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Directors' Dealing Influence on Stock Price Development in the German Stock Market

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DIPLOMA THESIS

submitted in partial fulfillment of the requirements for the degree of

Diplom-Ingenieur

in

Software Engineering & Internet Computing

by

BSc Valentin - Mihai Neacsu
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to the Faculty of Informatics
at the TU Wien

Advisor: a.o. Univ.-Prof. Dr. Wolfgang Aussenegg

Vienna, 23rd November, 2018

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Erklärung zur Verfassung der Arbeit

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Wien, 23. November 2018

Valentin - Mihai Neacsu

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Kurzfassung

Unser Ziel ist, den Beinfluss der Insidertransaktionen auf die Entwicklung der Stock Preise für öffentliche Gesellschaften im Deutschen Raum, zu analysieren. In diesem Sinn implementieren wir drei etablierte Test Statistiken aus der Event Study Methodologien und wenden diese auf einen Datensatz bestehend aus über 3000 Ankündigungen von etwa 100 deutschen Firmen. Die Forschungsergebnisse werden hier entsprechend dokumentiert. Ein wichtiges Resultat ist die Bestätigung, dass Insider eine konträre Trading Strategie verwenden. Ausserdem, finden wir Hinweise darauf, dass der Markt auf Insider Transaktionsankündigungen reagiert, sodass die abnormalen Rendite nicht bei Null liegen. Trotzdem, können wir leider basierend darauf keine konsistente Trading Strategie ableiten, denn die Reaktionen sind in den meisten Fällen gemischt.

Abstract

We analyze the influence of insider transactions on the evolution of the underlying security's stock price for public companies in the German market. We implement towards this goal three well-established test statistics from the event study methodologies and apply them on a data set containing approximately 3000 announcement events from around 100 German companies, documenting the results accordingly. Our main findings confirm the contrarian behavior of the insiders for the companies in the data set considered. Furthermore, we find evidence of market reactions to insider announcements in terms of non-zero abnormal returns, but not to the extent to which we would be able to formulate a consistent trading strategy based on it.

Contents

CHAPTER 1

Introduction

In order to be effective, stock market investments need to rely on knowledge about the underlying companies. Timely access to information is therefore of high importance. Being involved in the day-to-day company's business, insiders are the first to have access to this information, granting them a great advantage over any other investor. It is due to this substantial information asymmetry, that insider dealing reports have become increasingly popular, based on the assumption that insiders might react to information, which is not yet available to the public.

Having this assumption as a starting point, the paper will focus on studying how directors' dealings influence the evolution of the underlying securities and if they can serve as valuable information to outside investors. We will mainly analyze the short-term effects of insider transactions for 102 German companies in the period between 2005 and 2013. The conducted research will check for abnormal returns within the time period of 20 days prior to the transaction announcements up to 20 days after those. The main questions addressed by this paper are following:

- *How do insider transactions influence the stock abnormal returns in the short term?*
- *Is there a consistent strategy that can be formulated based on directors' dealings and what would be the gains following that strategy?*

In order to answer those questions, the research will take into consideration how results vary based on different characteristics of the transactions, as follows:

- *Transaction type (sell or buy)*
- *Transaction period (the total period 2005-2013, plus the 3 sub-periods 2005 - 2007, 2008 - 2010 and 2011 - 2013 will be considered)*

- *Industry sector*
- *Multiple trades on the same date for the same company*

The paper has the following structure: we review relevant literature in this field in the second chapter. On one side, we will analyze researches addressing similar questions, in order to motivate our assumptions and hypothesis. On the other side, we will describe the state of the art event studies methodologies, some of which we will employ in conducting the analysis on the actual data. In the third chapter we will describe our methodological approach, followed by the documentation and interpretation of the collected results in the forth chapter. The concluding remarks are presented in the fifth chapter.

CHAPTER 2

State of the Art

2.1 Literature Review

Due to its increased popularity among financial professionals, the topic of directors' dealings influence on the stock market has been an active research topic for a while.

Lakonishok and Lee (2001) shows in his study that very little market movement is generated around the time when insiders trade. They did their research on a comprehensive data set containing more than a million trades on NYSE listed companies in the period between 1975 and 1995. They document abnormal returns below 0.5% following the announcements, which does not amount to net positive returns after removing expenses such as the transaction costs. However, they argue that insider trades convey valuable information, which although initially ignored by the market, has the potential to predict stock movements on longer horizons. This is especially interesting when considering aggregate insider trading, where they show that firms with extensive insider purchases over the past six months period outperform the ones with extensive insider sales by 7.8%. With all this, the authors still conclude that formulating an investment strategy based on insider trading is not straightforward and will lead to a poor investment performance.

In contrast, Bettis et al. (1997) report that investors can earn significant abnormal returns by mimicking insider trades. Their study focused on large volume trades, working with a data set containing around five thousand insider transactions of NYSE and Amex listed companies in the period between 1985 through 1990. The authors document that after excluding transaction costs, outsiders are able to generate cumulative average abnormal returns of up to 6.96% on purchase and 4.86% on sell announcements for a 52-week holding period.

For companies in the United Kingdom, Friederich et al. (2002) reports positive gross abnormal returns, which however are of little economic significance after excluding transaction costs. Their study contained more than four thousand trades between 1986 and 1994.

In Europe, the reports from previous research offered mixed results. Aussenegg et al. (2018) in their study on 7 continental Europe countries between 2006 and 2013 reveal that sell transactions convey significant information as well, in contrast with the findings in US (see Lakonishok and Lee (2001)). They document contrarian insiders behaviour and argue that market reactions to insider transactions are more prominent in German law countries, than in French law countries.

On the other hand, Dardas and Güttler (2011) in their study on 2800 companies in 8 European countries between 2003 and 2009 did not document significant market reactions to sell announcements, arguing that investors have different reasons to sell (e.g. liquidity needs, diversification), which are not necessarily related to bad news for the company. Their findings also showed that purchase announcements generate statistically significant abnormal returns in 4 out of the 8 countries. They document that effects are more prominent in countries with stricter regulations, in contrast to the findings of Aussenegg et al. (2018). For instance in Germany they observed an intensified announcements effect in countries such as Germany after implementation of the Market Abuse Directive 2003/6/EC given by the European Union.

Similar results have been reported also by Fidrmuc et al. (2013) in their study conducted with 240000 announcements between 2002 and 2007 for 15 European countries and the United States of America. They argue that a higher level of shareholder protection translates to a more positive impact on post trade cumulative abnormal returns for purchase announcements. That's why, in countries such as US, UK and France they document cumulative abnormal returns that are 1.1% higher, compared to countries where the shareholder protection is not as well implemented. For sell announcements the reported cumulative abnormal returns are close to 0%.

In contrast to the aforementioned studies, Gębka et al. (2017) did not find statistically significant abnormal trading profits in their research over 18 European countries with more than 166000 announcements from 1999 to 2013. Their observations even after the implementation of the EU Market Abuse Directive 2003/6/EC did not show any evidence of a systematic shift in the profitability of insider trading.

We also reviewed studies which focused only on Germany. Klinge (2005) analyzed around 1400 non-overlapping events made within the period after the new insider law implementation (2002-2004). On the short term, they document cumulative average abnormal returns for the event day and the day after of 0.6% for purchases (statistically significant) and 0.054% for sells. But more surprisingly, for the cumulative average abnormal returns 20 days after the announcement they report 2.29% for purchases and -7.4% for sells, concluding that sell transactions have a stronger signaling power. For a similar period in time, Stotz (2006) report cumulative average abnormal return values of 3% for purchases, respectively -3% for sells.

Dymke and Walter (2008) focused their study on transactions succeeded by ad-hoc news disclosures within 20 days after the trade, containing around 2600 events over 344 firms in the period 2002 to 2005. They observe for purchases cumulative average abnormal returns 21 days starting with the event day of 4%. They document however that the price reaction is slow, which might be an indication that the German capital market is not semi-strong efficient. For sells, they report a non-economically significant value of -1.47% for cumulative average abnormal returns over the same period.

In the following sections we explore the underlying state-of-the-art methodology common to the aforementioned studies and to all event studies in general.

2.2 Event Study Methodology

In order to study the impact of specific events on the security's prospects on the market, finance scholars have developed event study methodologies. In its most common form, the event study methodologies focus on the stock prices. One of the most prominent research paper in this area has been written by MacKinlay (1997), which gives a comprehensive description of the topic and an accurate step by step framework on how to apply event study methodologies towards the goal of understanding the effects of an event on the respective company.

At a conceptual level, the analysis is guided towards identifying the difference between the expected returns (in case the event had not happen) and the actual returns, which are generated due to the event occurrence. This difference is denoted as the *abnormal return*. Multiple methods have been proposed for the calculation of abnormal returns, depending on the way normal returns are estimated. The most frequently employed ones are described in section 2.2.2.

In order to test for the significance of the identified abnormal returns not to be negligible, one formulates a null hypothesis and tests it against an appropriate test statistic. Section 2.2.3 describes some of the well established test statistics in the area of event studies. Usually, event study researches are not focused on isolated abnormal returns, but they rather aggregate observations, in order to infer statistically significant conclusions. The aggregation can be done through time and/or across securities, as follows (seeMacKinlay (1997)):

- *average abnormal returns*, defined across securities in a sample for a specific day, where N is the total number of securities in the sample and $AR_{i,t}$ denotes the abnormal returns of security i on day t:

$$AAR_i(t) = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{2.1}$$

- *cumulative abnormal returns*, defined for a security within a period (t_1 up until t_2):

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{2.2}$$

- *cumulative average abnormal returns*, defined for a sample of securities within a period of time:

$$CAAR(t_1, t_2) = \frac{1}{N} \sum_{i=1}^{N} CAR(t_1, t_2) \tag{2.3}$$

2.2.1 Assumptions

Event studies rely on specific theoretical assumptions, essential to the accuracy and reliability of the obtained results. Brown and Warner (1980) have identified the following assumptions as being of central importance:

- The capital market is efficient, meaning that stock returns accurately reflect the economic impact of the event on the company. This assumes that liquidity on the stock market for the affected companies is provided.
- The event is unexpected. This assumes that information leakage prior to the event is non-existent, ensuring that the stock price confidently captures the market's reaction to the event.
- There are no other interfering events in the event window which might explain stock price changes.
- When using specific normal return estimation models, such as the market model, choosing an appropriate reference index is essential. One has to ensure the best correlation between the stock and the market index is provided and that the company's and reference index characteristics do not structurally change over the analyzed period.

2.2.2 Expected Returns Estimation Models

There is a common time line applicable to all normal return estimation models, one which has the following characteristics: an event period is chosen, around the actual event date, which is relevant for analyzing the effect impact. Prior to the event date, one fixes an estimation period, which should be large enough to allow proper predictions of the expected returns. Optionally, some studies might also define a post-event period, which is relevant for studies focusing on the long-term event effect. The three periods are usually non-overlapping and the most common granularity of the stock market returns is usually daily based, although in rare cases weekly or even monthly stock returns might also be employed. Figure 2.1 gives a visual indication of the described concept.

Constant Mean Return Model

The constant mean return is one of the simplest models available, where the normal return of a security i (denoted by $\overline{R_i}$) is defined as the mean of the returns in the estimation period. Therefore, the abnormal return of a security is given by equation (2.4) (see MacKinlay (1997)), where $R_{i,t}$ represents the security's i return on day t.

$$AR_{i,t} = R_{i,t} - \overline{R}_i \tag{2.4}$$

Although it is a rather simple approach, studies such as the one of Brown and Warner (1985) found that the model provides results comparable to those of more complex models.

Market Model

The market model is a statistical model, where the normal returns are calculated in relation to the market returns. In order to do so, one applies an ordinary least squares regression over the estimation period, using the market returns as the explanatory variable and the security's returns as the dependent variable. Knowing the expected normal returns, the abnormal returns are then computed according to equation (2.5) (see MacKinlay (1997)), where α_i and β_i are the estimated regression coefficients and $R_{m,t}$ stands for the market return on day t.

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t}) \tag{2.5}$$

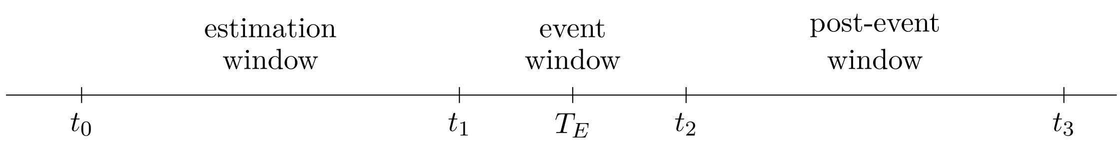
As stated by MacKinlay (1997), the market model improves upon the constant mean return model by reducing the portion of the stock returns variability, which is attributable to the market returns variation. Both its efficiency and simplicity makes it one of the most popular and most commonly employed models when conducting event studies.

Economic Models

Under this category, the following two models are the most common ones: the Capital Asset Pricing Model (CAPM) and the Asset Pricing Theory (APT). According to the CAPM, which is an equilibrium theory, the normal returns are calculated based on the covariance with the market portfolio, as of Sharpe (1964). The APT, as proposed by Ross (1976), calculates normal returns as a linear combination of multiple risk factors.

Although common in event studies back in the 70s, the two models are no longer a popular choice in recent ones. The reason for that is, on the one hand the questionable

Figure 2.1: Event study time line according to MacKinlay (1997)



validity of the restrictions imposed by the CAPM (see Fama and French (1996)) and on the other hand the little to no gains of using the APT over the market model, as argued by Brown and Weinstein (1985). Therefore, the market model became the preferred alternative over both models.

2.2.3 Test Statistics

Current event study literature generally groups significance tests in two categories: **parametric** and **non-parametric** tests. The main difference between the two lies in the fact that parametric tests assume a normal distribution of the company's abnormal returns, whereas non-parametric ones do not rely on such assumption (see MacKinlay (1997)). The main aspect to consider when deciding for an appropriate test statistic is that in the case of event-date clustering the following two phenomena are observed (see Boehmer et al. (1991)): the event-induced volatility distortions change and a cross-sectional correlation of abnormal returns is present. As a consequence, both issues lead to an overstatement of the t-statistic, i.e. to the over-rejection of the null-hypothesis.

We introduce in the following sections some of the well known and most commonly employed tests in the field of event studies. A summary of those is given in tables 2.1 and 2.2. Additionally, table 2.3 defines the common notation shared by all those tests, which we will consistently employ throughout the rest of the paper.

Table 2.1: Parametric Test Statistics Summary

Test Name	**Characteristics**
Traditional Test (Brown and Warner (1980))	+ simple − weak against event-induced volatility changes and cross-sectional correlations
Cross-Sectional Test (Boehmer et al. (1991))	+ no event-induced variance insignificance prerequisite − weak against cross-sectional correlations
Standardized Residual Test (Patell (1976))	+ prevents large variance securities from dominating the test − weak against event-induced volatility changes and cross-sectional correlations
Adjusted Standardized Residual Test (Kolari and Pynnönen (2010))	+ additionally to the Standardized Residual Test, accounts for cross-sectional correlations
Standardized Cross-Sectional Test (Boehmer et al. (1991))	+ accounts for event-induced volatility and serial correlation − weak against cross-sectional correlations
Adjusted Standardized Cross-Sectional Test (Kolari and Pynnönen (2010))	+ additionally to the Standardized Cross-Sectional Test, accounts for cross-sectional correlations

Traditional Test

The traditional test has been proposed by Brown and Warner (1980) and is a parametric test. Under the null hypothesis of zero average abnormal returns ($H_0 : AAR = 0$), its

Table 2.2: Non-Parametric Test Statistics Summary

Test Name	Characteristics
Sign Test (Cowan (1992))	− weak in the presence of event induced volatility
Generalized Sign Test (Cowan (1992))	+ accounts for returns skewness
Corrado Rank Test (Corrado and Zivney (1992))	− weak against cumulative abnormal return tests, especially with longer event periods
Generalized Rank Test (Kolari and Pynnönen (2011))	+ accounts for both serial and cross-sectional correlations and event-induced volatility

Table 2.3: Common notation consistently used by all event study test statistic equations handled in this paper

Symbol	Description
$AR_{i,t}$	Abnormal return of security i on day t
$AR_{i,E}$	Abnormal return of security i on the event day
$AAR(t)$	Average abnormal returns on day t
$CAAR(t_1, t_2)$	Cumulative average abnormal returns from day t_1 to t_2
$R_{i,t}$	Return of security i on day t
$R_{i,E}$	Return of security i on event day
$R_{m,t}$	Market return on day t
$R_{m,E}$	Market return on event day
$\overline{R}_i$	Average return of security i during the estimation period
$\overline{R}_m$	Average market return during the estimation period
T_E	The event day
T_0	First day of the estimation period
T_1	Last day of the estimation period
T_2	First day of the event period
T_3	Last day of the event period
N	Total number of securities in the sample
N_t	Number of securities in the sample without missing returns on day t
L_1	The estimation window length: $L_1 = T_1 - T_0 + 1$
L_2	The event window length: $L_2 = T_2 - T_1$
M_{1i}	The number of non-missing returns of security i in the estimation period
M_{2i}	The number of non-missing returns of security i in the event period
$\overline{r}$	Average event period residuals cross-correlation
$\hat{p}$	Proportion of positive returns in the event window for the sample

test statistic is defined in equation (2.6) as the sum of the abnormal returns in the event period, divided by the square root of the sum of the residual variances of all securities in the estimation period.

$$t_{AAR_E} = \frac{\sum_{i=1}^{N} AR_{i,E}}{\sqrt{\sum_{i=1}^{N} \frac{1}{M_{1i}-1} \sum_{t=T_0}^{T_1} \left(AR_{i,t} - \sum_{t=T_0}^{T_1} \frac{AR_{i,t}}{M_{1i}} \right)^2}} \tag{2.6}$$

Despite its simplicity, the traditional test assumes that the security abnormal returns are uncorrelated and that the event-induced variance is negligible. This leads to too frequent rejections of the true null hypothesis (see Boehmer et al. (1991)). The following sections present several other approaches, which attempt to compensate for this two statistical issues.

Cross-Sectional Test

Another parametric test is the ordinary cross-sectional test. It is defined in equation (2.7) (see Boehmer et al. (1991)) and same as the traditional test, it serves the purpose of testing the null hypothesis of zero average abnormal returns ($H_0 : AAR = 0$). Compared to the tradition test, the cross-sectional test adjusts the average event day abnormal return by its cross-sectional standard deviation.

$$t_{AAR_E} = \frac{\frac{1}{N} \sum_{i=1}^{N} AR_{i,E}}{\sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} \left(AR_{i,E} - \sum_{i=1}^{N} \frac{AR_{i,E}}{N} \right)^2}} \tag{2.7}$$

Although it does not require the event-induced variance to be insignificant, Brown and Warner (1985) have shown that the ordinary cross-sectional test still exhibits low power, especially in the presence of cross-correlation of the abnormal returns.

Standardized Residual Test

In this approach proposed by Patell (1976), the abnormal returns for the companies are standardized by the forecast error corrected standard deviation, as depicted in equation (2.8). This serves two purposes, first, to adjust for the fact that the event period abnormal returns are out-of-sample predictions and second, to avoid the scenario where securities with large variances will dominate the test (see Patell and Wolfson (1979)).

$$SAR_{i,t} = \frac{AR_{i,t}}{\sqrt{S^2_{AR_i} \left(1 + \frac{1}{M_{1i}} + \frac{(R_{m,E} - \overline{R}_m)^2}{\sum_{t=T_0}^{T_1} (R_{m,t} - \overline{R}_m)^2} \right)}} \tag{2.8}$$

S_{AR_i} in equation (2.8) represents the standard deviation of the residuals of security i in the estimation period, which according to the market model is defined as in equation (2.9) (see MacKinlay (1997)).

$$S^2_{AR_i} = \frac{1}{M_{1i} - 2} \sum_{t=T_0}^{T_1} (AR_{i,t})^2 \tag{2.9}$$

The Patell test is also a parametric test, with the standardized abnormal returns approximately $N(0,1)$ distributed (see Patell (1976)). Its test statistic divides the sum of the standardized residuals by an approximation of the number of firms in the sample, as shown in equation (2.10). The test statistic operates under the null hypothesis of zero average abnormal returns ($H_0 : AAR = 0$).

$$z_{Patell,E} = \frac{\sum\limits_{i=1}^{N} SAR_{i,E}}{\sqrt{\sum\limits_{i=1}^{N} \frac{M_{1i}-2}{M_{1i}-4}}} \tag{2.10}$$

Studies such as Kolari and Pynnönen (2010) and Campbell and Wesley (1993) have shown that the Patell test is sill affected by event-induced volatility changes.

Adjusted Standardized Residual Test

Kolari and Pynnönen (2010) developed an adjusted version of the Patell test, in order to account for the cross-sectional correlation effects. The adjustment is done using the average cross-correlation of the residuals in the estimation period ($\bar{r}$). Under the null hypothesis of zero average abnormal returns ($H_0 : AAR = 0$), the adjusted Patell test is defined in equation (2.11).

$$z_{ADJ\text{-}Patell,E} = z_{Patell,E} \sqrt{\frac{1}{1 + (N-1)\bar{r}}} \tag{2.11}$$

The ADJ-Patell is a parametric test. Note that in case of zero average residual cross-correlation ($\bar{r} = 0$), the ADJ-Patell statistic yields the same result as the Patell test.

Standardized Cross-Sectional Test

Boehmer et al. (1991) proposed this parametric test, also known as the BMP test, in order to address the shortcomings of the ordinary cross-sectional test. Their approach is a hybrid resulted by applying the ordinary-cross sectional test to the standardized-residuals (see equation (2.8)), as equation (2.12) depicts. Same as for the ordinary cross-sectional test, the null hypothesis against which the test statistic is computed is that of zero average abnormal returns ($H_0 : AAR = 0$).

$$z_{BMP,E} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i,E}}{\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\left(SAR_{i,E} - \sum_{i=1}^{N}\frac{SAR_{i,E}}{N}\right)^2}} \tag{2.12}$$

This method is robust against event-induced volatility changes, however, as Kolari and Pynnönen (2010) have shown, it over-rejects the true null hypothesis in the presence of cross-sectional correlation of abnormal returns.

Adjusted Standardized Cross-Sectional Test

Kolari and Pynnönen (2010) developed an adjusted version of the BMP test, known as the ADJ-BMP test. The adjusted version accounts for cross-sectional correlation effects, by making use of the average cross-correlation of the market model residuals in the estimation period ($\overline{r}$). Under the null hypothesis of zero average abnormal returns ($H_0 : AAR = 0$), the ADJ-BMP test is defined in equation (2.13).

$$z_{ADJ\text{-}BMP,E} = z_{BMP,E}\sqrt{\frac{1-\overline{r}}{1+(N-1)\overline{r}}} \tag{2.13}$$

The ADJ-BMP is a parametric test. Note that in case of zero average residual cross-correlation ($\overline{r} = 0$), the ADJ-BMP statistic yields the same result as the BMP test.

Sign Test

In its simplest version, the sign test checks whether the proportion of positive returns $\hat{p}$ in the event window is significantly different from 0.5. Equation (2.14) depicts the test statistic used for the sign test (see Cowan (1992)).

$$t_{sign} = \sqrt{N}\left(\frac{\hat{p} - 0.5}{0.5}\right) \tag{2.14}$$

One of the weaknesses associated with this test would be its inherent assumption that half of the abnormal returns are negative. In reality, security returns are skewed to the right, as the research of Brown and Warner (1980) shows.

Generalized Sign Test

One attempt to adjust for the skewness in the sign test, known as the generalized sign test is to compare the proportion of positive returns in the event window against the estimation window, as proposed by Cowan (1992). In this version, the proportion of positive returns $\hat{p}$ is calculated as in equation (2.15).

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{L_1}\sum_{t=T_0}^{T_1}\varphi_{i,t} \tag{2.15}$$

The value of $\varphi_{i,t}$ in equation (2.15) is 1 if the return of security i on day t is positive and 0 otherwise.

Under the null hypothesis of zero cumulative average abnormal returns ($H_0 : CAAR = 0$), the test statistic for the generalized sign test is defined in equation (2.16), where w represents the number of stocks with positive event period cumulative abnormal returns.

$$z_{gsign} = \frac{w - N\hat{p}}{\sqrt{N\hat{p}(1-\hat{p})}} \tag{2.16}$$

Corrado Rank Test

Corrado and Zivney (1992) define the rank test by mapping abnormal returns to ranks and standardize those by the number of non-missing values in the estimation and event windows. Under the null hypothesis of zero average abnormal returns ($H_0 : AAR = 0$), the test statistic for single day testing is given by equation (2.17).

$$t_{rank,t} = \frac{\overline{K}_t - 0.5}{S_{\overline{K}}} \tag{2.17}$$

$\overline{K}_t$ in equation (2.17) is the average of the abnormal return ranks on day t, standardized to adjust for missing values as defined in equation (2.18) (see Corrado and Zivney (1992)).

$$\overline{K}_t = \frac{1}{N}\sum_{i=1}^{N}\frac{rank(AR_{i,t})}{1 + M_{1i} + M_{2i}} \tag{2.18}$$

$S_{\overline{K}}$ is the standard deviation of the average standardized abnormal return ranks, given by equation (2.19).

$$S^2_{\overline{K}} = \frac{1}{L_1 + L_2}\sum_{t=T_0}^{T_2}\frac{N_t}{N}(\overline{K}_t - 0.5)^2 \tag{2.19}$$

Generalized Rank Test

As stated by Kolari and Pynnönen (2011), one of the major shortcomings of non-parametric test cases is their inability to perform well when extended to multiple day tests. In order to address this issues, they have proposed the generalized rank test, which squeezes the whole event window into one observation, the so called *"cumulative event* *day"*. The first step is to define the generalized standardized abnormal returns, as in equation (2.20).

$$GSAR_{i,t} = \begin{cases} SCAR_i^*, & \text{for } t \text{ in event window} \\ SAR_{i,t}, & \text{for } t \text{ in the estimation window} \end{cases} \tag{2.20}$$

The standardized abnormal returns ($SAR_{i,t}$) are calculted as in equation (2.8). $SCAR_i^*$ denotes the re-standardized cumulative abnormal returns by the cross-sectional standard deviation, in order to account for the event-induced volatility effects, as depicted in equation (2.21) (see Kolari and Pynnönen (2011)).

$$SCAR_i^* = \frac{SCAR_i}{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(SCAR_i - \frac{1}{N}\sum_{i=1}^{N} SCAR_i\right)}} \tag{2.21}$$

$SCAR_i$ is the standardized cumulative abnormal return of security i in the event window, defined as in equation (2.22), where S_{AR_i} is the market model standard deviation of the residuals of security i in the estimation period (see equation (2.9)).

$$SCAR_i = \frac{CAR_i}{\sqrt{S_{AR_i}^2\left(L_1 + L_2 + \frac{L_2}{L_1} + \frac{\sum_{t=T_1+1}^{T_2}(R_{m,t}-\overline{R}_m)^2}{\sum_{t=T_0}^{T_1}(R_{m,t}-\overline{R}_m)^2}\right)}} \tag{2.22}$$

Based on the generalized standardized abnormal returns, the standardized ranks are calculated as shown in equation (2.23) (see Kolari and Pynnönen (2011)).

$$K_{i,t} = \frac{rank(GSAR_{i,t})}{M_{1i} + 2} - 0.5 \tag{2.23}$$

Under the null hypothesis of zero cumulative average abnormal returns ($H_0 : CAAR = 0$), the generalized rank t-statistic is defined as in equation (2.24), with Z given by equation (2.25), where $\mathcal{T}$ is the set of days from the estimation window together with the *"cumulative event day"* (see Kolari and Pynnönen (2011)).

$$t_{grank} = Z\sqrt{\frac{L_1 - 1}{L_1 - Z^2}} \tag{2.24}$$

$$Z = \frac{\frac{1}{N_t}\sum_{i=1}^{N_t} K_{i,E}}{\sqrt{\frac{1}{L_1+1}\sum_{t\in\mathcal{T}} \frac{N_t}{N}\left(\frac{1}{N_t}\sum_{i=1}^{N_t} K_{i,t}\right)^2}} \tag{2.25}$$

CHAPTER 3

Data and Methodology

3.1 Sample Selection

The most critical aspect of the proposed analysis consists of the collection of the relevant data on directors' dealings and stock price evolution for the time period under research. The data set used in this research is provided by the Smart Insider company (https://www.smartinsider.com/) and contains announcements for German companies, as summarized in Table 3.1. A more in-depth statistical description of the companies included in the data set is provided in Appendix A.

Table 3.1: Directors' Dealing Events Summary

Time period	**Number of events**	**Number of companies**	**Number of industries**
2005 - 2013	3032	102	10

Information such as the company's ISIN, name and industry, executive name and function, transaction and announcement dates, transaction type, traded volume and value information are available for each event. The market data required for the analysis has been collected using the services provided by the Thomson Reuters Datastream platform (https://infobase.thomsonreuters.com). For the companies in our data set we have downloaded the associated *Total Return Index* time series, which is a metric starting at 100 on the day when the company first became public on the market and evolves based on the daily stock price changes, accounting for both artificial changes in the stock price (such as for example stock splits) and dividends. This metric offers the most realistic view on the actual value of the company and we use it therefore as a basis for calculating the daily stock returns. Apart from that, the Thomson Reuters Datastream also provided time series for the *Market Capitalization* and the *Daily Adjusted Prices* (without accounting for dividends), which we only stored for informative purposes.

Unfortunately, few of the companies in our data set (6 out of the 102) were not available from Thomson Reuters Datastream. For those and for the DAX index, we used market information as provided by the Yahoo Finance Historical Data API (https://finance.yahoo.com/). The Yahoo API gives access to daily adjusted stock prices, which similar to the Total Return Index also take into account stock splits and dividends. Based on the adjusted stock prices, we then calculated the respective daily returns. A note on the data downloaded using the Yahoo API is the fact that the prices listed there might not always be accurate. In few occasions, we ended up observing daily stock returns of more than 100%, which are highly implausible, indicating invalid data for those days. Thus we ignored the days, where such implausible returns were reported, effectively treating them same as if market data was missing on those respective days.

At this stage, an additional sanity check was made for the announcement events in our initial data set, during which we filtered out events for which we have missing or insufficient market data (e.g. too few returns available in the estimation period). As a result, 46 out of 3032 announcement events have been dropped. Table 3.2 provides a statistical description of the daily returns within the estimation and event periods associated to the events in the data set under evaluation.

Table 3.2: Descriptive statistics of daily returns for the evaluation data set events (2005-2013)

Min	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max**	**StdDev**	**Skewness**	**Kurtosis**
Panel A: Normal Returns (%)								
-39.04	-1.06	0.00	0.03	1.10	46.77	2.69	0.93	22.35
Panel B: Logarithmic Returns (%)								
-49.49	-1.07	0.00	-0.01	1.09	38.37	2.67	0.17	19.59

Out of the remaining announcement events, we built our samples according to the following criteria:

- *Transaction type*
  A single sample contains either *BUY* or *SELL* transactions. The rationale behind it is that mixing transaction types will not be informative. If information asymmetry is present, our expectation would be that buy announcements will result in a price increase and sell announcements on the contrary, in a price decrease.

- *Time period*
  We sample the events around the following periods: *2005-2013*, *2005 - 2007*, *2008 - 2010* and *2011 - 2013*. The motivation here is to check if there are any significant differences in the existence of information asymmetry for those different periods in time. If the observations made will exhibit significant differences in the considered sub-periods, we investigate to find plausible explanations why that might be the case. In such a scenario we will correlate with the market conditions and available legislation specific to each period.

- *Industry sector*
  The original data set contains events of companies in 10 different industries. However, after filtering out events with insufficient market data available, we are left with no events for one of the industries (Oil & Gas). Additionally, because of the fact that we are left with too few events for the telecommunications sector, to be able to draw statistically significant conclusions, we will merge it together with the technology sector and analyze them as one. The aim is to research if the information asymmetries differ for different business types. This might reveal hints if market reactions to insider transactions are more prominent in industries driven by fast paced innovation and high competition, such as the IT sector for example.

- *Multiple announcements made on the same day*
  We aggregate events occurring on the same day for the same company. Of course, we will only consider events where the transactions are of the same type, avoiding days where both buy and sell transactions are declared. The assumption here is that multiple announcements convey more information and might trigger stronger market reactions.

Based on the aforementioned criteria, 26 samples will be constructed, which are summarized in table 3.3.

3.2 Sample Analysis

In this section we present our methodological approach to analyze the samples constructed earlier.

3.2.1 Hypothesis Formulation

Our analysis will focus on the abnormal returns generated for the following periods:

- 20 days prior to the event day, in order to check for the presence of abnormal returns prior to the transaction announcements and potentially find hints about insiders' trading strategies.

- on the announcement day, aiming to test if there are any immediate market reactions, right after the transaction is made public.

- the event day and the day after, which is also focused on the short term market reactions.

- 20 days beginning with the announcement day, in order to observe the longer term effects on the market and check if there is any potential for abnormal returns other than the immediate ones.

Based on those facts, we formulate the following hypotheses:

Table 3.3: Constructed Announcement Events Samples Summary

Sample identifier	**Number of events**
01-buy-total	1871
02-buy-2005-2007	625
03-buy-2008-2010	771
04-buy-2011-2013	475
05-buy-basic-materials	316
06-buy-consumer-goods	276
07-buy-consumer-services	205
08-financials	156
09-buy-health-care	148
10-buy-industrials	516
11-buy-tech-telco	174
12-buy-utilities	61
13-buy-multi	183
14-sell-total	1115
15-sell-2005-2007	601
16-sell-2008-2010	245
17-sell-2011-2013	269
18-sell-basic-materials	65
19-sell-consumer-goods	105
20-sell-consumer-services	93
21-sell-financials	202
22-sell-health-care	95
23-sell-industrials	358
24-sell-tech-telco	157
25-sell-utilities	8
26-sell-multi	156

- $H_0 : CAAR(-20, -1) = 0$
- $H_0 : AAR(0) = 0$
- $H_0 : CAAR(0, 1) = 0$
- $H_0 : CAAR(0, 20) = 0$

3.2.2 Abnormal Returns Calculation

For the calculation of the abnormal returns, the market model is used, as presented by MacKinlay (1997). Because the announcement events considered are all on German companies, the DAX index serves as the market reference, against which the abnormal returns are estimated. As basis for the computation, daily logarithmic returns are used, with an estimation period of 200 days and an event window of 41 days surrounding the event day.

3.2.3 Test Statistics

In order to conduct our analysis we implemented three well-known test statistics, which proved to be amongst the most powerful available in the current event studies literature. Two of them, namely the *BMP* and *ADJ-BMP* tests, are parametric and one, the *GRANK* test is non-parametric. The rationale behind implementing all three tests lies in the fact that it enables to double check the plausibility of the obtained results, minimizing the probability of implementation errors. Any strong deviations will raise awareness of potential miscalculations, indicating the need to review the implemented scripts.

The programming language used for the implementation was R. Following subsections discuss each of the test statistics in more detail, exposing their implementation details and assumptions. The equations defined use the same notations as described in 2.3.

BMP test

The BMP test has been implemented starting from the formula proposed by Boehmer et al. (1991). In order to accommodate for cumulative average abnormal returns tests, we used the extension described on the website of Schimmer et al. (2019).

The first computation step was to calculate the standardized cumulated abnormal returns within the observed event window for each event in the sample, according to equation (3.1). It can be easily shown that when considering single day event windows ($M_{2i} = 1$), the formula is equivalent to equations (2.8) and (2.9), in the original approach proposed by Boehmer et al. (1991).

$$SCAR_i = \frac{\sum_{t=T_2}^{T_3} AR_{i,t}}{\sqrt{\left(\frac{1}{M_{1i}-2}\sum_{t=T_0}^{T_1} AR_{i,t}^2\right) * \left(M_{2i} + \frac{M_{2i}^2}{M_{1i}} + \frac{\left(\sum_{t=T_2}^{T_3}(R_{m,t}-\overline{R}_m)\right)^2}{\sum_{t=T_0}^{T_1}(R_{m,t}-\overline{R}_m)^2}\right)}} \tag{3.1}$$

We mention that events, which had less than 50 returns in the estimation window or which had no returns in the event window, have been excluded from the calculation of the test statistic value. Based on the standardized cumulative abnormal returns, the final value of the BMP test statistic was calculated according to the formula in equation (2.12). From the z_{BMP} score we derive the two-sided p value under the normal distribution assumption (see Boehmer et al. (1991)) and interpret it at a 95% confidence level to test the statistical significance of rejecting the null hypothesis.

ADJ-BMP test

The ADJ-BMP has been implemented according to Kolari and Pynnönen (2010), as depicted in equation (2.13). The value of z_{BMP} is calculated using the same approach as defined in the former section.

For the estimation period residuals average cross-correlation calculation we use the formula depicted in equation (3.2), which has been derived from equation (3) in Kolari and Pynnönen (2010), where ρ_{ij} denotes the cross-correlation of the estimation period residuals for events i and j.

$$\overline{r} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} \rho_{ij} \tag{3.2}$$

Similar to the BMP test, from the $z_{ADJ-BMP}$ score we again derive the two-sided p value under the normal distribution assumption (see Kolari and Pynnönen (2010)) and interpret it at a 95% confidence level in order to evaluate the null hypothesis rejection.

GRANK test

The GRANK test has been implemented according to the equations (2.20) to (2.25), as defined by Kolari and Pynnönen (2011). Same as for the BMP test, we ignore events, which had less than 50 returns in the estimation window or which had no returns in the event window.

In the case of the GRANK test, from the t_{GRANK} score we derive the two-sided p value, assuming that t_{GRANK} is t-distributed with $L_1 - 1$ degrees of freedom (see Kolari and Pynnönen (2011)). Same as for the other two tests, we will consider a 95% confidence level when testing the null hypothesis.

Validation

In order to ensure a good code quality for the implemented test statistics and reduce the probability for implementation errors, we employed a test driven development approach. For this purpose we developed a suite of unit test cases parallel to implementing the actual production code for the test statistics in order to have a confirmation and a first validation that the test statistics behave as expected. More concrete, we run the test statistics against different sets of generated market data, for which we have a predefined well-known expected outcome. For this, we simply considered a set of random events to which we assign normally distributed random daily returns. Based on the desired outcome to either reject or not reject the null hypothesis, we chose different mean and standard deviation values for the returns normal distribution. Table 3.4 documents the results obtained as part of executing the test suite with the generated data sets.

Table 3.4: Test statistics results on generated market data with predefined expected outcome

Returns Distribution **# events** **CAAR(0, 5)**	**BMP**		**ADJ-BMP**		**GRANK**	
$N(0\%, 2\%)$			$\overline{r}$	$2.339 \cdot 10^{-5}$		
50 *events*	z	0.510	z	0.510	t	1.003
0.34%	*p-value*	0.610	*p-value*	0.610	*p-value*	0.317
$N(-0.4\%, 2\%)$			$\overline{r}$	$2.339 \cdot 10^{-5}$		
50 *events*	z	-3.156	z	-3.154	t	-2.839
-2.06%	***p-value****	$1.602 \cdot 10^{-3}$	***p-value****	$1.612 \cdot 10^{-3}$	***p-value****	$4.992 \cdot 10^{-3}$
$N(0.2\%, 2\%)$			$\overline{r}$	$2.339 \cdot 10^{-5}$		
50 *events*	z	2.343	z	2.341	t	2.827
1.54%	***p-value****	0.019	***p-value****	0.019	***p-value****	$5.176 \cdot 10^{-3}$

*Statistical significance at 5% level.

CHAPTER 4

Results and Discussion

4.1 Cumulative average abnormal returns for event period (-20, -1)

Table 4.1 and Table 4.2 summarize the results obtained for buy, respectively sell announcements, under the null hypothesis of zero cumulative average abnormal returns in the period starting 20 days prior to the event day up to the day before the event day.

We document results consistent with prior studies, which align with the assumption that insiders follow a contrarian trading strategy (see Aussenegg et al. (2018) for similar observations). This is especially the case for buy announcements. With a few exceptions, we mostly observe significant negative cumulative average abnormal returns of up to -3.78% in the period prior to the event day. Our observations also suggest a more prominent than average effect in the case of multiple same day buy announcements (-3.42% compared to the other samples where the average was between -2% and -3%).

In the case of sell announcements, the results are not as definite as for buy announcements. In general, the registered cumulative average abnormal returns are not as high as for the buy announcements. Also, it seems that multiple same day sell announcements are not accompanied by abnormal returns larger than for the other cases. Similar observations have been reported in previous studies as well (see Fidrmuc et al. (2013) and Dardas and Güttler (2011)).

An interesting result is obtained for two of the samples considered (*12-buy-utilities* and *22-sell-health-care*), where the BMP test statistic rejects the null hypothesis, while the other two tests fail to do so. When considering a 99% confidence interval, we would observe the same effect for samples *21-sell-financials* and *24-sell-tech-telco*. This emphasizes the importance for test statistics to account for cross-sectional correlations, in order to minimize the probability for false positive results.

Table 4.1: Buy announcement results under $H_0 : CAAR(-20, -1) = 0$

Sample identifier **# events** **CAAR(-20, -1)**	**BMP**		**ADJ-BMP**		**GRANK**	
01-buy-total			$\overline{r}$	$5.714 \cdot 10^{-4}$		
1871 *events*	z	-10.190	z	-7.083	t	-6.738
-2.2%	***p-value****	$2.204 \cdot 10^{-24}$	***p-value****	$1.412 \cdot 10^{-12}$	***p-value****	$1.678 \cdot 10^{-10}$
02-buy-2005-2007			$\overline{r}$	$1.661 \cdot 10^{-3}$		
625 *events*	z	-5.728	z	-4.011	t	-3.621
-2.51%	***p-value****	$1.014 \cdot 10^{-8}$	***p-value****	$6.055 \cdot 10^{-5}$	***p-value****	$3.724 \cdot 10^{-4}$
03-buy-2008-2010			$\overline{r}$	$1.535 \cdot 10^{-3}$		
771 *events*	z	-7.653	z	-5.178	t	-5.266
-2.51%	***p-value****	$1.956 \cdot 10^{-14}$	***p-value****	$2.248 \cdot 10^{-7}$	***p-value****	$3.593 \cdot 10^{-7}$
04-buy-2011-2013			$\overline{r}$	$1.203 \cdot 10^{-3}$		
475 *events*	z	-3.805	z	-3.034	t	-2.547
-1.28%	***p-value****	$1.421 \cdot 10^{-4}$	***p-value****	$2.412 \cdot 10^{-3}$	***p-value****	0.012
05-buy-basic-materials			$\overline{r}$	$2.621 \cdot 10^{-3}$		
316 *events*	z	-6.671	z	-4.931	t	-4.356
-3.78%	***p-value****	$2.543 \cdot 10^{-11}$	***p-value****	$8.191 \cdot 10^{-7}$	***p-value****	$2.119 \cdot 10^{-5}$
06-buy-consumer-goods			$\overline{r}$	$3.869 \cdot 10^{-4}$		
276 *events*	z	-3.768	z	-3.581	t	-3.485
-2.33%	***p-value****	$1.649 \cdot 10^{-4}$	***p-value****	$3.421 \cdot 10^{-4}$	***p-value****	$6.038 \cdot 10^{-4}$
07-buy-consumer-services			$\overline{r}$	$1.399 \cdot 10^{-3}$		
205 *events*	z	-1.606	z	-1.416	t	-0.902
-0.84%	*p-value*	0.108	*p-value*	0.157	*p-value*	0.368
08-buy-financials			$\overline{r}$	$3.131 \cdot 10^{-4}$		
156 *events*	z	-4.670	z	-4.560	t	-4.046
-2.64%	***p-value****	$3.013 \cdot 10^{-6}$	***p-value****	$5.119 \cdot 10^{-6}$	***p-value****	$7.429 \cdot 10^{-5}$
09-buy-health-care			$\overline{r}$	0.014		
148 *events*	z	-4.659	z	-2.666	t	-2.161
-3.45%	***p-value****	$3.181 \cdot 10^{-6}$	***p-value****	$7.665 \cdot 10^{-3}$	***p-value****	0.032
10-buy-industrials			$\overline{r}$	$1.569 \cdot 10^{-3}$		
516 *events*	z	-4.230	z	-3.143	t	-3.300
-2.04%	***p-value****	$2.341 \cdot 10^{-5}$	***p-value****	$1.671 \cdot 10^{-3}$	***p-value****	$1.145 \cdot 10^{-3}$
11-buy-tech-telco			$\overline{r}$	$5.657 \cdot 10^{-3}$		
174 *events*	z	-1.549	z	-1.098	t	-0.585
-1.08%	*p-value*	0.121	*p-value*	0.272	*p-value*	0.559
12-buy-utilities			$\overline{r}$	0.035		
61 *events*	z	-2.015	z	-1.127	t	-1.043
-0.95%	***p-value****	0.044	*p-value*	0.260	*p-value*	0.298
13-buy-multi			$\overline{r}$	$-8.651 \cdot 10^{-4}$		
183 *events*	z	-4.250	z	-4.632	t	-3.769
-3.42%	***p-value****	$2.136 \cdot 10^{-5}$	***p-value****	$3.616 \cdot 10^{-6}$	***p-value****	$2.157 \cdot 10^{-4}$

*Statistical significance at 5% level.

Table 4.2: Sell announcement results under $H_0 : CAAR(-20, -1) = 0$

Sample identifier **# events** **CAAR(-20, -1)**	**BMP**		**ADJ-BMP**		**GRANK**	
14-sell-total			$\overline{r}$	$6.965 \cdot 10^{-4}$		
1115 *events*	z	4.544	z	3.409	t	3.715
0.87%	***p-value****	$5.513 \cdot 10^{-6}$	***p-value****	$6.526 \cdot 10^{-4}$	***p-value****	$2.637 \cdot 10^{-4}$
15-sell-2005-2007			$\overline{r}$	$1.843 \cdot 10^{-3}$		
601 *events*	z	3.730	z	2.568	t	2.596
0.78%	***p-value****	$1.912 \cdot 10^{-4}$	***p-value****	0.010	***p-value****	0.010
16-sell-2008-2010			$\overline{r}$	$2.566 \cdot 10^{-3}$		
245 *events*	z	0.188	z	0.147	t	0.312
0.69%	*p-value*	0.851	*p-value*	0.883	*p-value*	0.755
17-sell-2011-2013			$\overline{r}$	$1.766 \cdot 10^{-3}$		
269 *events*	z	3.701	z	3.047	t	3.162
1.25%	***p-value****	$2.147 \cdot 10^{-4}$	***p-value****	$2.315 \cdot 10^{-3}$	***p-value****	$1.811 \cdot 10^{-3}$
18-sell-basic-materials			$\overline{r}$	$5.370 \cdot 10^{-4}$		
65 *events*	z	-0.188	z	-0.185	t	-0.017
0.32%	*p-value*	0.851	*p-value*	0.853	*p-value*	0.987
19-sell-consumer-goods			$\overline{r}$	$3.980 \cdot 10^{-3}$		
105 *events*	z	4.457	z	3.741	t	3.378
2.22%	***p-value****	$8.314 \cdot 10^{-6}$	***p-value****	$1.834 \cdot 10^{-4}$	***p-value****	$8.786 \cdot 10^{-4}$
20-sell-consumer-services			$\overline{r}$	$8.592 \cdot 10^{-3}$		
93 *events*	z	1.904	z	1.416	t	1.863
1.5%	*p-value*	0.057	*p-value*	0.157	*p-value*	0.064
21-sell-financials			$\overline{r}$	$1.613 \cdot 10^{-3}$		
202 *events*	z	-2.783	z	-2.417	t	-1.603
-1.14%	***p-value****	$5.385 \cdot 10^{-3}$	***p-value****	0.016	*p-value*	0.111
22-sell-health-care			$\overline{r}$	0.012		
95 *events*	z	2.280	z	1.549	t	1.742
0.61%	***p-value****	0.023	*p-value*	0.121	*p-value*	0.083
23-sell-industrials			$\overline{r}$	$2.482 \cdot 10^{-3}$		
358 *events*	z	3.988	z	2.900	t	2.883
1.54%	***p-value****	$6.669 \cdot 10^{-5}$	***p-value****	$3.731 \cdot 10^{-3}$	***p-value****	$4.376 \cdot 10^{-3}$
24-sell-tech-telco			$\overline{r}$	$6.191 \cdot 10^{-3}$		
157 *events*	z	2.590	z	1.842	t	2.131
1.45%	***p-value****	$9.595 \cdot 10^{-3}$	*p-value*	0.066	***p-value****	0.034
25-sell-utilities			$\overline{r}$	0.270		
8 *events*	z	-1.311	z	-0.659	t	-0.599
-1.73%	*p-value*	0.190	*p-value*	0.510	*p-value*	0.550
26-sell-multi			$\overline{r}$	$-9.899 \cdot 10^{-4}$		
156 *events*	z	2.376	z	2.584	t	2.751
0.73%	***p-value****	0.017	***p-value****	$9.769 \cdot 10^{-3}$	***p-value****	$6.478 \cdot 10^{-3}$

*Statistical significance at 5% level.

4.2 Average abnormal returns on the event day

Table 4.3 and Table 4.4 summarize the results obtained for buy, respective sell announcements, under the null hypothesis of zero average abnormal returns on the event day.

Our tests do not report statistically significant average abnormal returns for the samples under observation. The only sample which signals the null hypothesis rejection is the *25-sell-utilities*, however due to the low number of contained events, we are careful to infer any conclusions out of it.

The sample *10-buy-industrials* again shows the need for test statistics to account for cross-sectional correlation effects. The ADJ-BMP and GRANK tests both do not reject the null hypothesis, while the BMP test triggers a false positive when considering a 95% confidence level.

Table 4.3: Buy announcement results under $H_0 : AAR(0) = 0$

Sample identifier	**BMP**		**ADJ-BMP**		**GRANK**	
# events						
AAR(0)						
01-buy-total			$\overline{r}$	$5.714 \cdot 10^{-4}$		
1861 *events*	z	1.155	z	0.803	t	1.219
0.14%	*p-value*	0.248	*p-value*	0.422	*p-value*	0.224
02-buy-2005-2007			$\overline{r}$	$1.661 \cdot 10^{-3}$		
617 *events*	z	−0.995	z	−0.696	t	0.298
0.01%	*p-value*	0.320	*p-value*	0.486	*p-value*	0.766
03-buy-2008-2010			$\overline{r}$	$1.535 \cdot 10^{-3}$		
769 *events*	z	1.886	z	1.276	t	1.196
0.24%	*p-value*	0.059	*p-value*	0.202	*p-value*	0.233
04-buy-2011-2013			$\overline{r}$	$1.203 \cdot 10^{-3}$		
475 *events*	z	0.949	z	0.757	t	0.523
0.14%	*p-value*	0.343	*p-value*	0.449	*p-value*	0.602
05-buy-basic-materials			$\overline{r}$	$2.621 \cdot 10^{-3}$		
314 *events*	z	−1.004	z	−0.742	t	−1.016
−0.16%	*p-value*	0.316	*p-value*	0.458	*p-value*	0.311
06-buy-consumer-goods			$\overline{r}$	$3.869 \cdot 10^{-4}$		
276 *events*	z	1.547	z	1.471	t	1.873
0.32%	*p-value*	0.122	*p-value*	0.141	*p-value*	0.062
07-buy-consumer-services			$\overline{r}$	$1.399 \cdot 10^{-3}$		
205 *events*	z	0.138	z	0.121	t	−0.076
0.09%	*p-value*	0.891	*p-value*	0.904	*p-value*	0.940
08-buy-financials			$\overline{r}$	$3.131 \cdot 10^{-4}$		
156 *events*	z	−0.611	z	−0.597	t	0.382
0.01%	*p-value*	0.541	*p-value*	0.550	*p-value*	0.703
09-buy-health-care			$\overline{r}$	0.014		
148 *events*	z	0.138	z	0.079	t	0.568
0.19%	*p-value*	0.890	*p-value*	0.937	*p-value*	0.571
10-buy-industrials			$\overline{r}$	$1.569 \cdot 10^{-3}$		
508 *events*	z	2.242	z	1.666	t	1.666
0.32%	***p-value****	0.025	*p-value*	0.096	*p-value*	0.097
11-buy-tech-telco			$\overline{r}$	$5.657 \cdot 10^{-3}$		
174 *events*	z	0.112	z	0.079	t	0.188
0.12%	*p-value*	0.911	*p-value*	0.937	*p-value*	0.851
12-buy-utilities			$\overline{r}$	0.035		
61 *events*	z	−0.148	z	−0.083	t	−0.219
0.04%	*p-value*	0.883	*p-value*	0.934	*p-value*	0.827
13-buy-multi			$\overline{r}$	$-8.651 \cdot 10^{-4}$		
182 *events*	z	0.064	z	0.069	t	−0.340
0.04%	*p-value*	0.949	*p-value*	0.945	*p-value*	0.734

*Statistical significance at 5% level.

Table 4.4: Sell announcement results under $H_0 : AAR(0) = 0$

Sample identifier **# events** **AAR(0)**	**BMP**		**ADJ-BMP**		**GRANK**	
14-sell-total			$\bar{r}$	$6.965 \cdot 10^{-4}$		
1110 *events*	z	0.433	z	0.325	t	1.321
0.08%	*p-value*	0.665	*p-value*	0.745	*p-value*	0.188
15-sell-2005-2007			$\bar{r}$	$1.843 \cdot 10^{-3}$		
601 *events*	z	−0.150	z	−0.103	t	1.045
0.05%	*p-value*	0.881	*p-value*	0.918	*p-value*	0.297
16-sell-2008-2010			$\bar{r}$	$2.566 \cdot 10^{-3}$		
244 *events*	z	1.423	z	1.115	t	1.148
0.2%	*p-value*	0.155	*p-value*	0.265	*p-value*	0.252
17-sell-2011-2013			$\bar{r}$	$1.766 \cdot 10^{-3}$		
265 *events*	z	−0.279	z	−0.230	t	−0.137
0.04%	*p-value*	0.780	*p-value*	0.818	*p-value*	0.891
18-sell-basic-materials			$\bar{r}$	$5.370 \cdot 10^{-4}$		
64 *events*	z	−0.039	z	−0.038	t	−0.448
0.23%	*p-value*	0.969	*p-value*	0.969	*p-value*	0.655
19-sell-consumer-goods			$\bar{r}$	$3.980 \cdot 10^{-3}$		
105 *events*	z	−0.574	z	−0.482	t	0.128
−0.09%	*p-value*	0.566	*p-value*	0.630	*p-value*	0.898
20-sell-consumer-services			$\bar{r}$	$8.592 \cdot 10^{-3}$		
92 *events*	z	−1.897	z	−1.412	t	−1.384
−0.51%	*p-value*	0.058	*p-value*	0.158	*p-value*	0.168
21-sell-financials			$\bar{r}$	$1.613 \cdot 10^{-3}$		
202 *events*	z	−0.731	z	−0.634	t	−0.293
−0.12%	*p-value*	0.465	*p-value*	0.526	*p-value*	0.770
22-sell-health-care			$\bar{r}$	0.012		
95 *events*	z	0.257	z	0.174	t	0.489
−0.01%	*p-value*	0.797	*p-value*	0.862	*p-value*	0.625
23-sell-industrials			$\bar{r}$	$2.482 \cdot 10^{-3}$		
355 *events*	z	1.465	z	1.065	t	1.500
0.21%	*p-value*	0.143	*p-value*	0.287	*p-value*	0.135
24-sell-tech-telco			$\bar{r}$	$6.191 \cdot 10^{-3}$		
157 *events*	z	1.617	z	1.149	t	1.432
0.48%	*p-value*	0.106	*p-value*	0.250	*p-value*	0.154
25-sell-utilities			$\bar{r}$	0.270		
8 *events*	z	−8.542	z	−4.294	t	−2.642
−1.07%	***p-value****	$1.324 \cdot 10^{-17}$	***p-value****	$1.755 \cdot 10^{-5}$	***p-value****	$8.892 \cdot 10^{-3}$
26-sell-multi			$\bar{r}$	$-9.899 \cdot 10^{-4}$		
156 *events*	z	1.618	z	1.760	t	2.167
0.27%	*p-value*	0.106	*p-value*	0.078	***p-value****	0.031

*Statistical significance at 5% level.

4.3 Cumulative average abnormal returns for event period (0, 1)

Table 4.5 and Table 4.6 summarize the results obtained for buy, respectively sell announcements, under the null hypothesis of zero cumulative average abnormal returns on the event day and the day immediate after the event day. The results here do not signal statistically significant cumulative average abnormal returns for this short period. This is especially true for the sell announcements. The only two samples, where all the three tests reject the null hypothesis at a confidence level of 95% are *06-buy-consumer-goods* and *25-sell-utilities*. Unfortunately due to the low number of observations in the later sample, it would not be accurate to infer any conclusion for it.

Analyzing previous research in the field, Lakonishok and Lee (2001) and Friederich et al. (2002) have found similar results, where insider trading did not generate statistically significant abnormal returns in the short term period immediate the day after the announcements were made public. On the other hand, Agrawal and Cooper (2015), which focused on firms involved in accounting scandals, report statistically significant short term abnormal returns generated by insider trading activities in fraudulent companies. However, for their control sample, comprised of trustful firms, the results match to ours.

Table 4.5: Buy announcement results under $H_0 : CAAR(0, 1) = 0$

Sample identifier **# events** **CAAR(0, 1)**	**BMP**		**ADJ-BMP**		**GRANK**	
01-buy-total			$\overline{r}$	$5.714 \cdot 10^{-4}$		
1867 *events*	z	3.219	z	2.238	t	1.702
0.32%	***p-value****	$1.284 \cdot 10^{-3}$	***p-value****	0.025	*p-value*	0.090
02-buy-2005-2007			$\overline{r}$	$1.661 \cdot 10^{-3}$		
623 *events*	z	0.530	z	0.371	t	0.182
0.17%	*p-value*	0.596	*p-value*	0.710	*p-value*	0.856
03-buy-2008-2010			$\overline{r}$	$1.535 \cdot 10^{-3}$		
769 *events*	z	3.038	z	2.055	t	1.534
0.48%	***p-value****	$2.384 \cdot 10^{-3}$	***p-value****	0.040	*p-value*	0.127
04-buy-2011-2013			$\overline{r}$	$1.203 \cdot 10^{-3}$		
475 *events*	z	1.764	z	1.407	t	1.155
0.25%	*p-value*	0.078	*p-value*	0.159	*p-value*	0.249
05-buy-basic-materials			$\overline{r}$	$2.621 \cdot 10^{-3}$		
314 *events*	z	0.657	z	0.486	t	0.214
0.22%	*p-value*	0.511	*p-value*	0.627	*p-value*	0.831
06-buy-consumer-goods			$\overline{r}$	$3.869 \cdot 10^{-4}$		
276 *events*	z	2.803	z	2.664	t	1.985
0.48%	***p-value****	$5.070 \cdot 10^{-3}$	***p-value****	$7.724 \cdot 10^{-3}$	***p-value****	0.049
07-buy-consumer-services			$\overline{r}$	$1.399 \cdot 10^{-3}$		
205 *events*	z	0.090	z	0.079	t	−0.552
−0.09%	*p-value*	0.929	*p-value*	0.937	*p-value*	0.581
08-buy-financials			$\overline{r}$	$3.131 \cdot 10^{-4}$		
156 *events*	z	−0.202	z	−0.197	t	0.094
0.03%	*p-value*	0.840	*p-value*	0.844	*p-value*	0.925
09-buy-health-care			$\overline{r}$	0.014		
148 *events*	z	1.273	z	0.729	t	0.709
0.66%	*p-value*	0.203	*p-value*	0.466	*p-value*	0.479
10-buy-industrials			$\overline{r}$	$1.569 \cdot 10^{-3}$		
514 *events*	z	2.743	z	2.039	t	1.644
0.49%	***p-value****	$6.082 \cdot 10^{-3}$	***p-value****	0.041	*p-value*	0.102
11-buy-tech-telco			$\overline{r}$	$5.657 \cdot 10^{-3}$		
174 *events*	z	0.263	z	0.186	t	0.298
0.3%	*p-value*	0.793	*p-value*	0.852	*p-value*	0.766
12-buy-utilities			$\overline{r}$	0.035		
61 *events*	z	−0.235	z	−0.132	t	−0.575
−0.07%	*p-value*	0.814	*p-value*	0.895	*p-value*	0.566
13-buy-multi			$\overline{r}$	$-8.651 \cdot 10^{-4}$		
183 *events*	z	0.990	z	1.079	t	−0.144
0.19%	*p-value*	0.322	*p-value*	0.280	*p-value*	0.886

*Statistical significance at 5% level.

Table 4.6: Sell announcement results under $H_0 : CAAR(0, 1) = 0$

Sample identifier **# events** **CAAR(0, 1)**	**BMP**		**ADJ-BMP**		**GRANK**	
14-sell-total			$\overline{r}$	$6.965 \cdot 10^{-4}$		
1111 *events*	z	-0.467	z	-0.350	t	0.220
0.02%	*p-value*	0.641	*p-value*	0.726	*p-value*	0.826
15-sell-2005-2007			$\overline{r}$	$1.843 \cdot 10^{-3}$		
601 *events*	z	-0.609	z	-0.419	t	0.362
-0.04%	*p-value*	0.542	*p-value*	0.675	*p-value*	0.718
16-sell-2008-2010			$\overline{r}$	$2.566 \cdot 10^{-3}$		
244 *events*	z	1.880	z	1.472	t	1.632
0.42%	*p-value*	0.060	*p-value*	0.141	*p-value*	0.104
17-sell-2011-2013			$\overline{r}$	$1.766 \cdot 10^{-3}$		
266 *events*	z	-1.724	z	-1.419	t	-1.664
-0.2%	*p-value*	0.085	*p-value*	0.156	*p-value*	0.098
18-sell-basic-materials			$\overline{r}$	$5.370 \cdot 10^{-4}$		
64 *events*	z	0.106	z	0.105	t	-0.089
0.35%	*p-value*	0.915	*p-value*	0.917	*p-value*	0.929
19-sell-consumer-goods			$\overline{r}$	$3.980 \cdot 10^{-3}$		
105 *events*	z	0.106	z	0.089	t	0.095
-0.08%	*p-value*	0.915	*p-value*	0.929	*p-value*	0.924
20-sell-consumer-services			$\overline{r}$	$8.592 \cdot 10^{-3}$		
92 *events*	z	-1.419	z	-1.056	t	-0.749
-0.32%	*p-value*	0.156	*p-value*	0.291	*p-value*	0.455
21-sell-financials			$\overline{r}$	$1.613 \cdot 10^{-3}$		
202 *events*	z	-1.018	z	-0.884	t	-0.248
-0.14%	*p-value*	0.309	*p-value*	0.377	*p-value*	0.804
22-sell-health-care			$\overline{r}$	0.012		
95 *events*	z	1.408	z	0.957	t	1.403
0.21%	*p-value*	0.159	*p-value*	0.339	*p-value*	0.162
23-sell-industrials			$\overline{r}$	$2.482 \cdot 10^{-3}$		
356 *events*	z	-0.428	z	-0.312	t	-0.436
0.02%	*p-value*	0.668	*p-value*	0.755	*p-value*	0.664
24-sell-tech-telco			$\overline{r}$	$6.191 \cdot 10^{-3}$		
157 *events*	z	1.298	z	0.923	t	0.936
0.35%	*p-value*	0.194	*p-value*	0.356	*p-value*	0.350
25-sell-utilities			$\overline{r}$	0.270		
8 *events*	z	-8.881	z	-4.464	t	-2.532
-1.1%	***p-value****	$6.642 \cdot 10^{-19}$	***p-value****	$8.027 \cdot 10^{-6}$	***p-value****	0.012
26-sell-multi			$\overline{r}$	$-9.899 \cdot 10^{-4}$		
156 *events*	z	1.078	z	1.172	t	1.556
0.22%	*p-value*	0.281	*p-value*	0.241	*p-value*	0.121

*Statistical significance at 5% level.

4.4 Cumulative average abnormal returns for event period (0, 20)

Table 4.7 and Table 4.8 summarize the results obtained for buy, respectively sell announcements, under the null hypothesis of zero cumulative average abnormal returns in the period starting on the event day up to 20 days after the event day.

We document statistically significant results for the full period samples, both for purchase and sell transactions. In the case of buy events, the period before the financial crisis did not register statistically significant cumulative average abnormal returns. Sell announcements had a similar pattern, except that they also did not show statistically significant results during the financial crisis period. Compared with previous research, our $CAAR(0, 20)$ results share similarities with the findings of Aussenegg et al. (2018).

From industries, only the consumer goods and consumer services industries had statistically significant effects for purchase announcements. In the case of sell announcements, only the financials industry had all three tests reject the null hypothesis. Worth mentioning are the samples *24-sell-tech-telco* and *25-sell-utilities*, which demonstrate again the potential effects of events cross-correlation if not properly accounted for within the test statistics. Here the BMP test notifies statistically significance at 5% level, while the other two tests fail to reject the null hypothesis.

Table 4.7: Buy announcement results under $H_0 : CAAR(0, 20) = 0$

Sample identifier **# events** **CAAR(0, 20)**	**BMP**		**ADJ-BMP**		**GRANK**	
01-buy-total			$\overline{r}$	$5.714 \cdot 10^{-4}$		
1871 *events*	z	4.051	z	2.816	t	4.050
1.07%	***p-value****	$5.107 \cdot 10^{-5}$	***p-value****	$4.868 \cdot 10^{-3}$	***p-value****	$7.325 \cdot 10^{-5}$
02-buy-2005-2007			$\overline{r}$	$1.661 \cdot 10^{-3}$		
625 *events*	z	1.511	z	1.058	t	1.264
0.03%	*p-value*	0.131	*p-value*	0.290	*p-value*	0.208
03-buy-2008-2010			$\overline{r}$	$1.535 \cdot 10^{-3}$		
771 *events*	z	2.713	z	1.836	t	3.366
1.9%	***p-value****	$6.660 \cdot 10^{-3}$	*p-value*	0.066	***p-value****	$9.140 \cdot 10^{-4}$
04-buy-2011-2013			$\overline{r}$	$1.203 \cdot 10^{-3}$		
475 *events*	z	2.784	z	2.221	t	2.156
1.1%	***p-value****	$5.364 \cdot 10^{-3}$	***p-value****	0.026	***p-value****	0.032
05-buy-basic-materials			$\overline{r}$	$2.621 \cdot 10^{-3}$		
316 *events*	z	0.974	z	0.720	t	1.386
1.18%	*p-value*	0.330	*p-value*	0.472	*p-value*	0.167
06-buy-consumer-goods			$\overline{r}$	$3.869 \cdot 10^{-4}$		
276 *events*	z	3.413	z	3.244	t	2.812
1.62%	***p-value****	$6.424 \cdot 10^{-4}$	***p-value****	$1.178 \cdot 10^{-3}$	***p-value****	$5.422 \cdot 10^{-3}$
07-buy-consumer-services			$\overline{r}$	$1.399 \cdot 10^{-3}$		
205 *events*	z	3.641	z	3.209	t	3.965
2.41%	***p-value****	$2.718 \cdot 10^{-4}$	***p-value****	$1.331 \cdot 10^{-3}$	***p-value****	$1.020 \cdot 10^{-4}$
08-buy-financials			$\overline{r}$	$3.131 \cdot 10^{-4}$		
156 *events*	z	0.999	z	0.976	t	0.886
1.12%	*p-value*	0.318	*p-value*	0.329	*p-value*	0.377
09-buy-health-care			$\overline{r}$	0.014		
148 *events*	z	−1.655	z	−0.947	t	−0.374
−1.04%	*p-value*	0.098	*p-value*	0.344	*p-value*	0.709
10-buy-industrials			$\overline{r}$	$1.569 \cdot 10^{-3}$		
516 *events*	z	1.315	z	0.977	t	2.211
0.81%	*p-value*	0.189	*p-value*	0.329	***p-value****	0.028
11-buy-tech-telco			$\overline{r}$	$5.657 \cdot 10^{-3}$		
174 *events*	z	0.687	z	0.487	t	0.549
0.46%	*p-value*	0.492	*p-value*	0.626	*p-value*	0.584
12-buy-utilities			$\overline{r}$	0.035		
61 *events*	z	0.107	z	0.060	t	−0.099
0.58%	*p-value*	0.915	*p-value*	0.953	*p-value*	0.921
13-buy-multi			$\overline{r}$	$-8.651 \cdot 10^{-4}$		
183 *events*	z	1.541	z	1.680	t	1.633
1.35%	*p-value*	0.123	*p-value*	0.093	*p-value*	0.104

*Statistical significance at 5% level.

Table 4.8: Sell announcement results under $H_0 : CAAR(0, 20) = 0$

Sample identifier **# events** **CAAR(0, 20)**	**BMP**		**ADJ-BMP**		**GRANK**	
14-sell-total			$\overline{r}$	$6.965 \cdot 10^{-4}$		
1115 *events*	z	-3.288	z	-2.467	t	-2.226
-0.63%	**p-value***	$1.007 \cdot 10^{-3}$	**p-value***	0.014	**p-value***	0.027
15-sell-2005-2007			$\overline{r}$	$1.843 \cdot 10^{-3}$		
601 *events*	z	-1.549	z	-1.066	t	-0.519
-0.89%	*p-value*	0.121	*p-value*	0.286	*p-value*	0.604
16-sell-2008-2010			$\overline{r}$	$2.566 \cdot 10^{-3}$		
245 *events*	z	-0.562	z	-0.440	t	-0.424
0.39%	*p-value*	0.574	*p-value*	0.660	*p-value*	0.672
17-sell-2011-2013			$\overline{r}$	$1.766 \cdot 10^{-3}$		
269 *events*	z	-4.361	z	-3.590	t	-3.486
-1%	**p-value***	$1.294 \cdot 10^{-5}$	**p-value***	$3.308 \cdot 10^{-4}$	**p-value***	$6.021 \cdot 10^{-4}$
18-sell-basic-materials			$\overline{r}$	$5.370 \cdot 10^{-4}$		
65 *events*	z	-0.643	z	-0.632	t	-1.001
0.03%	*p-value*	0.520	*p-value*	0.527	*p-value*	0.318
19-sell-consumer-goods			$\overline{r}$	$3.980 \cdot 10^{-3}$		
105 *events*	z	0.066	z	0.055	t	-0.425
-0.82%	*p-value*	0.948	*p-value*	0.956	*p-value*	0.671
20-sell-consumer-services			$\overline{r}$	$8.592 \cdot 10^{-3}$		
93 *events*	z	-1.917	z	-1.427	t	-2.773
-1.18%	*p-value*	0.055	*p-value*	0.154	**p-value***	$6.076 \cdot 10^{-3}$
21-sell-financials			$\overline{r}$	$1.613 \cdot 10^{-3}$		
202 *events*	z	-3.245	z	-2.818	t	-2.899
-0.64%	**p-value***	$1.173 \cdot 10^{-3}$	**p-value***	$4.831 \cdot 10^{-3}$	**p-value***	$4.164 \cdot 10^{-3}$
22-sell-health-care			$\overline{r}$	0.012		
95 *events*	z	1.714	z	1.165	t	1.901
0.48%	*p-value*	0.087	*p-value*	0.244	*p-value*	0.059
23-sell-industrials			$\overline{r}$	$2.482 \cdot 10^{-3}$		
358 *events*	z	-1.460	z	-1.062	t	-0.427
-0.46%	*p-value*	0.144	*p-value*	0.288	*p-value*	0.670
24-sell-tech-telco			$\overline{r}$	$6.191 \cdot 10^{-3}$		
157 *events*	z	-2.513	z	-1.787	t	-1.051
-1.4%	**p-value***	0.012	*p-value*	0.074	*p-value*	0.295
25-sell-utilities			$\overline{r}$	0.270		
8 *events*	z	-2.095	z	-1.053	t	-1.154
-1.9%	**p-value***	0.036	*p-value*	0.292	*p-value*	0.250
26-sell-multi			$\overline{r}$	$-9.899 \cdot 10^{-4}$		
156 *events*	z	0.251	z	0.273	t	0.883
0.07%	*p-value*	0.802	*p-value*	0.785	*p-value*	0.378

*Statistical significance at 5% level.

CHAPTER 5

Conclusion

Throughout the course of this paper we examined the influence of directors' dealings on the stock prices evolution. We mainly focused on analyzing the short-term effects of insider transactions for German companies in the period between 2005 and 2013. Our data set was comprised of a total of 3032 announcement events, featuring 102 firms and 10 industries, from which we built 26 sample groups, based on criteria such as the transaction type, time period, industry type and multiple events disclosed on the same day. The considered samples were then tested to check for evidence of short-term cumulative average abnormal returns using an event window ranging 41 days around the announcement day.

As part of the process, three separate event study test statistics were implemented: two parametric tests, the BMP test (see Boehmer et al. (1991)) and the ADJ-BMP test (see Kolari and Pynnönen (2010)) and one non-parametric test, namely the GRANK test (see Kolari and Pynnönen (2011)). Summarizing the results obtained by executing the three tests on the constructed samples, we can formulate the following conclusions regarding insider trading within public companies in the German market:

- Insiders tend to follow a contrarian trading strategy. This phenomena is best observed for buy transactions, where the cumulative average abnormal returns are significantly negative in the period prior to the event day. This confirms the results reported by previous research, such as the ones of Lakonishok and Lee (2001), Piotroski and Roulstone (2005) and Aussenegg et al. (2018).
- It is not feasible to formulate a profitable short term trading strategy based on insider transactions. In general, our samples did no exhibit statistically significant cumulative average abnormal returns on the event day and the day thereafter. Similar observations are documented by previous researches as well (see Lakonishok and Lee (2001) and Friederich et al. (2002)). Although for the longer horizon of

20 days after the trade disclosure some samples registered statistically significant results, for most of the industries, the tests did not reject the null hypothesis. Therefore, we cannot infer a consistent trading strategy in the general case.

- Multiple announcements made on the same day do not trigger more prominent market reactions in the short period after events disclosure. As the results show, cumulative average abnormal returns are not statistically significant in this case.

APPENDIX A

Director's Dealings Data Set Statistics

In this section we provide a statistical description for the companies in the data set we used for the research conducted in the paper. As a first step, we have grouped the companies based on their industry. For each company, we summed up daily returns to calculate cumulative monthly returns. Per industry group, we then took the average of the cumulative monthly returns and compared it against the evolution of the DAX index. The second part targets the comparison of daily returns between the industry groups and the DAX index. The results are depicted in the graphics shown throughout the rest of this section.

Figure A.1: Statistics of stock price returns of the Basic Materials industry in our data set in comparison with the DAX Index

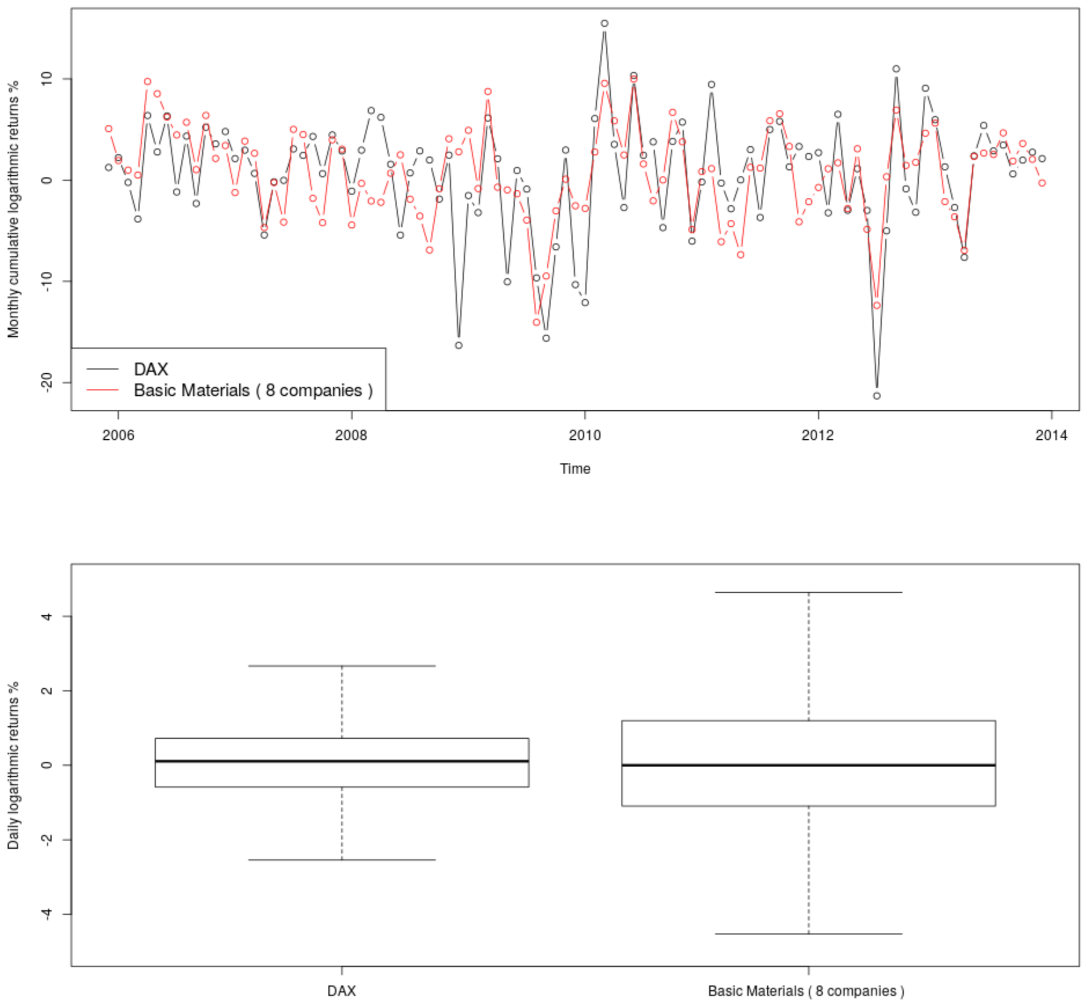


Figure A.2: Statistics of stock price returns of the Consumer Goods industry in our data set in comparison with the DAX Index

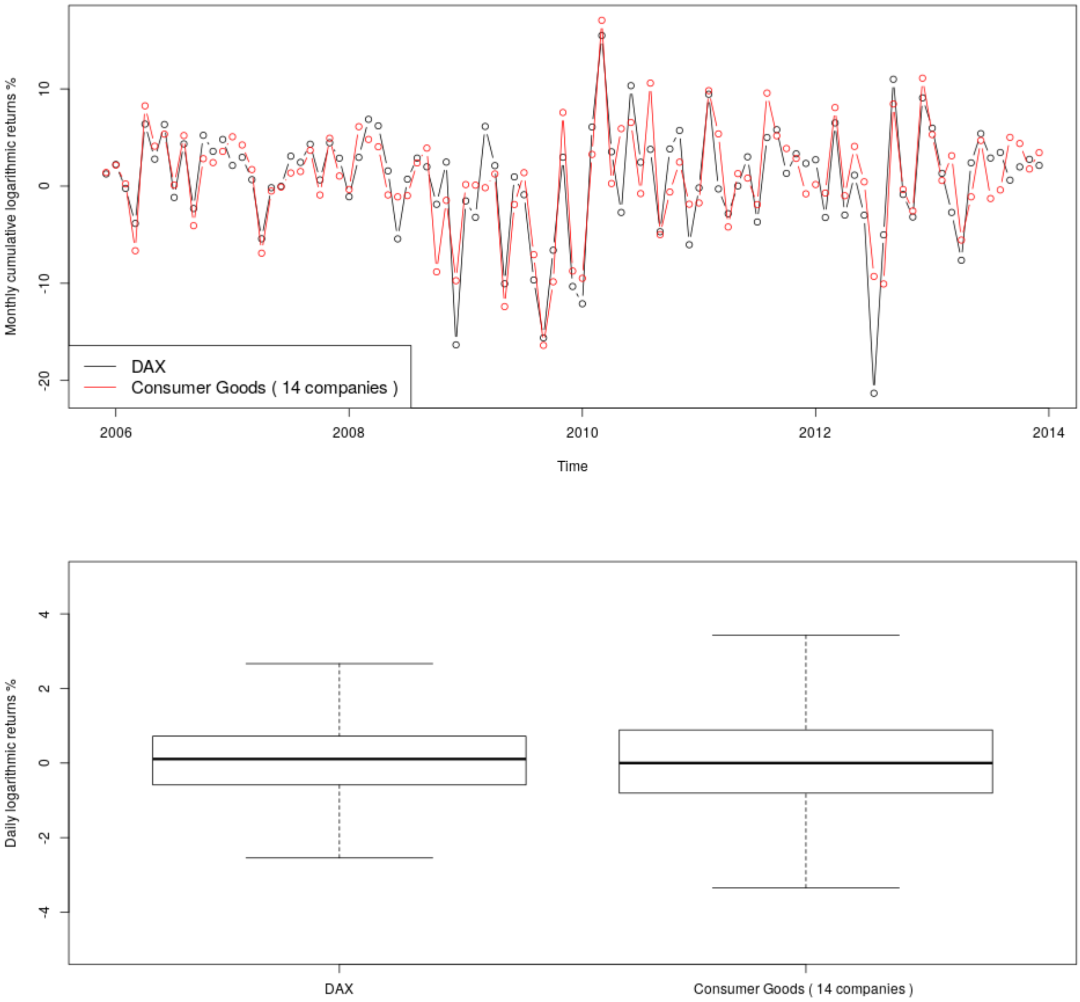


Figure A.3: Statistics of stock price returns of the Consumer Services industry in our data set in comparison with the DAX Index

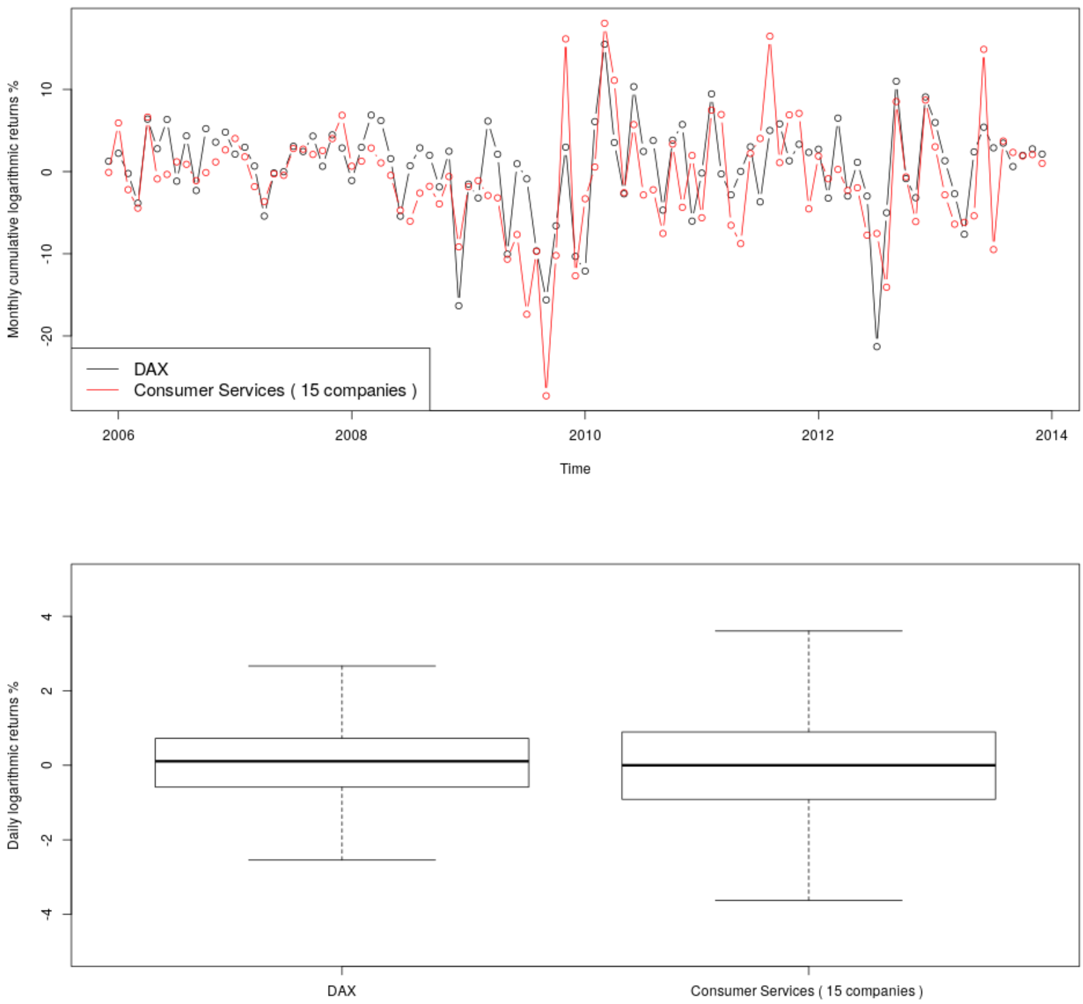
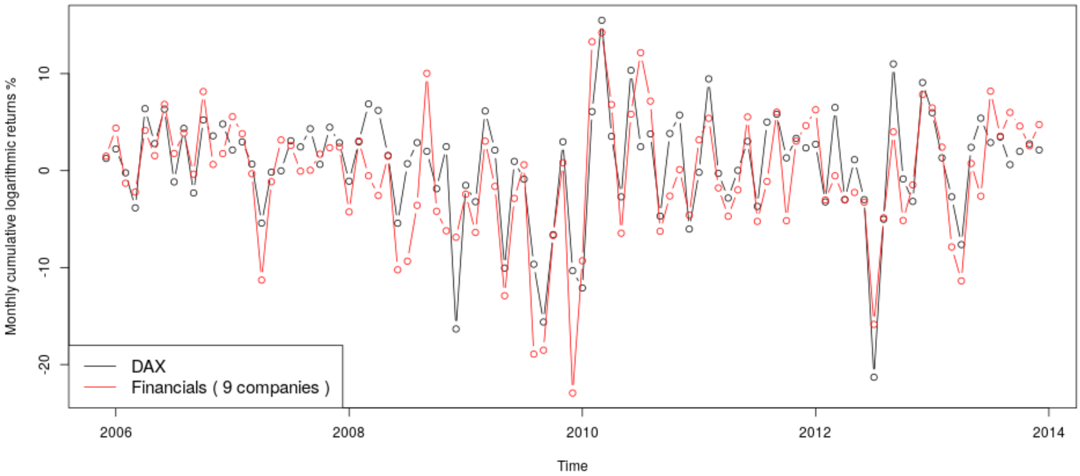


Figure A.4: Statistics of stock price returns of the Financials industry in our data set in comparison with the DAX Index



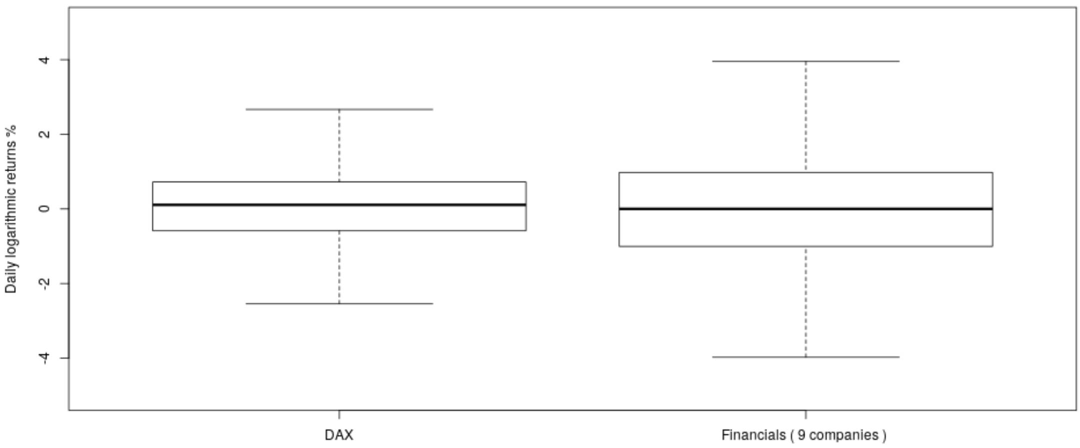


Figure A.5: Statistics of stock price returns of the Health Care industry in our data set in comparison with the DAX Index

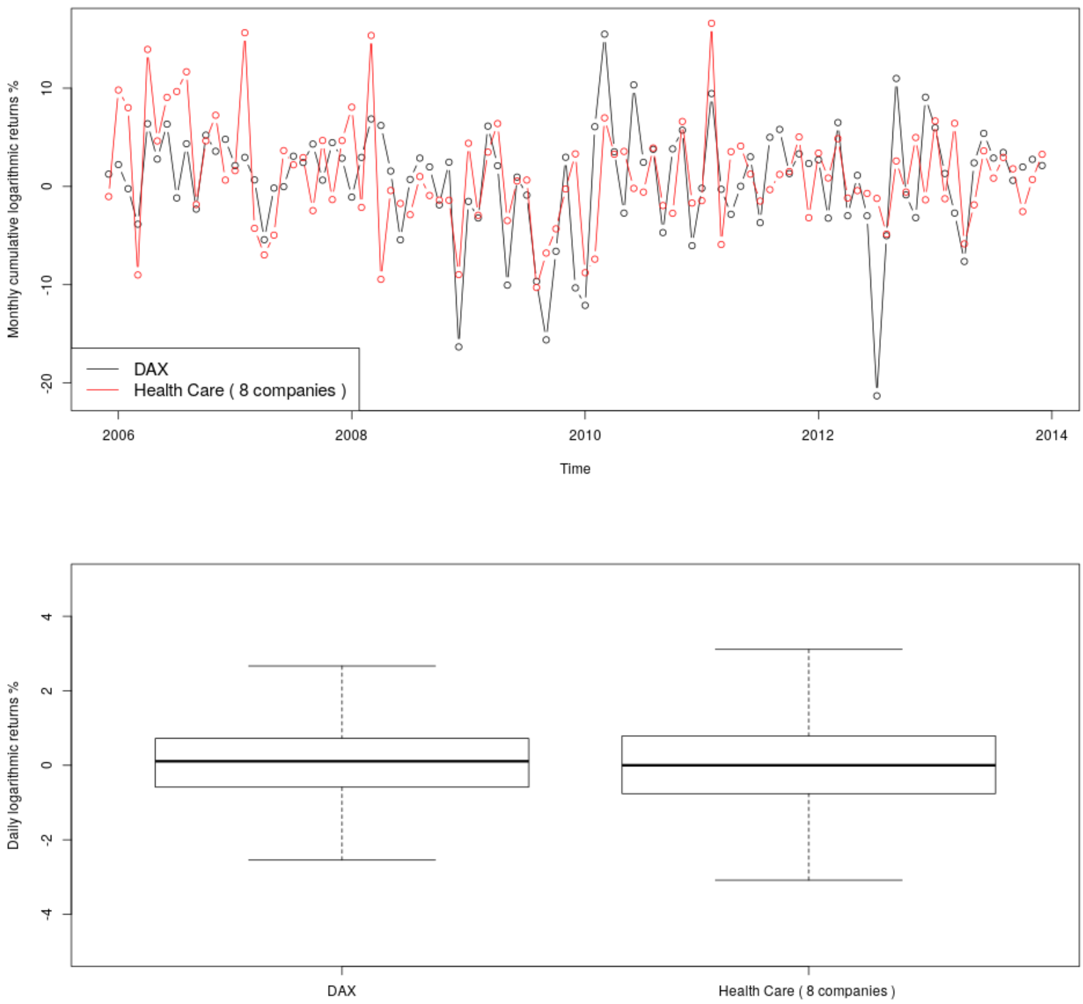
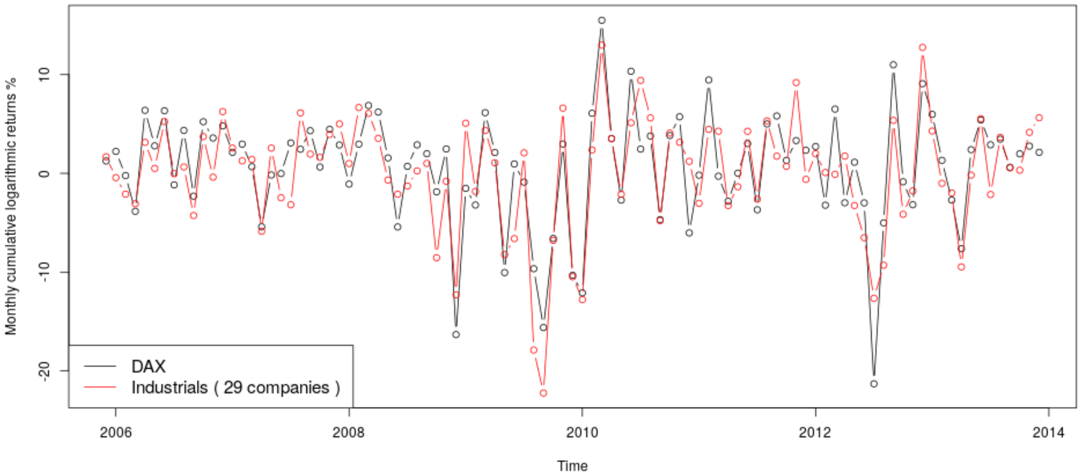


Figure A.6: Statistics of stock price returns of the Industrials industry in our data set in comparison with the DAX Index



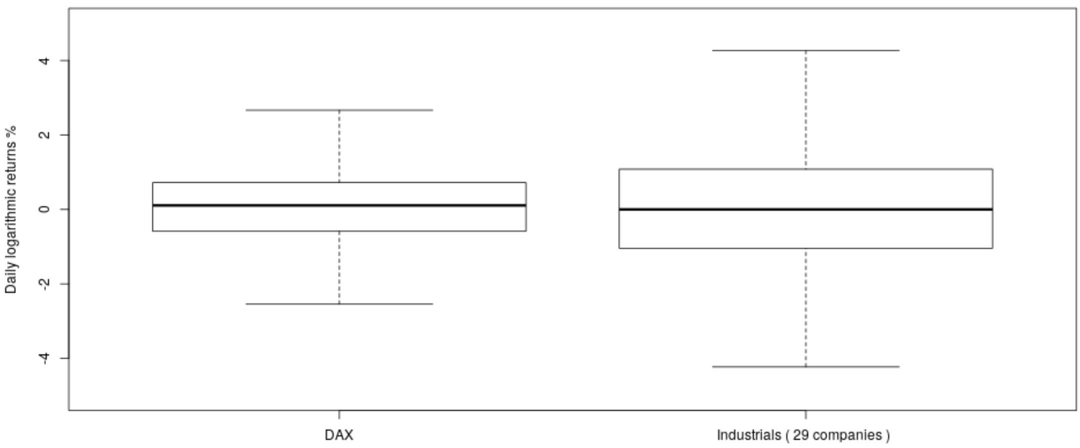
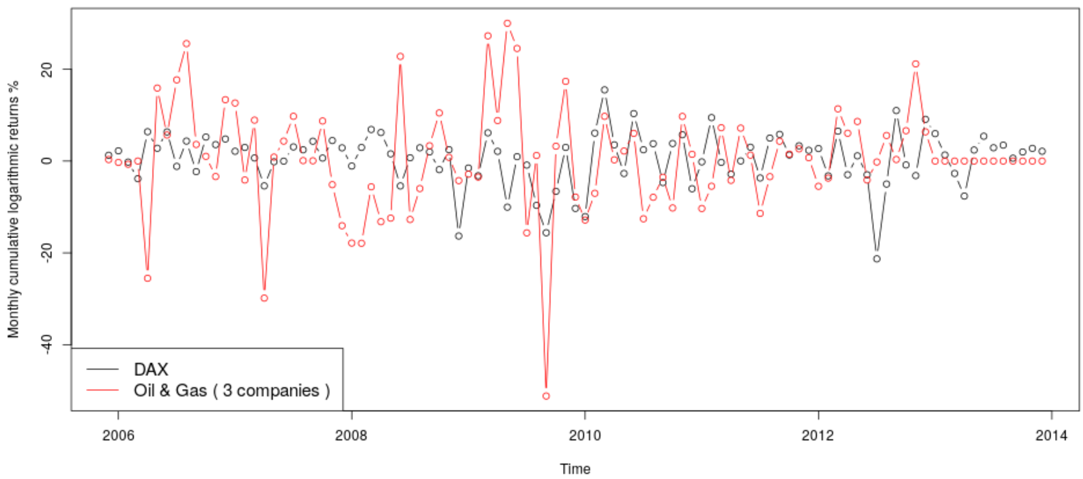


Figure A.7: Statistics of stock price returns of the Oil & Gas industry in our data set in comparison with the DAX Index



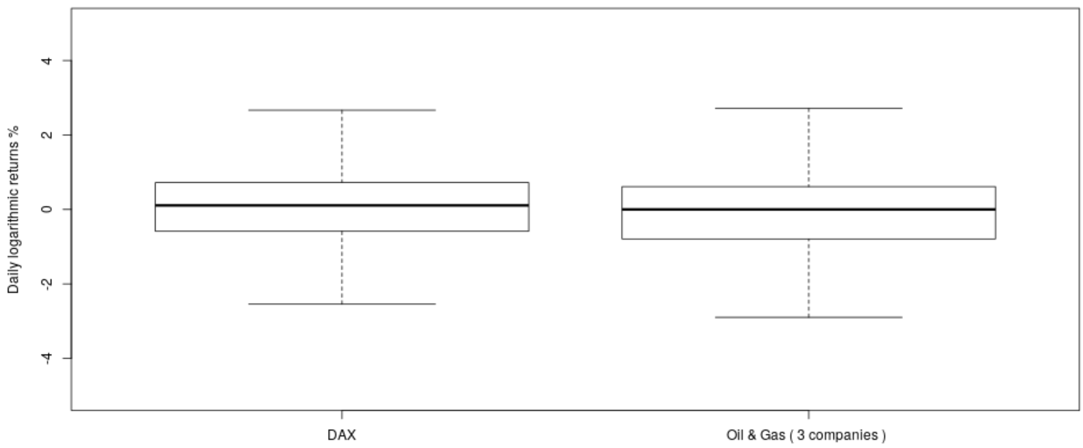


Figure A.8: Statistics of stock price returns of the Technology industry in our data set in comparison with the DAX Index

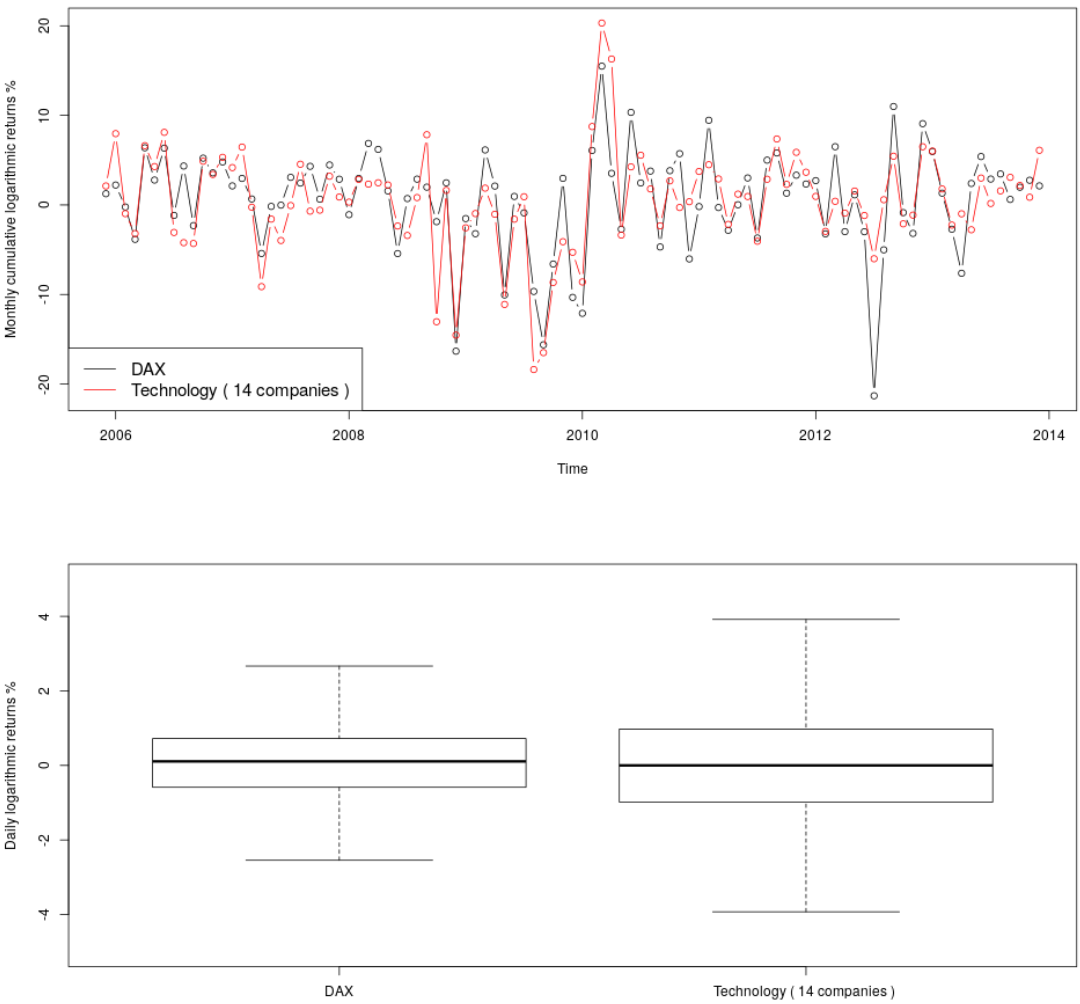
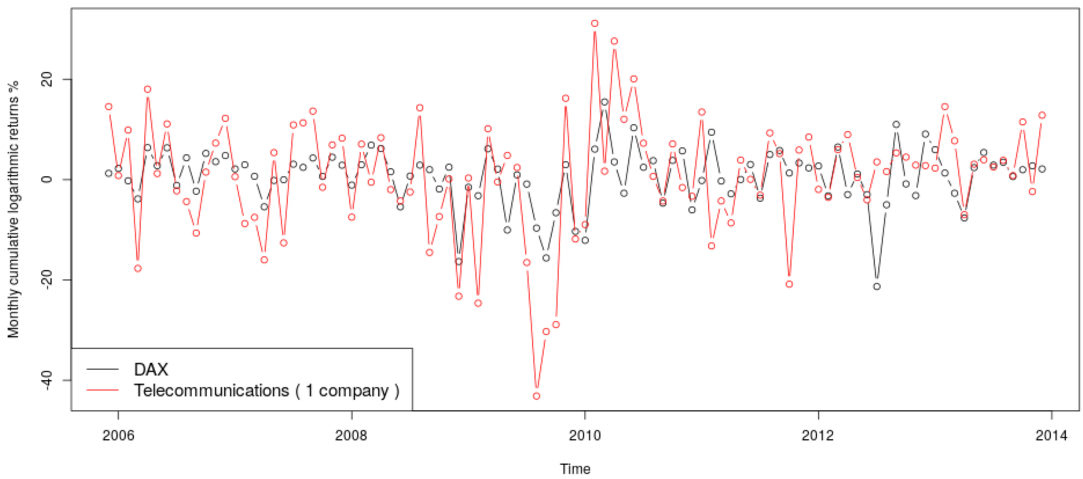


Figure A.9: Statistics of stock price returns of the Telecommunications industry in our data set in comparison with the DAX Index



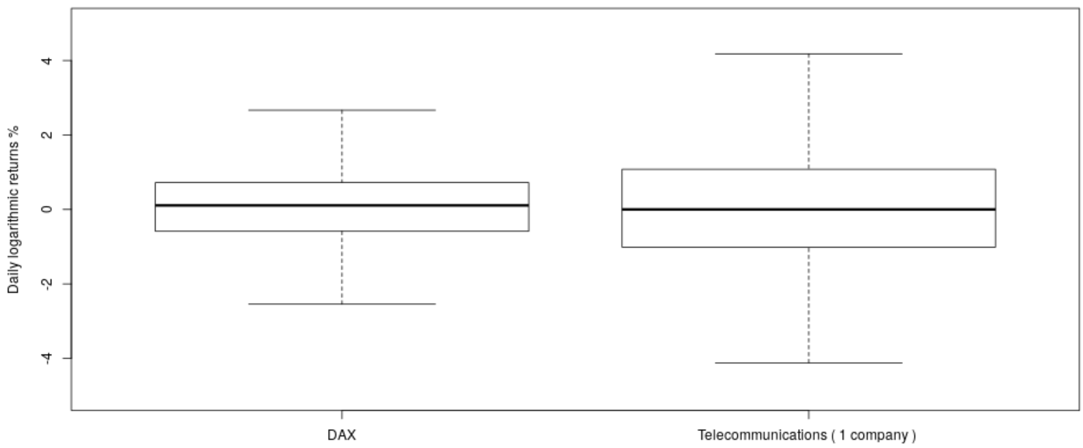
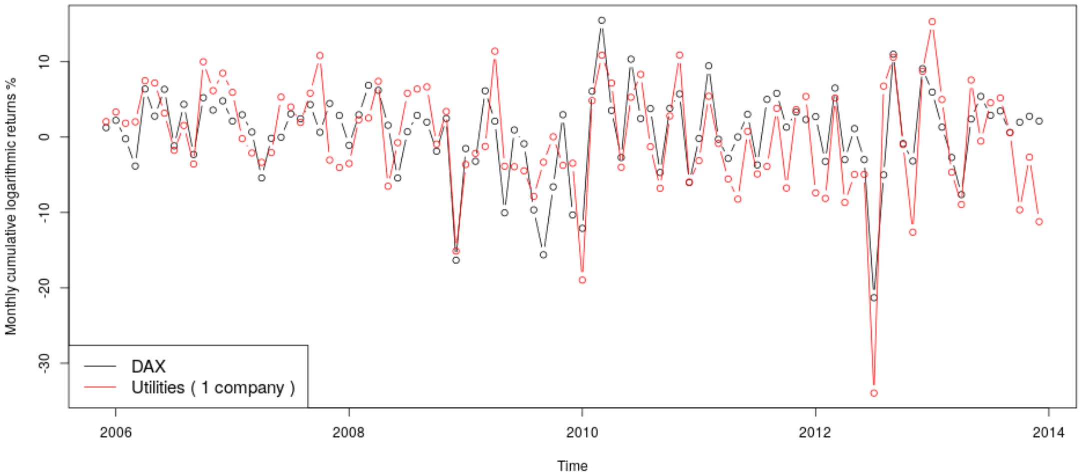
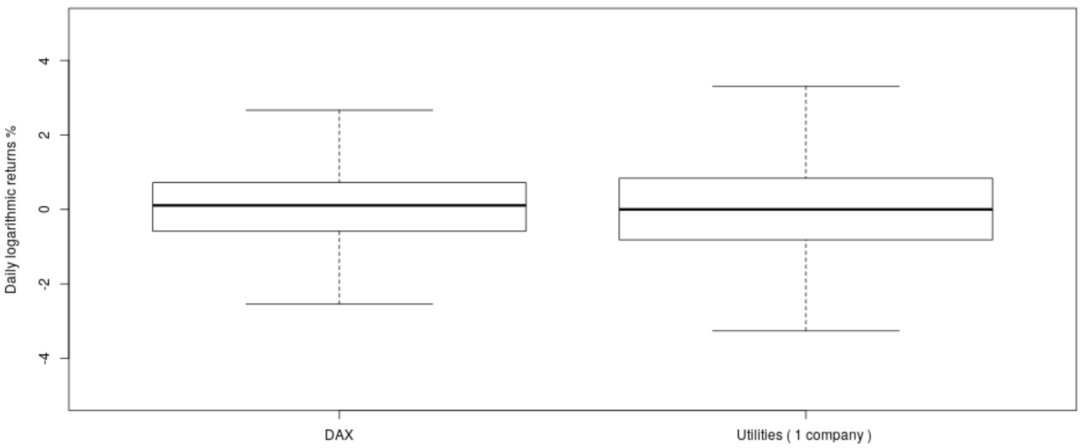


Figure A.10: Statistics of stock price returns of the Utilities industry in our data set in comparison with the DAX Index





List of Figures

List of Tables

Bibliography

Agrawal, A. and Cooper, T. (2015). Insider trading before accounting scandals. *Journal of Corporate Finance*, 34:169 – 190.

Aussenegg, W., Jelic, R., and Ranzi, R. (2018). Corporate insider trading in europe. *Journal of International Financial Markets, Institutions and Money*, 54:27–42.

Bettis, C., Vickrey, D., and Vickrey, D. W. (1997). Mimickers of corporate insiders who make large-volume trades. *Financial Analysts Journal*, 53(5):57–66.

Boehmer, E., Masumeci, J., and Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, 30:253–272.

Brown, S. J. and Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, 8:205–258.

Brown, S. J. and Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1):3–31.

Brown, S. J. and Weinstein, M. I. (1985). Derived factors in event studies. *Journal of Financial Economics*, 14(3):491 – 495.

Campbell, C. J. and Wesley, C. E. (1993). Measuring security price performance using daily nasdaq returns. *Journal of Financial Economics*, 33(1):73–92.

Corrado, C. J. and Zivney, T. L. (1992). The specification and power of the sign test in event study hypothesis tests using daily stock returns. *The Journal of Financial and Quantitative Analysis*, 27(3):465–478.

Cowan, A. R. (1992). Nonparametric event study tests. *Review of Quantitative Finance and Accounting*, 2(4):343–358.

Dardas, K. and Güttler, A. (2011). Are directors' dealings informative? evidence from european stock markets. *Financial Markets and Portfolio Management*, 25(2):111–148.

Dymke, B. M. and Walter, A. (2008). Insider trading in germany — do corporate insiders exploit inside information? *Business Research*, 1(2):188–205.

Fama, E. F. and French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1):55–84.

Fidrmuc, J. P., Korczak, A., and Korczak, P. (2013). Why does shareholder protection matter for abnormal returns after reported insider purchases and sales? *Journal of Banking & Finance*, 37(6):1915–1935.

Friederich, S., Gregory, A., Matatko, J., and Tonks, I. (2002). Short-run returns around the trades of corporate insiders on the london stock exchange. *European Financial Management*, 8(1):7–30.

Gębka, B., Korczak, A., Korczak, P., and Traczykowski, J. (2017). Profitability of insider trading in europe: A performance evaluation approach. *Journal of Empirical Finance*, 44:66 – 90.

Klinge, M. (2005). Abnormal returns in the vicinity of insider transactions: Unbiased estimates for germany. *SSRN Electronic Journal*.

Kolari, J. W. and Pynnönen, S. (2010). Event study testing with cross-sectional correlation of abnormal returns. *Review of Financial Studies*, 23:3996–4025.

Kolari, J. W. and Pynnönen, S. (2011). Nonparametric rank tests for event studies. *Journal of Empirical Finance*, 18:953–971.

Lakonishok, J. and Lee, I. (2001). Are insider trades informative? *The Review of Financial Studies*, 14(1):79–111.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1):13–39.

Patell, J. M. (1976). Corporate forecasts of earnings per share and stock price behavior: Empirical test. *Journal of Accounting Research*, 14(2):246–276.

Patell, J. M. and Wolfson, M. A. (1979). Anticipated information releases reflected in call option prices. *Journal of Accounting and Economics*, 1:117–140.

Piotroski, J. D. and Roulstone, D. T. (2005). Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? *Journal of Accounting and Economics*, 39(1):55 – 81.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341 – 360.

Schimmer, M., Levchenko, A., and Müller, S. (2019). EventStudyTools (Research Apps), St.Gallen (2014). Available on: `https://www.eventstudytools.com/significance-tests`. Accessed on: 06.01.2019.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.

Stotz, O. (2006). Germany's new insider law: The empirical evidence after the first year. *German Economic Review*, 7(4):449–462.