92%	**2,06%**	**4,01**

= Insignificant at a 5%-confidence level

The results of constructing index-neutral portfolios can be seen in Table 7. Controlling for index composition does not reduce the average monthly return. In contrast, via this strategy the success of the momentum strategy could be strengthened further (from 1.03% to 1.92%). As the portfolios are well diversified in the sense that they have the same index allocation it can be subsumed that the momentum's profitability cannot be explained by index-related factors. Instead, the momentum effect is existent for every single index. Especially, the TecDAX (3.61%), the SDAX (2.86%) and the MDAX (2.21%) show strong momentum tendencies. It is interesting to see that via index-diversification the index-neutral portfolio dominates the W-L-portfolio with respect to return and standard deviation. The index-neutral portfolio has a higher mean (1.92% vs. 1.03%) and a lower standard deviation at the same time (2.06% vs. 2.23%).

Compared with the return of the industry-neutral portfolio the return could be increased from 0.73% to 1.92%. However, as the higher return is accompanied by a higher standard deviation (2.06% vs. 1.88%) it cannot be said that one portfolio dominates the other.

Figure 8: Average monthly returns of index-neutral portfolios for each calendar month



When analyzing the average monthly returns of the index-neutral portfolios for each calendar month (Figure 8) it can be seen that the winner portfolios are constantly outperforming the loser portfolios by at least 1%. While the winner portfolios gain positive returns on average in every month – with showing the best performance from September until November (around 2%), the loser portfolios exhibit negative returns from April to October and slightly positive returns in the remaining months. Hence, the momentum is not just a seasonal anomaly, but is apparent through the entire year. It is also interesting to see that distribution exhibits similar wave moment as the returns of industry-neutral portfolio, even though on a higher level and with higher swings.

Table 8: CAPM regression parameters for index-neutral portfolios

	α	t(α)	β	t(β)
Loser	-0,0196	-4,7661	0,4811	7,9000
Winner	-0,0025	-0,7720	0,4446	9,2197
W-L	**0,0171**	**8,0913**	**-0,0365**	**-0,8455**

=Insignificant at a 5%-confidence level (critical value: ±1.98)

In Table 8 it can be seen that the winner-loser portfolio yields a significant excess return of 1.71% over the expected return. This means that via adjusting the index-neutral portfolios for market risk the average monthly return is decreased from 1.92% to 1.71%. Again, the beta-values of the winner and loser portfolios are smaller than 1, suggesting that the success of the index-neutral portfolios can be attributed to an increased CAPM risk.

6 Conclusion

This paper investigates whether the CDAX is market efficient in the sense that there is no systematic way to constantly beat the market. To do so a momentum strategy is implemented in a way that every month the stocks listed on the CDAX are ranked according to their past performance in the previous j months (j=3, 6, 9, 12). The top decile forms the winner portfolio and the bottom decile the loser portfolio. In every month the winner portfolio is bought and held for k month (k=3, 6, 9, 12) while the loser portfolio is sold. Via this strategy return continuation tendencies, i.e. past winner stay winners and past loser stay losers, should be exploited.

The results do not indicate a clear picture of market inefficiencies. In 67% of the cases, the winner portfolios outperform the loser portfolios, while in 33% of the cases the loser gain higher returns. Moreover, the overall success rate is 53%, meaning that in 53% of the cases the winner portfolio outperforms the loser portfolios. Additionally, these results show statistical significance in just 50% of a time. Hence, these findings could also have occurred by chance which is in line with market efficiency "in the beat-the-market sense", i.e. there is no way to systematically beat the market.

However, what remains puzzling is the robustness, with which some of these strategies exhibit momentum. In this paper, the J6K6-strategy is further analyzed to check whether momentum (1.03%) can be attributed to certain factors. Therefore, several adaptations are carried out. In a first test it is shown that the momentum return cannot be explained by higher risk. Dividing the sample period in three sub-periods exhibits momentum tendencies for every sub-period, even though with notable deviations with each other. Even for each calendar month momentum is visible on average. In a next step, industry-neutral portfolios are created. Although 4 industry sectors show statistical significant contrarian returns, an overall positive return of 0.73% is obtained via the momentum strategy. Index effects cannot be named as cause for momentum as well. Instead, creating index-neutral portfolios increases the success of the momentum strategy.

It remains interesting to follow how the Efficient Market Hypothesis holds out against the already observable anomalies. Therefore, further studies on this area will enrich the discussion between those in favour of the EMH and those against it, which leads inevitable to a detection of further anomalies. This, however, must - as we have seen - not logically result in the abandonment of the efficiency concept. It rather helps to get a clearer picture and to better understand the stock markets. When it comes to momentum tendencies for formation and holding periods of 6 months it remains a puzzle, why this is the case. Usually speculative or arbitrage traders – in search for lucrative investment opportunities - ensure such anomalies to fade away. Why this has not taken place so far, is a possible topic for further research. In this context it might be interesting to see whether and to which degree respectively transaction costs and taxes influence such strategies.

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VI Appendix

Appendix 1: Criteria for a listing on the CDAX (Deutsche B rse, 2008)

Main criteria for the first admission of shares:

- The issuer must have existed as a company for at least three years.
- The anticipated market value of the shares to be admitted or – if an estimate is not possible – the equity of the company amounts to at least 1.25 million.
- The minimum number of shares is 10,000 for no-par value shares.
- Free float of at least 25 percent. According to § 9 B rsZulV (Stock Exchange Admission Regulation) exceptions are possible.
- The admission document is a listing prospectus with information about the actual and legal circumstances which are essential for the assessment of the issuer and the security. The listing prospectus must be accurate and complete and must include the balance sheets, income statements and cash flow statements of the last three fiscal years and the notes as well as the management report of the last fiscal year.
- Publication language is German, for foreign issuers also English.
- The decision-making body is the Admissions Office of the Frankfurt Stock Exchange.

Main follow-up obligations for the issuers of shares:

- Publication of annual financial statements
- Publication of an interim report for the first six months of the fiscal year
- Ad-hoc disclosure in accordance with § 15 WpHG
- Duty of notification in accordance with § 21 WpHG

Appendix 2: Testing for stationarity

Stationarity is an important character when it comes to statistical properties of estimators. In cases of non-stationarity spurious regressions are obtained, i.e. variables appear strongly, related, when in fact, they are not. To test stationarity an augmented Dickey-Fuller test with the following hypothesis is applied:

$$\Delta y_t = \alpha y_{t-1} + \beta \Delta y_{t-1} + \varepsilon_t$$

H_0: y contains a unit root

H_1: y is stationary

As the t-statistics exceed the critical values for a level of 5% in all cases (see Table 9) the null hypothesis can be rejected, so that the data is stationary and no adjustments have to be made.

Table 9: t-statistics from the augmented Dickey-Fuller test to detect stationarity

	Momentum Portfolio		Industry neutral Portfolio		Index neutral Portfolio		Market Portfolio
	Loser	Winner	Loser	Winner	Loser	Winner	
t-statistics	-4,26	-4,06	-3,61	-4,13	-4,09	-3,48	-5,68
Critical value	-2,89	-2,89	-2,89	-2,89	-2,89	-2,89	-2,89

Appendix 3: Testing the OLS assumptions

According to Brooks (2008) there are five assumptions that should be fulfilled when applying the method of the ordinary least squares (OLS). If the assumptions 1) – 4) hold, then the estimators determined by the OLS are BLUE (**B**est **L**inear **U**nbiased **E**stimator).

1. $E(\varepsilon_t) = 0$

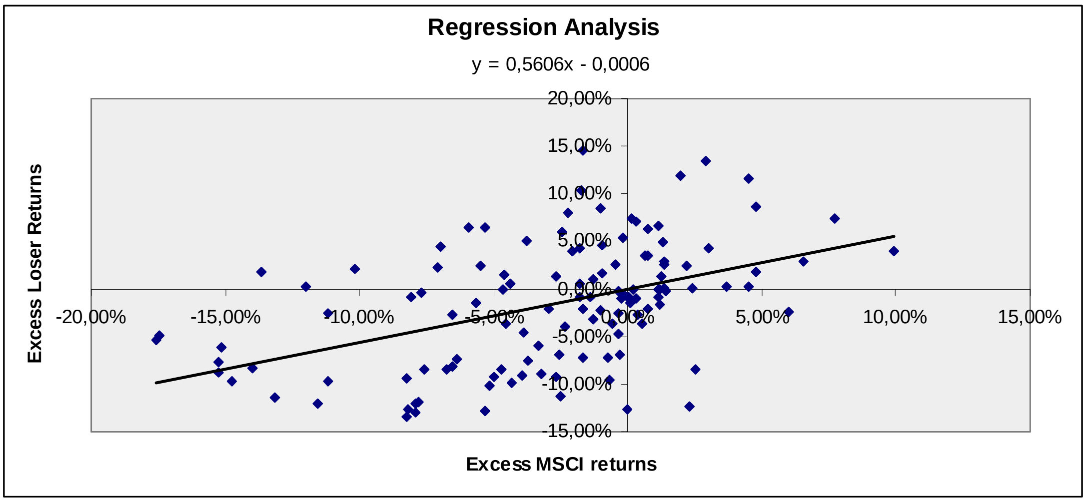
The first assumption is that the average value of the error term is equal to zero. As a constant term is included, it is obviously fulfilled.

2. $\mathrm{var}(\varepsilon_t) = \sigma^2 < \infty$

The second assumption is the assumption of homoscedasticity and requires the variance of the error term to be constant. In case, the errors are heteroscedastic OLS still provides unbiased coefficient estimates. However, they are no longer BLUE.

To get a first impression the excess returns are plotted against the excess market returns. Figure 9 shows an example, in which the excess returns of the loser portfolio are plotted against the excess returns of the market portfolio. However, using graphical methods might not be entirely accurate and the form and degree of heteroscedasticity cannot be diagnosed.

Figure 9: Plot of excess returns of loser portfolios against excess returns of market portfolio



Therefore, the standard errors estimated via regression are replaced by White's Heteroscedasticity consistent standard error, which is calculated via the following formulae:

$$\hat{\text{var}}(\beta) = \frac{\sum\left[\left(x_t - \bar{x}\right)^2 \hat{\varepsilon}_t^2\right]}{\left[\sum\left(x_t - \bar{x}\right)^2\right]^2};\ \hat{se}(\beta) = \sqrt{\hat{\text{var}}(\beta)}$$

Via these calculations the following White's standard errors are obtained. These new values are used to calculate the corrected t-statistics and confidence intervals.

Table 10: (Corrected) t-statistics using White's Heteroscedasticity Consistent Standard Errors

	Momentum Portfolio		Industry neutral Portfolio		Index neutral Portfolio	
	t(β)	adj. t(β)	t(β)	adj. t(β)	t(β)	adj. t(β)
Loser	5,77	6,66	6,54	7,95	7,03	7,90
Winner	6,55	7,94	7,13	8,43	8,16	9,22
W-L	-2,09	-1,88	-2,43	-2,99	-1,04	-0,85

=Insignificant at a 5%-confidence level (critical value: ±1.98)

3. $\text{cov}(\varepsilon_i, \varepsilon_j) = 0$

If there are patterns in the residuals from a model, then there is autocorrelation. The consequences of ignoring autocorrelation are comparable to those when neglecting heteroscedasticity. The coefficients are still unbiased, but they are not efficient, i.e. BLUE. This could lead to wrong standard error estimates. To detect autocorrelation a Durbin-Watson test is applied.

$$DW = \frac{\sum_{t=2}^{T}\left(\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1}\right)^2}{\sum_{t=1}^{T} e_t^2}$$

H_0= No evidence of autocorrelation

H_1= Evidence of autocorrelation

Table 11: t-statistics from the Durbin-Watson test to detect autocorrelation

	Momentum Portfolio		Industry neutral Portfolio		Index neutral Portfolio	
	Loser	Winner	Loser	Winner	Loser	Winner
t-statistics	0,39	0,52	0,49	0,60	0,58	0,75
upper bound	1,69		1,69		1,69	
lower bound	1,65		1,65		1,65	

As can be seen by Table 1Table 11 the DW-values lie outside the critical values. Hence, the null hypothesis of no autocorrelation has to be rejected. Additionally, as the DW-values are smaller than the lower bound, this is evidence of positive autocorrelation. One alternative to handle autocorrelation is the Cochrane-Orcutt procedure.

4. $\text{cov}(\varepsilon_t, x_t) = 0$

The fourth assumption demands the data to be non-stochastic. However, even when the data is stochastic, the coefficients are still consistent and unbiased. Therefore, this assumption has not to be tested further.

5. $\varepsilon_t \sim N(0, \sigma^2)$

The fifth assumption requires the error term being normally distributed. To measure whether this assumption is fulfilled a Jarque-Bera test is applied:

$$JB = \frac{T}{6}\left(S^2 \frac{(K-3)^2}{4} \right)$$

with: $S = \dfrac{\sum_{i=1}^{T} \hat{e}_i^3 / T}{\hat{\sigma}^3}$ and $K = \dfrac{\sum_{i=1}^{T} \hat{e}_i^4 / T}{\hat{\sigma}^4}$ and $\hat{\sigma} = \sqrt{\dfrac{1}{T}\sum_{i=1}^{T} \hat{e}_i^2}$

H_0= Error terms are normally distributed

H_1= Error terms are not normally distributed

Table 12: p-values from the Jarque-Bera test for normality

	Momentum Portfolio		Industry neutral Portfolio		Index neutral Portfolio	
	Loser	**Winner**	**Loser**	**Winner**	**Loser**	**Winner**
p-value	0,59	0,38	0,32	0,46	0,59	0,30

As some values are smaller than the 5% test level, the null hypothesis that the error terms are normally distributed has to be rejected. However, as the data set is sufficiently large this violation does not attach any great importance and can be neglected at this point.