The influence of the presidential election of Donald Trump on the U.S. industry performance

A research on abnormal returns generated in the U.S. stock market as a results of the 2016 presidential election outcome

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Abstract:

Stock markets try to incorporate new information of political events into stock prices. Against all the odds, Donald Trump was elected as U.S. president in November 2016. Trump's policy will aim the country at a completely different path than during the last four years. With these new governmental focus points, some industries will benefit of the changes and some industries will suffer due to a change in governmental decisions. The abnormal returns of eight American industries are examined in this research to investigate the industry performance in the first eight weeks after the Trump election. Significant average abnormal daily returns are observed for all of the industries, indicating the industries respond to industry-specific events. However, only the mining industry and the wholesale trade industry showed significant results for the cumulative average abnormal returns, indicating a positive aggregate effect over time on the industry performance, because of the presidential election of Trump.

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1 Introduction

Political events are a major influence on financial markets. New information becomes available by political decision making, with markets trying to incorporate this information in stock prices. Because of this reason, investors tend to follow political decisions closely to revise their expectations based on the outcome of these events. After elections, the voting people have no more influence in the political decision-making process. As such, the election of a new political leader is a unique event, because every individual with voting rights can affect the outcome of this event.

On November 8th 2016, the American people elected their new president, the Republican presidential candidate Donald Trump was elected as the president of the United States of America. During his entire presidential campaign, polls predicted a hopeless defeat for Trump against his Democratic opponent Hillary Clinton, but against all the odds Trump became the next president of America. The surprising victory of Trump was directly reflected on the financial markets, where the U.S. dollar currency plummeted at first, but rose significantly the days following the election (Irwin, 2016).

So the election of Trump shook up the financial markets, but what does that mean to the performance of America's stock market? It is worth investigating. This paper examines the relationship between the election of Donald Trump as the president of the United States of America and the industry performance of the U.S. stock market.

Since Trump announced that he would run for president in the elections of 2016, his campaign was full of controversy. His statements about, among others, immigration, environment, women and fellow politicians caused a lot of criticism from the nation and the rest of the world, as well as his ideas about Wall Street and the economic crisis. Before turning to politics, Trump earned a fortune with multiple businesses in investments and real estate. As such, his economic policy is greatly influenced by his background as a former businessman. Moreover, multiple vacancies in the Trump administration are filled with former Goldman Sachs executives, which is remarkable considering Trump's ideas about Wall Street.

The focus of Trump's economic policy lies in the deregulation of the financial sector and to recover the free market. The first step in order to achieve this, Trump aims to greatly change or eliminate the Dodd-Frank Act. In 2010, this law was introduced as a measure against the economic crisis and was designed to prevent future crises. The Act consists of a series of regulations and obliged banks, among others, to increase the amount of reserves. In addition, Trump mentioned reformations of tax rates for businesses (Diamond, 2016).

Furthermore, Trump mentioned multiple times in his campaign the abolition of the Affordable Care Act, better known as Obamacare, the nation-wide regulation of healthcare insurance. Obamacare is set up by his Democratic predecessor Barack Obama to get the entire American population a health insurance (Diamond, 2016).

Another important point on the Trump agenda is the 'America first' quote, which he directly gave strength by withdrawing America from the Trans-Pacific Partnership, which is a trade agreement between a selection of countries across the world (Diamond, 2016).

In addition to the 'America first' attitude, in 2012 Trump tweeted that the global warming was only created to make the American manufacturing industry non-competitive. He also tends to revive the coal market as a source for creating jobs by limiting the restrictions on the production of coal.

Overall, with the election of Donald Trump as president of the United States of America, the country will aim for a completely different path than during the last four years under Obama. All these ideas, expectations and upcoming changes in legislation will have a huge impact on the stock market. With these new governmental focus points, some industries will benefit of the changes and some industries will suffer due to a change in priorities.

To examine the relationship between the election of Donald Trump as president of America and the U.S. stock market performance, the following hypothesis will be tested in this paper:

- *The American stock market generated abnormal returns at industry level after the presidential election of Donald Trump.*

The hypothesis will be tested for various industries, to examine if there are any industry-specific idiosyncrasies.

First the relevant literature will be discussed in chapter two, followed by a description of the data used in the research in chapter three. In chapter four the methodology used for the research will be explained and the corresponding results will be presented in chapter five. Finally, the conclusion and limitations of the research will be described in chapter six. Additionally, in chapter seven the references used in this research will be mentioned and the appendix will be presented in chapter eight.

2 Literature review

This thesis covers the topics of a standard event methodology and the relationship between the election of a U.S. president and American stock returns at industry level.

Event study methodology

Brown and Warner (1985) examined event study methodologies used with daily stock returns. They describe how certain characteristics of daily stock returns can affect the assessment of the impact an event has on the stock price. Their findings are mostly consistent with their previous work in 1980, when they conducted a similar research about event study methodologies and monthly stock returns. Both empirical researches find that the characteristics of monthly data as well as daily data present few difficulties in event studies testing abnormal returns.

Strong (1992) describes a guide for the modelling of abnormal returns in event study researches. The paper covers, among other models, the Capital Asset Pricing Model (CAPM) and the Market Model (MM). The CAPM and the Market Model are very similar and both show a linear relationship between individual stock returns and the return of a market portfolio. However, the intercept of both models differs from each other, where the CAPM uses the risk-free rate of return as intercept while the Market Model uses a free intercept which can be estimated by regression analysis. Abnormal returns then can be calculated by filling in the intercept- and beta estimations in the linear equation, which incorporates the market risk. In addition, Strong mentioned adjustments for the size effect, which also has been done in de Fama-French three-factor model.

Fama and French (1992) criticized the CAPM, because the model only explained the market risk in assessing expected stock returns. They examined additional variables that could help explaining expected returns, other than the market risk. They found a negative relationship between a company's average return and market capitalization, as well as a positive relationship between a company's average return and book-to-market value. Fama and French incorporated these variables in an extension of the CAPM, the Fama-French three-factor model.

Carhart (1997) published a paper, where he presented an extended model of the Fama-French three-factor model. Jegadeesh and Titman (1993) observed in their research that good performing stock will continue performing well for several months and vice versa. This phenomenon is called the momentum effect. Carhart's four-factor model incorporated the market premium factor, the size factor and the value premium factor from the Fama-French three-factor model and added the momentum factor of Jegadeesh and Titman.

In order to see which model is best applicable to explain abnormal stock returns, Rehnby (2016) compared the Fama-French three-factor model and the Carhart four-factor model with the well-known CAPM in the Swedish stock market. He finds that the Fama-French model and the Carhart four-factor model both outperformed the CAPM model in explaining portfolio excess returns. In addition, he finds that the Carhart four-factor model slightly had a better explanatory value than the Fama-French model, indicating that Carhart's four-factor model is the preferred model for explaining excess stock returns.

However, Brown and Warner (1980) examined various event study methodologies to measure abnormal stock performance and their findings are in contradiction with the findings of Rehnby (2016). The purpose of this research is not to point out one methodology as best model, but to describe different methodologies compared with each other. They found no evidence that more complicated models are better capable of estimating abnormal stock performance. Even worse, the study shows in some cases that more complicated models perform worse compared to the relatively simple Market Model. Finally, they mentioned that their study does not show that existing models cannot be improved, but it is an indication that even old issues of journals still can be of great value in event study methodologies.

In addition, the study of Cable and Holland (1999) found a tendency among researchers of using simpler event study methodologies, despite the growing number of more complex alternatives. The results show a strong preference for regression-based models, with the Market Model outperforming the Capital Asset Pricing Model.

Concluding there is a broad variety of findings about the use of which methodology is best fit for event studies.

U.S. president event studies

In the past, the relationship between U.S. presidents and stock price returns turned out to be a popular subject of interest, resulting in a lot of relevant research studies. However, most of the empirical evidence covers stock price returns of the overall U.S. stock market, but do not examine the stock price returns at industry level.

Oehler and Walker (2013) investigates the relationship between U.S. presidents and stock price returns at industry level between 1976 and 2008. The research covers a total of nine presidential elections and eight industry groups. They prove the existence of a statistically significant effect of election outcomes on stock price returns at industry level. In addition, no evidence is found for a systematic pattern of industry performance after a victory for one of the two parties. Consistent with these findings is the research study of Homaifar, Randolph, Helms and Haddad (1988). They examine the effect of presidential elections on the stock returns in the defense sector, resulting in weak support for a relationship between the political party elected and price changes in defense stocks. Moreover, they did find strong support for a relationship between the election of presidents and excess returns of stocks in the defense industry.

However, Niederhoffer, Gibbs and Bullock (1970) and Riley and Luksetich (1980) both examined the existence of the '*Wall street folklore'*, indicating a market preference for Republicans. Both research studies found some evidence for the existence of such a market preference, at least in the short run. On the other hand, Huang (1985) finds significant cases of higher stock returns under Democratic administrations. This contradicts the aforementioned findings about the effect of the elected party on stock price returns, resulting in no conclusion can be made about a market preference for a specific party.

Stovall (1992) discovered that U.S. stock prices followed a specific pattern after a president is elected, the presidential cycle. In general, during the first two years after a president is elected, stock prices fall and during the second half of a presidency stock prices rise. Wong and McAleer (2009) found evidence that U.S. stocks still follow the presidential election cycle. They find a much more significant pattern for Republican administrations than for Democratic administrations, indicating a manipulation policy towards reelections.

Market manipulation by government is a direct result of the governmental policy applied. The study of Leblang and Mukherjee (2005) examines the sensitivity of stock markets to elections and political partisanship. They found evidence that important decisions about monetary and fiscal policies adopted by the incumbent party affect the economy and result in changing stock prices.

On the other hand, the market tries to influence the governmental policy by, for instance, lobbyism and financial support of political parties by corporates. This positive correlation between stocks of specific firms and the probability of a presidential candidate's victory is described by Mattozzi (2008).

Event studies at industry level

To distinguish different industries in the market, some classification systems are developed. The best known classification system is the Standard Industrial Classification (SIC) codes, a four-digit code available since 1939 to categorize every company in the world. In 1987, these SIC codes, and therefore the industries they represent, were updated for the last time. Due to economic developments and changes, the SIC received a lot of criticism and was decided the classification system needed an update. In 1997, the North American countries (the United States, Canada and Mexico) updated the SIC system and changed it into the North American Industry Classification System (NAICS).

Bhojraj, Lee and Oler (2003) compared different types of industry classification systems, including the SIC and the NAICS. Their findings suggest that significantly better explanations are provided by the Global Industry Classification Standard (GICS) compared to other classification systems. The GICS is a jointly developed classification system by Standard & Poor's and Morgen Stanley Capital International. However, they also mentioned that in absence of GICS code, the NAICS code is the best substitute.

Müller (2015) summarizes different statistical approaches of event study methodologies. To calculate abnormal returns in the first place, expected returns have to be estimated using a return generating model as discussed earlier in the chapter. To perform a research about abnormal returns at industry level, the cumulative average abnormal returns (CAAR) have to be calculated by adding daily average abnormal returns together. The results can be tested on significance by using a student t-test. In addition, Beller, Kling and Levinson (1998) examined the predictability of cumulative industry stock returns and found significant evidence for the predictability of industry stock returns.

The already available literature serves as a guideline for this thesis, but cannot be applied directly to the presidential election of 2016. Because of all the controversy around Donald Trump and his presidential campaign, is it useful to examine this case separately.

3 Data

To perform an event study about the effect of Donald Trump as president of America on the U.S. stock market, companies and matching stock data has to be selected to include in the research. De data used in this paper to perform the research is retrieved from two financial databases, Orbis and the Warton Research Data Services (WRDS). Stock data of WRDS is received from the Center of Research in Security Prices (CRSP), which is a specific part of the WRDS database focused on the American stock market.

The first step in collecting data to conduct the research is setting up the sample group, a list of companies included in the research. The Orbis database provided peer companies and specific company characteristics, including the ticker symbol and the NAICS code. Some filters are applied to the Orbis database to achieve a representative sample group, consisting of only active, publicly traded U.S. companies with a minimal operating revenue of 1 million U.S. dollar.

To perform the research at industry level, the group of peer companies is divided in several industries by the North American Industry Classification System (NAICS) code. The NAICS code categorizes the North-American market in 20 industries. Due to the filter applied on the database, incomplete data and a shortage of companies to make the industry peer group relevant (below 50 companies) for this research, some industries are excluded in the research. Eight of the NAICS industries are selected for research purposes in this paper and presented in table 1 below.

Table 1

Overview of industry peer groups

NAICS Code	Industry	Number of companies
21XX	Mining	161
23XX	Construction	55
31XX – 33XX	Manufacturing	864
42XX	Wholesale trade	101
44XX – 45XX	Retail trade	152
48XX – 49XX	Transportation and warehousing	101
52XX	Finance and insurance	251
62XX	Healthcare and social assistance	50

After constructing the industry peer groups, stock characteristics per company are retrieved from the CRSP database, based on the ticker symbol, which is unique for every company. Over a period of one year before Trump's election and two months after this event, daily stock returns are extracted from the database, as well as the one-month U.S. treasury bill rate as a proxy for the risk-free rate of return. In addition, the factors for market premium, size effect, value premium and the momentum effect are also retrieved from the CRSP database.

The collected data will be processed by the statistical program STATA and the analytical program Microsoft Excel.

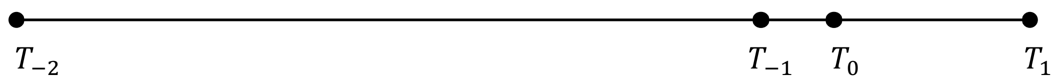
4 Methodology

The effect of the presidential election of Donald Trump on the stock market is examined by an event study methodology. Per industry, abnormal returns will be calculated as a measure of market outperformance, which are being tested for significance by a student t-test.

As mentioned earlier in this thesis, Trump was elected as president of America on November 8th, 2016 and succeeded Barack Obama, the Democratic president who fulfilled two presidential terms of four years. Since this is a relatively recent event, the WRDS database is not as up to date as the latest developments around the Trump presidency. Therefore, the event window used in this research is limited to the first eight weeks since election-day, where the last trading day of 2016 equals the latest point of observation, December 30th, 2016. So this paper focuses on the short-run effects of the election outcome of the 2016 U.S. presidential election.

The estimation period in this paper is set at one year before the election**.** The last two weeks before the election are excluded from the estimation period and included in the event window, because the close relation between election polls and election outcomes can cause biased data around the election date. In order to capture the effect of the presidential election on the stock market, it is important to include the pre-election data in the regression. In this way it is possible for the model to calculate stock return estimates like if the event never happened. The observed post-election stock returns will be compared to the estimations of the model, resulting in abnormal returns caused by the election. The estimation period and the event window are presented in figure 1 below.

Figure 1



where:
T_{-2}: October 26th, 2015
T_{-1}: October 24th, 2016
T_0: November 8th, 2016
T_1: December 30th, 2016

T_0 represents the date the event occurred, (T_{-2}, T_{-1}) represents the estimation period, while (T_{-1}, T_1) represents the event window.

In order to investigate a certain relationship between a specific event and abnormal returns, the data received from the CRSP database must be converted from stock price to stock return using the following formula:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1}$$

where the return of company i at day t equals the natural logarithm of the stock price of company i at day t divided by the stock price of company i a day earlier.

The following formula is used to calculate daily abnormal returns of company i at day t:

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] \tag{2}$$

where $R_{i,t}$ represents the observed stock return of company i at day t, while $E[R_{i,t}]$ represents the expected return of company i at day t.

To estimate expected returns, the Carhart four-factor model is used in this research. Relevant researches are presented in chapter two, including fairly similar researches related to abnormal returns after presidential elections. Cable and Holland (1999) found a tendency among researchers of using simpler methodologies in event studies and Brown and Warner (1980) found no evidence that more complex methodologies in better estimations for expected returns. However, they also mentioned that despite simpler methodologies are still of great value, it is also useful to improve existing models. The findings of Rehnby (2016) supports that statement while comparing the CAPM, Fama-French three-factor model and the Carhart four-factor model. Both the more complex models outperform the CAPM, with the Carhart model slightly outperforming the Fama-French model. Finally, the study of Oehler and Walker (2012) shows strong similarities with research about the relationship between abnormal returns at industry level and American presidential elections, and uses the Carhart four-factor model in their research. Based on this relevant literature, the Carhart four-factor model will be used in this research.

The expected returns are calculated using the Carhart four-factor model:

$$E\left[R_{i,t}\right] = R_{f,t} + \beta_{i,1} * (R_{m,t} - R_{f,t}) + \beta_{i,2} * SMB_t + \beta_{i,3} * HML_t + \beta_{i,4} * WML_t \qquad (3)$$

where $R_{f,t}$ represents the risk-free rate of return, which is the one-month U.S. treasury bill in this research, $(R_{m,t} - R_{f,t})$ represents the market premium, SMB_t represents the small-minus-big factor to capture size effects of the sample group, HML_t represents the high-minus-low factor to capture the value effect, WML_t represents the winners-minus-losers factor to capture momentum effects in the sample group and β_i represents the firm-specific risk exposure related to the market return.

After conducting the abnormal return calculations per day per company, the average abnormal returns (AAR) per day are calculated to help eliminating firm-specific idiosyncrasies.

AAR's are calculated using the following formula:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \qquad (4)$$

where AAR_t represents the average abnormal return on day t, while the component on the right side of the equation represents the sum of abnormal returns on day t from each company i divided by the number of companies N, which are included in the sample group of the industry. In order to analyze the aggregate effect of the abnormal returns over multiple days, the cumulative average abnormal returns per industry j ($CAAR_j^{Industry}$) are calculated using the following formula:

$$CAAR_j^{Industry} = \sum_{i=1}^{N} AAR_t \qquad (5)$$

where the cumulative average abnormal return per industry j is equal to the sum of average abnormal returns realized each day by all companies belonging to a specific industry j.

Now that the cumulative average abnormal returns per industry are known, the results have to be tested for significance to determine the explanatory power these results have. The average abnormal returns per industry are tested using a student t-test:

$$\text{T statistic} = \frac{CAAR_j^{Industry}}{\hat{S}\left(CAAR_j^{Industry}\right) / \sqrt{N}} \tag{6}$$

where $CAAR_j^{Industry}$ represents the cumulative average abnormal returns per industry j, while $\hat{S}\left(CAAR_j^{Industry}\right)$ represents the standard deviation of the cumulative average abnormal returns per industry j and N represents the number of companies included in the research.

5 Results

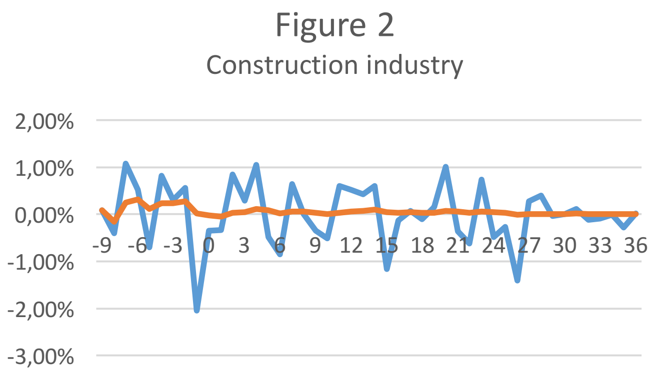
In this chapter, the results of the event study about Trumps presidential election are presented and analyzed. The research is conducted exactly as described in the previous chapter, where the average abnormal return (AAR) variable is an indicator for abnormal returns per individual day in the event window. In addition, the cumulative abnormal return (CAAR) variable shows the aggregate effect of the individual daily abnormal returns over time. Both variables are presented, as well as the number of companies the research is based on and the corresponding t-statistic as an indicator for significant results. Significant results will be marked with asterisks, one for significance at a 10% level, two asterisks for significance at a 5% level and three asterisks for significance at a 1% level. In order to capture industry specific effects, results will be discussed for each industry individually.

Construction industry

The construction sector first shows alternating average abnormal returns in the ten days before the event date, with an extreme negative value of -2,05% the day before the event date (t_{-1}). A possible explanation for this could be a government announcement of revising the procedures for procuring supplies and services, effective from November 7th, 2016 (Commonwealth of Massachusetts). At event date, average abnormal returns rose and continued rising some days after the election. Later on the average abnormal returns returned to the original alternating pattern. In both the pre-election period and the post-election period as well, the average abnormal returns showed some significant results, indicating there might be a relationship observed between the performance of the construction industry and the presidential election of Trump.

The cumulative average abnormal returns show some high values in pre-election period. The drop in CAAR right before the election, remained constant around zero later on. This could be an indicating that the performance of the construction industry is not affected by the presidential election of Donald Trump. In addition, none of the cumulative average abnormal returns after the event date is tested positive for significance, which means that there is not found any evidence for an aggregate effect of the election on the industry performance of construction stocks.

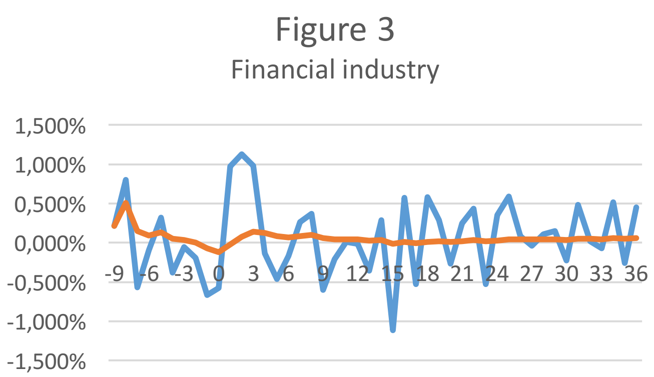
In table 2 in the appendix, the results for AAR and CAAR of the *construction industry* are presented. In Figure 2 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the aggregate effect of the cumulative average abnormal returns.



Financial industry
The financial sector shows an alternating pattern of mostly significant abnormal returns between approximately -0,5% and 0,5% in both pre-election period and post-election period as well. Two striking observations are exceptions of this alternating pattern: a positive peak of average abnormal returns at t_1 and a negative peak of average abnormal returns at t_{15}. The positive peak at the first day after the event date indicates a positive reaction of the financial markets on the Trump election. A possible explanation of the negative peak on t_{15}, November 23th, could be the news headliner that Trump's Democratic opponent, Hillary Clinton, would have won the election on popular votes with a surplus of over two million votes. This could result in a decrease in confidence in the Trump administration. Besides these two peaks, the average abnormal returns in the financial industry followed the original alternating pattern. (Schleifer, 2016)

The cumulative average abnormal returns decreased in the pre-election period, followed by a positive initial reaction of the *financial industry* on the event date, corrected by the market and later on the CAAR continued rising very slowly. A positive peak is observed right after the event date, which is an indication of a positive reaction of the financial markets on the election outcome. However, none of the results around the event date and later on are tested positive, resulting in no evidence is found for the existence of a relationship between the election outcome and abnormal returns in the financial sector.

In table 3 in the appendix, the results for AAR and CAAR of the *financial industry* are presented. In Figure 3 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the aggregate effect of the cumulative average abnormal returns.

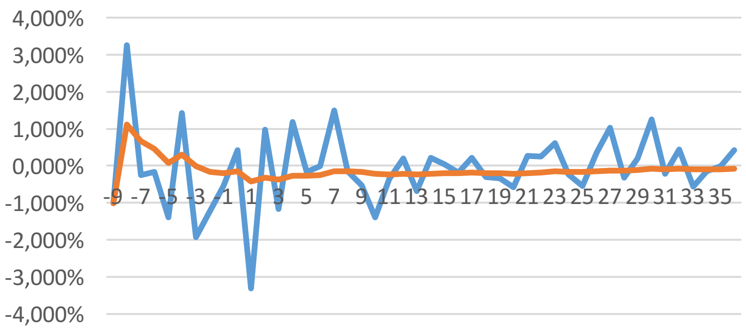


Healthcare industry
The healthcare sector shows an alternating pattern, with more extreme average abnormal returns in the period before the election day and the first week after election day. At event date a significant negative peak is observed, indicating an aversion of the healthcare industry to the presidential election of Donald Trump. The negative shock at t_1 is directly followed by a reaction of the market in opposite direction, which probably explains the negative peak as emotional trading. Overall it can be observed that after election day, the market moved to a less volatile situation.

The cumulative average abnormal returns show a decreasing pattern in the pre-election days, but the aggregate effect increases slightly over time. At event date, an initial negative reaction is observed, followed by a slight increase of CAAR over time. A possible explanation for this pattern is that Trump advocated the abolition of the Obamacare, the nation-wide regulation of health insurance. The significant decrease in the pre-election period is probably due to the uncertainty about the election, the small negative peak at election day also supports this view. Later on, Trump mentioned more moderate statements about the Obamacare, resulting in a slightly rising CAAR. However, none of the results are tested positive for significance, indicating no relationship between the election and the industry performance can be proven.

In table 4 in the appendix, the results for AAR and CAAR of the *healthcare industry* are presented. In Figure 4 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the aggregate effect of the cumulative average abnormal returns.

Figure 4
Healthcare industry

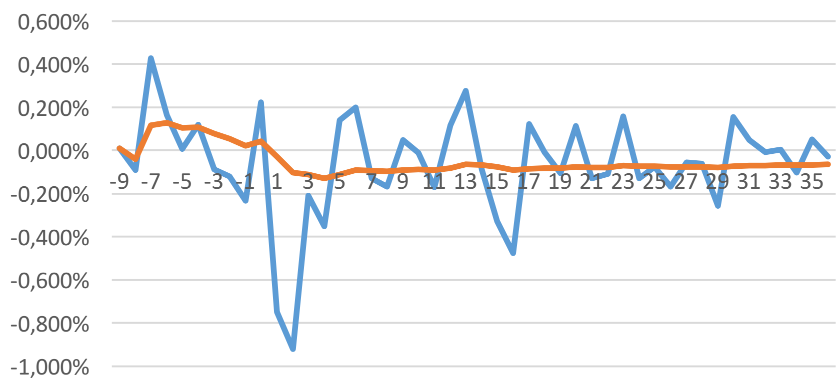


Manufacturing industry
The average abnormal returns of the manufacturing industry show an alternating pattern, with a large negative peak at t_1 and a less extreme negative peak at t_{15}. Both of the peaks are tested positive for significance, indicating the manufacturing industry generated average abnormal returns. Notable is the significant positive reaction at election day t_0, followed by the extreme negative shock at t_1 which is corrected by the market within three days. From that moment on, the pattern of generated abnormal returns keeps fluctuating around zero.

The cumulative average abnormal returns decreased in the pre-election days, rose slightly at election day, decreased even further after the election and started to rise slowly from that moment. From the second day after the election on, the abnormal returns generated a negative aggregated effect on the stock performance in the manufacturing industry, but continued rising slowly. The results of the significance tests are remarkable, with only significant cumulative average abnormal returns in the pre-election period. Therefore, there is no evidence found for the existence of an aggregated effect over time on the *manufacturing industry* performance caused by the Trump election.

In table 5 in the appendix, the results for AAR and CAAR of the *manufacturing industry* are presented. In Figure 5 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the aggregate effect of the cumulative average abnormal returns.

Figure 5
Manufacturing industry

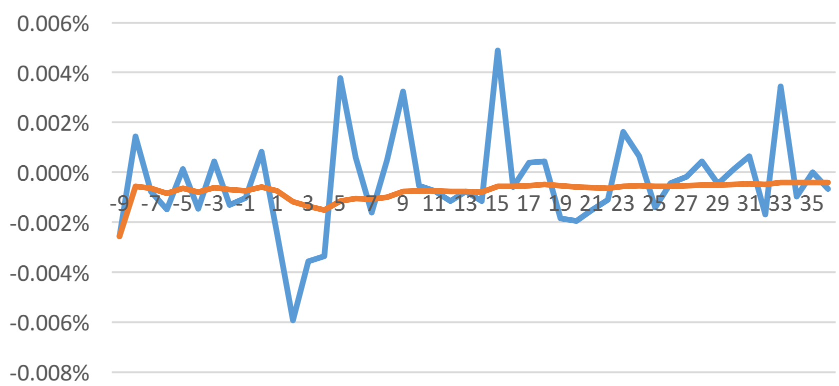


Mining industry
The average abnormal returns generated by the mining industry show an alternating pattern just below zero. However, the first week after event date, the AAR became more volatile, starting with a decrease in average abnormal returns at t_1, resulting in a negative peak at t_2. Furthermore, the extreme negative values were corrected by the market, resulting in positive peaks at t_5 and t_9. The mining industry needed some time to recover from the initial negative response on the presidential election of Trump, but thereafter the AAR show an alternating pattern with more positive values then before. Supported with mostly significant results, this could be an indication of a slightly positive reaction of the mining industry on the Trump election overall.

The cumulative average abnormal returns show during the pre-election period an almost constant aggregate effect of around -0.7%, followed by a negative reaction at event date. After the decrease at t_0, the CAAR slowly rose and continued rising slowly the entire post-election period. Mostly all of the CAAR results are significant at a 1% significance level, which is an indication of evidence for a positive aggregate effect of the Trump election on the performance of the mining industry.

In table 6 in the appendix, the results for AAR and CAAR of the *mining industry* are presented. In Figure 6 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the aggregate effect of the cumulative average abnormal returns.

Figure 6
Mining industry

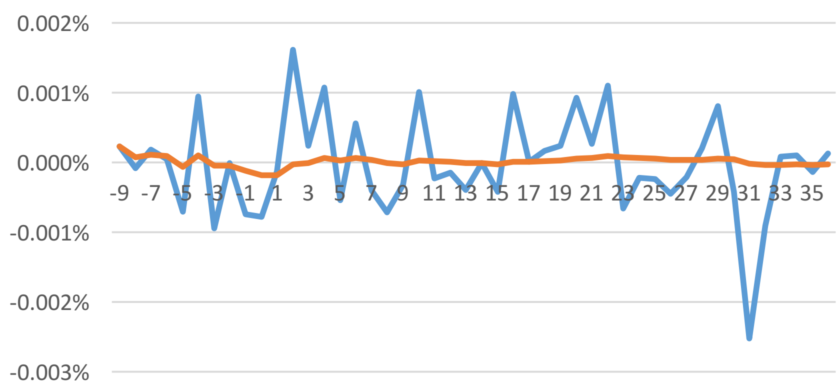


Retail industry
The average abnormal returns generated by the retail industry show an alternating pattern, with an initial slightly negative reaction at event date, followed by a correction of opposite direction. The alternating pattern does not show major peaks in average abnormal returns generated by the retail industry, with an exception made for a large negative shock at t_{31}. At December 22th, which is 31 days after the election (t_{31}), president-elect Donald Trump noted he might impose a tariff on foreign import products, which is cost-increasing, and therefore disastrous for the retail industry (Criss, 2016). Approximately half of the average abnormal results are tested positive for significance, an indication of evidence for the relationship between the presidential election and abnormal stock performance of the retail industry.

The cumulative abnormal returns decreased in the pre-election period, with the event date as turning point. From then on, the CAAR rose and returned to the original pattern fluctuating around 0%. However, only the aggregate effect at t_0 and t_1 are tested positive for significance, indicating there is some evidence for the existence of a short-term relationship between the Trump election and an aggregate effect on the stock performance of the retail industry.

In table 7 in the appendix, the results for AAR and CAAR of the *retail industry* are presented. In Figure 7 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the aggregate effect of the cumulative average abnormal returns.

Figure 7
Retail industry

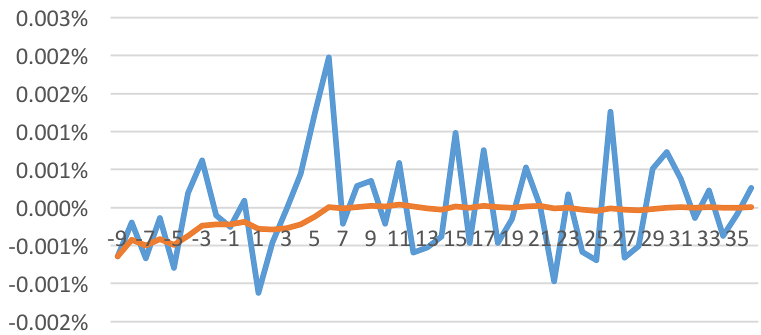


Transportation industry
The average abnormal returns generated by the transportation industry shows an alternating pattern. A striking observation is that around the event date, the magnitude of the fluctuations grew, followed by smaller fluctuations after approximately a week after the election, but these are still fluctuations of greater magnitude then before. At event date, the market responded on the Trump election with a large negative peak at t_1, directly followed by increasing abnormal returns with an even larger positive peak at t_6. After both these shocks, the stock average abnormal returns returned to an alternating pattern. Some of the results found are tested positive for significance, indicating there is evidence for a relationship between abnormal returns and the presidential election of Trump.

The cumulative average abnormal returns rose in the pre-election period and continued rising till the sixth day after the election (t_6). From then on, the CAAR remained constant around zero, indicating there is no aggregate effect over time on the abnormal stock performance in the transportation industry caused by the presidential election of Trump. However, only the increasing aggregate effect observed till t_4 is tested positive for significance, indicating at very short term there is a significant aggregate effect observed on the abnormal transportation industry performance caused by the Trump election.

In table 8 in the appendix, the results for AAR and CAAR of the *transportation industry* are presented. In Figure 8 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the positive aggregate effect of the cumulative average abnormal returns.

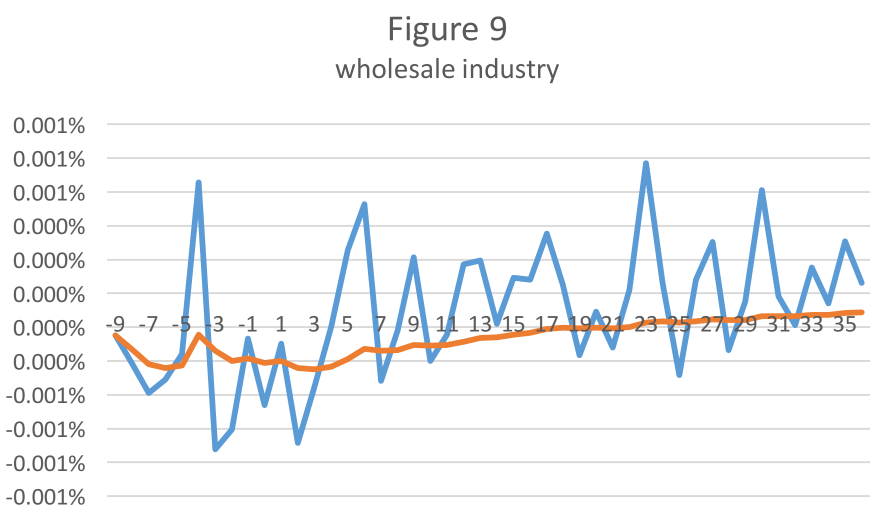
Figure 8
Transportation industry



Wholesale industry
The average abnormal returns generated by the wholesale industry are characterized by a fluctuating pattern with a positive trend. In the pre-election period, both positive and negative peaks are observed. Around the fifth day after the election t_4, the average abnormal returns rose positive and remained at that level. Some of the results are tested positive for significance, indicating that there is evidence for the existence of a relationship between die presidential election and abnormal stock performance of the wholesale industry.

The aggregate effect of average abnormal returns, measured by the CAAR, shows an increasing positive effect starting at the fourth day after the elections (t_4). The period before the fourth day, the cumulative average abnormal returns shows in general an aggregate effect of approximately -0.4%. Almost all of the cumulative average abnormal returns are tested positive for significance, indicating that there is evidence for the existence of a relationship between the Trump election and the abnormal stock performance of the wholesale industry.

In table 9 in the appendix, the results for AAR and CAAR of the *wholesale industry* are presented. In Figure 9 below, the graphs of the AAR and CAAR are presented, showing the alternating average abnormal returns and the positive aggregate effect of the cumulative average abnormal returns.



Now that all of the industries are analyzed separately, it is possible to compare the different industries with each other. Based on the initial reaction at the event date and the pattern of the cumulative average abnormal returns, the industries can be divided into three categories.

The industries *mining, wholesale trade* and *healthcare* all show an initial negative reaction on the election outcome, followed by an increasing pattern of the cumulative average abnormal returns. Both the *mining industry* and *wholesale trade industry* show very significant results for the CAAR, indicating a positive relationship between the presidential election of Trump and the abnormal returns generated in those industries. However, the *healthcare industry* does not show any significant results, indicating there is no evidence found in this research for such a relationship.

The industries *construction, retail trade* and *transportation* all show an initial positive reaction on the election outcome, followed by the cumulative average abnormal returns returning to a constant pattern. However, for the *construction industry* only a few (pre-election period) results are tested positive for significance, for the *retail trade industry* only the initial reaction is tested positive for significance and the *transportation industry* combines both these results with only the initial reaction and all of pre-election period results as well tested positive for significance. These findings indicate that there is no evidence found in this research for the existence of a relationship between the Trump election and industry performance.

The *financial industry* and the *manufacturing industry* both show an initial positive reaction on the election outcome, followed by increasing cumulative average abnormal returns. For both industries, only a few results are significant, all belonging to the pre-election period. So in this case as well, there is no evidence found for an aggregate effect on the industry performance, caused by the Trump election.

6 Conclusion and limitations

The research focused on the question how various American industries responded on the presidential election of Donald Trump. This is examined by an event study, performed for each industry separately. Expected returns are estimated by the Carhart four-factor model and then compared to the returns observed in the stock market. The research presents daily average abnormal returns per industry and combines these industry results to show the aggregate effect the abnormal returns had per industry. In this research, only two industries show an increasing pattern of cumulative average abnormal returns, namely the *mining industry* and the *wholesale industry*.

The *mining industry* shows in the pre-election period a constant pattern for the cumulative average abnormal returns, with a slightly larger negative impact at the election date. This is corrected by the market and the CAAR continues rising very slowly thereafter. Almost all of the results are tested positive for significance in this event study, including the initial negative reaction on the election date. So there is found evidence for the existence of a relationship between the presidential election of Trump and the *mining industry* performance. Based on these results, the conclusion can be made that despite the initial negative reaction, the *mining industry* is affected slightly positive by the presidential election of Trump. This result is supported by Trump's statements about the environment and his ideas about creating jobs (Diamond, 2016).

The *wholesale trade industry* shows an increasing pattern of the cumulative average abnormal returns, supported by positive results when tested at significance. Based on these results, the conclusion can be made that the Trump election had a positive effect on the *wholesale industry* over time. The *wholesale industry* supplies companies engaged in other industries and therefore the performance of the *wholesale industry* can be seen in this research as a proxy for the *mining industry, manufacturing industry and retail industry* (Bureau of Labor Statistics).

The *transportation industry* shows an increase in the pre-election period and the first four days after the election, followed by a constant CAAR around zero over time. These results are supported by the results of the significance tests, because all of the results for the increasing CAAR are tested positive for significance and none of the constant CAAR results are tested positive for significance. Based on these results, the conclusion can be made that there is no evidence found for the Trump election affecting the *transportation industry* over time.

The *retail industry* shows a slightly decreasing pattern in the pre-election period, a positive initial reaction, followed by the CAAR returning to a constant pattern around zero. From all of the CAAR results, only the initial positive reaction on the election has tested positive for significance, indicating the *retail industry* is favored by the presidential election of Trump. This is supported by Trump's 'American first' attitude towards trading ties, which tried to stimulate the domestic trading. However, based on these results, there is not enough evidence found in this research to conclude that the *retail industry* performance is affected by the Trump election.

The *manufacturing industry* generated significant positive abnormal returns in the pre-election period. However, after the event date, the CAAR decreased sharply till below zero, indicating a strong negative effect of the presidential election of Trump on the industry performance. Followed by a continued slowly rising CAAR, which could be overall a positive reaction on the Trump election. Both the negative results and positive results are not tested positive for significance though, so based on the findings of this research, there is no evidence found for a relationship between the *manufacturing industry* performance and the presidential election of Trump.

The CAAR of the *healthcare industry* shows at first an aversion to Trump, but started to rise very slowly later on. The development of Trump's attitude towards the Obamacare supports these results (Diamond, 2016). However, none of the results for CAAR are tested positive for significance, so based on this research there is found no evidence for a relationship between the presidential election of Trump and the *healthcare industry* performance.

The *financial industry* shows no general pattern in cumulative average abnormal returns. After a decrease in the pre-election period and an initial positive response, the CAAR starts rising at the event date and continued rising very slowly later on. The positive reaction of the financial sector is supported by the policy Trump has in mind for Wall Street Diamond, 2016). However, only a few pre-election period results are tested positive for significance, resulting in no evidence is found for the relationship between the presidential election of Trump and the *financial industry* performance, based on the results of this research.

The *construction industry* generated significant, positive cumulative average abnormal returns in the pre-election period, followed by a decrease in CAAR, which none of them is tested positive for significance. However, the drop in CAAR from pre-election period to post-election period is not tested positive for significance, resulting in no evidence is found in this research for the existence of a relationship between the Trump election and abnormal returns in the

For all of the industries, there are found significant results of average abnormal returns in both the pre-election period and post-election period as well. This is probably an indication of industry-specific responses on specific daily events. The aggregate effect of these industry-specific responses on specific daily events is captured by the cumulative average abnormal returns. However, the CAAR is not found significant for every industry, but only for the *mining industry* and *wholesale industry.* Based on these findings, the conclusion in this research can be made that only for those two industries evidence is found for the existence of an aggregate effect on the industry performance, caused by the presidential election of Donald Trump.

For the other industries, a notable observation is that if there are any significant results for CAAR, those are mainly found in the pre-election period. A possible explanation for this is the unexpected victory of Donald Trump in the presidential election. If the general belief was a victory of Hillary Clinton, people were behaving before the election like the outcome of the election was already clear. This could be reflected in the stock market by the relative large number of significant results in the pre-election period. When suddenly Trump was elected as president, the shock among the people can be reflected on the stock market, resulting in insignificant results after the event date.

Overall, most of the findings of this research turned out to be insignificant. Eight different industries were captured in the research and a meaningful conclusion can me drawn about

two of them. Because the event occurred relative recently, it is possible some conclusions in this research are interpreted in a wrong way, due to a lack of available data.
In this research, data is included from a year before the election till two months after the election to see if the election had any effect on the industry performances. An event window of two months is very small in context of a complete presidential term of four years. Still this research is of value, because the period between election and inauguration covers the first response of the stock market on the new president.

Another point of interest in this research is the way the different industries are composed. In this research, industry peer groups are used as a proxy for the entire industry. The danger in using peer groups is that the peer group turns out not to be representative for the entire industry. To check for this pitfall is difficult.

In the future, this research can be extended in several ways. The expected return estimation model used in the research could be analyzed and maybe be replaced by another more complex or more accurate estimation model. Besides, the industry peer groups could be analyzed and adjusted.

Finally, another possibility to extend this research is to examine the international effect the election of Donald Trump had on the industry stock performance. It is an interesting field of interest, because of the growth of America, the trading ties the nation has around the world and the influence American companies have on the global stock market.

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8 Appendix

Table 2

Abnormal returns in the construction industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	0,09%	0,265	0,088%	0,265	55
-8	-0,40%	-1,224	-0,155%	-0,669	55
-7	1,08%	4,061***	0,257%	1,401	55
-6	0,52%	2,150**	0,323%	2,146**	55
-5	-0,71%	-2,115**	0,117%	0,838	55
-4	0,82%	2,306**	0,233%	1,783*	55
-3	0,30%	0,814	0,243%	1,963*	54
-2	0,56%	1,712*	0,281%	2,436**	54
-1	-2,05%	-0,233	0,022%	0,022	55
0	-0,35%	-1,186	-0,015%	-0,017	55
1	-0,34%	-0,706	-0,045%	-0,056	55
2	0,84%	2,519**	0,030%	0,040	55
3	0,29%	0,543	0,050%	0,073	55
4	1,06%	2,785***	0,122%	0,193	55
5	-0,48%	-1,849**	0,082%	0,138	55
6	-0,85%	-2,805***	0,023%	0,042	55
7	0,65%	3,079***	0,060%	0,116	55
8	0,01%	0,054	0,058%	0,117	55
9	-0,35%	-1,560	0,036%	0,077	55
10	-0,51%	-1,112	0,009%	0,020	55
11	0,61%	2,323**	0,037%	0,088	55
12	0,52%	2,346**	0,059%	0,147	55
13	0,42%	2,066**	0,075%	0,195	55
14	0,60%	2,688***	0,097%	0,263	55
15	-1,16%	-4,267***	0,047%	0,131	55
16	-0,13%	-0,456	0,040%	0,116	55
17	0,08%	0,241	0,041%	0,125	55
18	-0,10%	-0,370	0,036%	0,113	55
19	0,16%	0,513	0,040%	0,131	55
20	1,02%	3,883***	0,073%	0,245	55
21	-0,36%	-1,351	0,059%	0,204	55
22	-0,61%	-2,223**	0,038%	0,135	55
23	0,74%	3,445***	0,059%	0,218	55
24	-0,48%	-1,908**	0,043%	0,164	55
25	-0,26%	-1,226	0,034%	0,135	55
26	-1,40%	-6,303***	-0,006%	-0,022	55
27	0,28%	1,103	0,002%	0,009	55
28	0,40%	1,621	0,013%	0,054	55
29	-0,03%	-0,163	0,011%	0,050	55
30	0,00%	0,015	0,011%	0,050	55
31	0,12%	0,568	0,014%	0,063	55
32	-0,12%	-0,438	0,011%	0,050	55
33	-0,09%	-0,567	0,008%	0,040	55
34	0,00%	-0,010	0,008%	0,040	55
35	-0,28%	-1,105	0,002%	0,009	55
36	0,02%	0,116	0,002%	0,011	55

*Significance level *: 10%, **: 5%, ***: 1%*

Table 3

		Abnormal returns in the financial industry			
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	0,218%	2,042**	0,218%	2,042**	251
-8	0,804%	6,564***	0,511%	6,216***	251
-7	-0,569%	-4,591***	0,151%	2,123**	251
-6	-0,095%	-1,187	0,089%	1,567	251
-5	0,317%	4,132***	0,135%	2,800***	251
-4	-0,383%	-5,787***	0,049%	1,160	251
-3	-0,056%	-0,464	0,034%	0,848	251
-2	-0,192%	-3,079***	0,006%	0,154	251
-1	-0,663%	-0,122	-0,069%	-0,114	251
0	-0,577%	-8,684***	-0,120%	-0,220	251
1	0,975%	6,346***	-0,020%	-0,041	251
2	1,123%	8,588***	0,075%	0,166	251
3	0,976%	6,080***	0,145%	0,346	251
4	-0,137%	-1,156	0,124%	0,320	251
5	-0,463%	-2,544**	0,085%	0,235	251
6	-0,171%	-1,803*	0,069%	0,204	251
7	0,261%	2,968***	0,080%	0,252	251
8	0,366%	2,662***	0,096%	0,319	251
9	-0,599%	-6,815***	0,060%	0,209	251
10	-0,211%	-2,842***	0,046%	0,170	251
11	0,010%	0,153	0,044%	0,172	251
12	-0,015%	-0,282	0,042%	0,169	251
13	-0,354%	-4,723***	0,025%	0,104	251
14	0,289%	1,604	0,036%	0,157	251
15	-1,113%	-9,649***	-0,010%	-0,048	251
16	0,572%	6,182***	0,012%	0,057	251
17	-0,525%	-7,177***	-0,008%	-0,039	251
18	0,583%	1,050	0,013%	0,068	251
19	0,285%	2,717***	0,023%	0,120	251
20	-0,267%	-1,677*	0,013%	0,071	251
21	0,246%	1,948*	0,020%	0,116	251
22	0,431%	4,270***	0,033%	0,194	251
23	-0,524%	-5,665***	0,016%	0,099	251
24	0,355%	4,924***	0,026%	0,164	251
25	0,592%	4,651***	0,043%	0,272	251
26	0,081%	0,666	0,044%	0,286	251
27	-0,035%	-0,269	0,042%	0,280	251
28	0,107%	1,486	0,043%	0,299	251
29	0,146%	1,783*	0,046%	0,326	251
30	-0,224%	-0,823	0,039%	0,285	251
31	0,486%	8,788***	0,050%	0,373	251
32	0,017%	0,282	0,049%	0,376	251
33	-0,070%	-1,337	0,046%	0,363	251
34	0,519%	8,155***	0,057%	0,458	251
35	-0,262%	-4,085***	0,050%	0,410	251
36	0,453%	7,767***	0,059%	0,492	251

*Significance level *: 10%, **: 5%, ***: 1%*

Table 4

Abnormal returns in the healthcare industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	-1,010%	-2,5265**	-1,010%	-2,5265**	50
-8	3,249%	0,6326	1,120%	0,4354	50
-7	-0,245%	-0,5462	0,665%	0,3868	50
-6	-0,171%	-0,3391	0,456%	0,3522	50
-5	-1,403%	-2,7881***	0,084%	0,0809	50
-4	1,428%	3,0329***	0,308%	0,3537	50
-3	-1,937%	-1,3386	-0,013%	-0,0162	50
-2	-1,229%	-2,2004**	-0,165%	-0,2413	50
-1	-0,548%	-0,4755	-0,207%	-0,3345	50
0	0,427%	0,4509	-0,144%	-0,2544	50
1	-3,310%	-2,6737***	-0,432%	-0,8187	50
2	0,966%	1,4333	-0,315%	-0,6475	50
3	-1,173%	-2,0130**	-0,381%	-0,8440	50
4	1,187%	2,4821**	-0,269%	-0,6392	50
5	-0,165%	-0,4213	-0,262%	-0,6658	50
6	-0,004%	-0,0072	-0,246%	-0,6640	50
7	1,497%	1,3348	-0,143%	-0,4041	50
8	-0,146%	-0,1406	-0,144%	-0,4222	50
9	-0,534%	-1,1950	-0,164%	-0,5082	50
10	-1,401%	-4,3545***	-0,226%	-0,7352	50
11	-0,352%	-1,1289	-0,232%	-0,7915	50
12	0,189%	0,8352	-0,213%	-0,7603	50
13	-0,679%	-1,8748*	-0,233%	-0,8691	50
14	0,215%	0,5203	-0,214%	-0,8323	50
15	0,038%	0,0899	-0,204%	-0,8244	50
16	-0,186%	-0,4979	-0,204%	-0,8529	50
17	0,210%	0,7873	-0,188%	-0,8184	50
18	-0,298%	-0,8558	-0,192%	-0,8650	50
19	-0,344%	-1,3462	-0,197%	-0,9195	50
20	-0,577%	-1,2250	-0,210%	-1,0093	50
21	0,263%	0,6593	-0,195%	-0,9653	50
22	0,241%	0,8364	-0,181%	-0,9258	50
23	0,618%	1,2778	-0,157%	-0,8246	50
24	-0,230%	-0,5040	-0,159%	-0,8589	50
25	-0,555%	-1,0125	-0,170%	-0,9435	50
26	0,346%	0,8083	-0,156%	-0,8867	50
27	1,022%	2,5074**	-0,125%	-0,7271	49
28	-0,319%	-0,6971	-0,130%	-0,7744	49
29	0,193%	0,5938	-0,122%	-0,7431	50
30	1,258%	2,5622**	-0,087%	-0,5440	50
31	-0,220%	-0,6946	-0,090%	-0,5777	50
32	0,434%	1,7555*	-0,078%	-0,5095	50
33	-0,566%	-2,7848***	-0,089%	-0,5974	50
34	-0,155%	-0,5725	-0,091%	-0,6211	50
35	-0,011%	-0,0607	-0,089%	-0,6226	50
36	0,419%	1,4917	-0,078%	-0,5568	50

*Significance level *: 10%, **: 5%, ***: 1%*

Table 5

Abnormal returns in the manufacturing industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	0,009%	0,107	0,009%	0,107	864
-8	-0,091%	-0,877	-0,041%	-0,598	864
-7	0,427%	4,570***	0,115%	2,086**	864
-6	0,165%	2,147**	0,128%	2,795***	864
-5	0,007%	0,074	0,103%	2,530**	864
-4	0,119%	1,300	0,106%	2,841***	864
-3	-0,087%	-0,670	0,079%	2,125**	864
-2	-0,120%	-1,142	0,054%	1,539	864
-1	-0,234%	-0,049	0,022%	0,040	864
0	0,223%	2,674***	0,042%	0,087	864
1	-0,749%	-4,225***	-0,030%	-0,069	864
2	-0,919%	-4,210***	-0,104%	-0,259	864
3	-0,211%	-2,080**	-0,112%	-0,302	864
4	-0,353%	-2,601***	-0,130%	-0,375	864
5	0,141%	1,618	-0,111%	-0,346	864
6	0,199%	2,135**	-0,092%	-0,304	864
7	-0,130%	-1,742*	-0,094%	-0,331	864
8	-0,169%	-2,466**	-0,098%	-0,366	864
9	0,048%	0,693	-0,091%	-0,356	864
10	-0,010%	-0,151	-0,087%	-0,358	864
11	-0,171%	-1,579	-0,091%	-0,394	864
12	0,116%	1,983**	-0,081%	-0,370	864
13	0,277%	4,297***	-0,066%	-0,312	864
14	-0,089%	-1,278	-0,067%	-0,331	864
15	-0,328%	-2,611***	-0,077%	-0,398	864
16	-0,477%	-3,857***	-0,092%	-0,497	864
17	0,122%	1,761*	-0,085%	-0,471	864
18	-0,008%	-0,123	-0,082%	-0,473	864
19	-0,105%	-1,620	-0,083%	-0,495	864
20	0,114%	1,263	-0,076%	-0,471	864
21	-0,131%	-1,458	-0,078%	-0,498	864
22	-0,110%	-1,395	-0,079%	-0,521	864
23	0,157%	2,070**	-0,072%	-0,488	864
24	-0,131%	-2,049**	-0,073%	-0,515	864
25	-0,077%	-1,294	-0,073%	-0,531	864
26	-0,168%	-2,876***	-0,076%	-0,565	864
27	-0,057%	-0,796	-0,076%	-0,577	864
28	-0,061%	-0,765	-0,075%	-0,589	864
29	-0,258%	-3,346***	-0,080%	-0,643	864
30	0,155%	2,294**	-0,074%	-0,610	864
31	0,048%	0,719	-0,071%	-0,601	864
32	-0,009%	-0,207	-0,070%	-0,602	864
33	0,004%	0,057	-0,068%	-0,602	864
34	-0,104%	-1,757*	-0,069%	-0,623	864
35	0,052%	1,294	-0,066%	-0,612	864
36	-0,030%	-0,511	-0,065%	-0,618	864

*Significance level *: 10%, **: 5%, ***: 1%*

Table 6

Abnormal returns in the mining industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	-2,560%	-6,580***	-2,560%	-6,580***	161
-8	1,442%	0,839	-0,552%	-0,621	161
-7	-0,771%	-2,427**	-0,625%	-1,037	161
-6	-1,492%	-2,888***	-0,839%	-1,781*	161
-5	0,128%	0,415	-0,648%	-1,691*	161
-4	-1,455%	-3,709***	-0,783%	-2,403**	161
-3	0,441%	1,385	-0,607%	-2,147**	161
-2	-1,297%	-3,841***	-0,694%	-2,766***	161
-1	-1,024%	-3,272***	-0,731%	-3,238***	161
0	0,822%	2,015**	-0,576%	-2,777***	161
1	-2,428%	-5,539***	-0,744%	-3,849***	161
2	-5,921%	-13,859***	-1,176%	-6,405***	161
3	-3,571%	-8,439***	-1,362%	-7,866***	161
4	-3,350%	-9,897***	-1,505%	-9,241***	161
5	3,775%	8,332***	-1,149%	-7,304***	161
6	0,589%	2,314**	-1,039%	-7,000***	161
7	-1,617%	-4,545***	-1,073%	-7,595***	161
8	0,500%	1,801*	-0,986%	-7,331***	161
9	3,241%	10,255***	-0,761%	-5,872***	161
10	-0,529%	-1,668*	-0,750%	-6,038***	161
11	-0,733%	-2,656***	-0,749%	-6,295***	161
12	-1,154%	-5,590***	-0,767%	-6,736***	161
13	-0,765%	-2,978***	-0,767%	-7,007***	161
14	-1,155%	-4,426***	-0,783%	-7,428***	161
15	4,896%	8,148***	-0,558%	-5,289***	161
16	-0,594%	-1,521	-0,559%	-5,454***	161
17	0,403%	0,801	-0,524%	-5,210***	161
18	0,452%	1,201	-0,489%	-4,992***	161
19	-1,849%	-7,073***	-0,536%	-5,640***	161
20	-1,951%	-5,206***	-0,584%	-6,292***	161
21	-1,509%	-4,788***	-0,614%	-6,791***	161
22	-1,089%	-3,488***	-0,628%	-7,137***	161
23	1,615%	3,190***	-0,561%	-6,450***	161
24	0,646%	1,528	-0,525%	-6,156***	161
25	-1,413%	-5,059***	-0,551%	-6,610***	161
26	-0,438%	-1,389	-0,547%	-6,722***	161
27	-0,181%	-0,590	-0,538%	-6,747***	161
28	0,439%	1,652	-0,512%	-6,567***	161
29	-0,451%	-1,805*	-0,510%	-6,697***	161
30	0,147%	0,641	-0,494%	-6,627***	161
31	0,651%	2,481**	-0,465%	-6,379***	161
32	-1,683%	-2,192**	-0,494%	-6,721***	161
33	3,457%	1,251	-0,403%	-4,176***	161
34	-0,972%	-4,046***	-0,415%	-4,400***	161
35	-0,007%	-0,030	-0,406%	-4,395***	161
36	-0,657%	-2,416**	-0,412%	-4,544***	161

*Significance level *: 10%, **: 5%, ***: 1%*

Table 7

Abnormal returns in the retail industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	0,222%	1,201	0,222%	1,201	152
-8	-0,086%	-0,252	0,068%	0,349	152
-7	0,183%	0,863	0,106%	0,720	152
-6	0,043%	0,294	0,090%	0,776	152
-5	-0,712%	-3,498***	-0,070%	-0,685	152
-4	0,945%	3,860***	0,098%	1,030	152
-3	-0,946%	-2,783***	-0,050%	-0,526	152
-2	-0,014%	-0,055	-0,046%	-0,511	152
-1	-0,748%	-3,712***	-0,124%	-1,498	152
0	-0,786%	-1,655*	-0,190%	-2,153**	152
1	-0,128%	-0,315	-0,185%	-2,087**	152
2	1,609%	4,034***	-0,034%	-0,390	152
3	0,235%	1,192	-0,014%	-0,164	152
4	1,073%	2,751***	0,064%	0,782	152
5	-0,540%	-1,921*	0,024%	0,302	152
6	0,556%	2,552**	0,057%	0,759	152
7	-0,407%	-1,198	0,030%	0,405	152
8	-0,722%	-2,738***	-0,012%	-0,170	152
9	-0,321%	-2,036**	-0,028%	-0,418	152
10	1,008%	3,980***	0,024%	0,358	152
11	-0,234%	-1,069	0,011%	0,178	152
12	-0,153%	-1,029	0,004%	0,062	152
13	-0,393%	-2,461**	-0,013%	-0,229	152
14	-0,014%	-0,072	-0,014%	-0,237	152
15	-0,421%	-1,288	-0,030%	-0,531	152
16	0,978%	2,634***	0,009%	0,160	152
17	0,008%	0,029	0,009%	0,163	152
18	0,164%	0,853	0,015%	0,272	152
19	0,233%	0,832	0,022%	0,421	152
20	0,927%	5,125***	0,052%	1,024	152
21	0,259%	1,090	0,059%	1,180	152
22	1,099%	0,725	0,092%	1,352	152
23	-0,659%	-3,184***	0,069%	1,042	152
24	-0,224%	-1,505	0,060%	0,936	152
25	-0,240%	-1,308	0,052%	0,823	152
26	-0,451%	-1,755*	0,038%	0,613	152
27	-0,211%	-0,929	0,031%	0,514	152
28	0,197%	1,319	0,035%	0,602	152
29	0,803%	1,885*	0,055%	0,946	152
30	-0,429%	-3,310***	0,043%	0,755	152
31	-2,520%	-11,826***	-0,020%	-0,355	152
32	-0,913%	-5,440***	-0,041%	-0,753	152
33	0,082%	0,495	-0,038%	-0,715	152
34	0,098%	0,608	-0,035%	-0,671	152
35	-0,143%	-1,172	-0,038%	-0,732	152
36	0,126%	0,945	-0,034%	-0,676	152

*Significance level *: 10%, **: 5%, ***: 1%*

Table 8

Abnormal returns in the transportation industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	-0,646%	-2,694***	-0,646%	-2,694***	100
-8	-0,199%	-0,658	-0,422%	-2,189**	100
-7	-0,668%	-1,896*	-0,505%	-2,898***	100
-6	-0,136%	-0,712	-0,413%	-2,964***	100
-5	-0,795%	-5,066***	-0,490%	-4,230***	100
-4	0,191%	0,918	-0,377%	-3,658***	100
-3	0,618%	1,799*	-0,236%	-2,325**	100
-2	-0,101%	-0,333	-0,219%	-2,271**	100
-1	-0,257%	-0,976	-0,224%	-2,466**	100
0	0,089%	0,292	-0,192%	-2,204**	100
1	-1,128%	-3,229***	-0,278%	-3,240***	100
2	-0,460%	-1,340	-0,293%	-3,505***	100
3	-0,023%	-0,059	-0,272%	-3,285***	100
4	0,441%	1,344	-0,222%	-2,750***	100
5	1,239%	3,288***	-0,125%	-1,560	100
6	1,977%	1,314	0,005%	0,043	100
7	-0,216%	-0,425	-0,008%	-0,068	100
8	0,280%	1,059	0,008%	0,071	100
9	0,347%	1,096	0,026%	0,240	100
10	-0,216%	-0,678	0,013%	0,131	100
11	0,583%	1,838*	0,041%	0,410	100
12	-0,593%	-3,352***	0,012%	0,125	100
13	-0,527%	-2,683*	-0,012%	-0,128	100
14	-0,381%	-1,702*	-0,027%	-0,309	100
15	0,982%	3,018***	0,014%	0,159	100
16	-0,468%	-1,585	-0,005%	-0,062	100
17	0,752%	4,393***	0,023%	0,289	100
18	-0,465%	-2,275**	0,006%	0,072	100
19	-0,155%	-0,932	0,000%	0,001	100
20	0,527%	2,462**	0,018%	0,243	100
21	0,026%	0,130	0,018%	0,254	100
22	-0,972%	-3,194***	-0,013%	-0,186	100
23	0,171%	0,702	-0,007%	-0,107	100
24	-0,586%	-2,534**	-0,024%	-0,370	100
25	-0,693%	-2,470**	-0,044%	-0,675	100
26	1,259%	3,028***	-0,008%	-0,119	100
27	-0,663%	-2,649***	-0,025%	-0,403	100
28	-0,507%	-2,490**	-0,038%	-0,619	100
29	0,512%	3,035***	-0,024%	-0,396	100
30	0,727%	3,864***	-0,005%	-0,082	100
31	0,373%	2,313**	0,005%	0,079	100
32	-0,142%	-1,223	0,001%	0,018	100
33	0,225%	1,573	0,006%	0,114	100
34	-0,372%	-2,983***	-0,002%	-0,045	100
35	-0,088%	-0,608	-0,004%	-0,082	100
36	0,258%	1,949*	0,001%	0,026	100

*Significance level *: 10%, **: 5%, ***: 1%*

Table 9

Abnormal returns in the wholesale industry					
t	**AAR**	**AAR t-stat**	**CAAR**	**CAAR t-stat**	**N**
-9	-0,249%	-0,817	-0,249%	-0,817	101
-8	-0,416%	-1,433	-0,332%	-1,584	101
-7	-0,590%	-1,564	-0,419%	-2,226**	101
-6	-0,510%	-1,707*	-0,441%	-2,767***	101
-5	-0,358%	-1,362	-0,425%	-3,078***	101
-4	0,659%	3,190***	-0,244%	-2,014**	101
-3	-0,923%	-1,550	-0,341%	-2,539**	101
-2	-0,806%	-1,733*	-0,399%	-3,043***	101
-1	-0,268%	-0,883	-0,384%	-3,170***	101
0	-0,663%	-1,806*	-0,412%	-3,581***	101
1	-0,296%	-0,608	-0,401%	-3,540***	101
2	-0,885%	-1,364	-0,442%	-3,772***	101
3	-0,552%	-1,767*	-0,450%	-4,067***	101
4	-0,201%	-0,429	-0,433%	-4,001***	101
5	0,257%	0,614	-0,387%	-3,695***	101
6	0,526%	1,807*	-0,330%	-3,298***	101
7	-0,519%	-2,344**	-0,341%	-3,591***	101
8	-0,218%	-0,976	-0,334%	-3,692***	101
9	0,213%	0,838	-0,305%	-3,515***	101
10	-0,399%	-1,249	-0,310%	-3,690***	101
11	-0,243%	-1,096	-0,307%	-3,803***	101
12	0,171%	0,935	-0,285%	-3,679***	101
13	0,196%	1,041	-0,264%	-3,541***	101
14	-0,179%	-0,960	-0,260%	-3,624***	101
15	0,094%	0,224	-0,246%	-3,468***	101
16	0,080%	0,221	-0,234%	-3,354***	101
17	0,355%	0,604	-0,212%	-2,999***	101
18	0,050%	0,164	-0,202%	-2,934***	101
19	-0,367%	-1,725	-0,208%	-3,107***	101
20	-0,107%	-0,482	-0,204%	-3,142***	101
21	-0,320%	-1,102	-0,208%	-3,271***	101
22	0,022%	0,112	-0,201%	-3,243***	101
23	0,771%	2,516	-0,171%	-2,815***	101
24	0,058%	0,330	-0,165%	-2,775***	101
25	-0,482%	-2,349**	-0,174%	-3,000***	101
26	0,082%	0,431	-0,167%	-2,947***	101
27	0,306%	1,040	-0,154%	-2,766***	101
28	-0,336%	-1,630	-0,159%	-2,914***	101
29	-0,048%	-0,190	-0,156%	-2,916***	101
30	0,612%	3,071***	-0,137%	-2,610**	101
31	-0,019%	-0,078	-0,134%	-2,602**	101
32	-0,186%	-1,253	-0,135%	-2,684***	101
33	0,152%	0,876	-0,128%	-2,602**	101
34	-0,058%	-0,351	-0,127%	-2,622**	101
35	0,307%	1,990*	-0,117%	-2,470**	101
36	0,062%	0,415	-0,113%	-2,435**	101

*Significance level *: 10%, **: 5%, ***: 1%*