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Do Analysts' Recommendations have Investment Value?

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DECLARATION

“I hereby declare that this Master's thesis, submitted to the Zürich University of Applied Sciences in complete fulfilment of the Master Thesis Module, is the result of my own work and that to the best of my knowledge, it has not been presented elsewhere for a higher degree. All sources of information have been acknowledged in the references.”

Signed:

Marie-Madeleine Meck

Winterthur, June 15, 2018

Preface and Acknowledgements

This master thesis *"Do Analysts' Recommendations have Investment Value",* which I have written between February 2018 until June 2018, is submitted as part of the Master's Program Banking and Finance at Zurich University of Applied Sciences- ZHAW -School of Management and Law. This research field in analyzing the investment value of analysts, especially of sell-side analysts, who are mainly employed at brokerage firms and investment banks, is in my point of view particularly of interest due to various reasons, firstly due to the remarkable high analyst coverage in the banking sector, secondly due to the absence of latest research on the value of analysts and lastly to the commonly known optimistic and crowding behavior in analysts' recommendations.

First and foremost, I would like to express my gratitude to my supervisor Professor Dr. Hans Brunner for his excellent guidance, taking time to answer my questions, for the useful comments and remarks through the learning process of this master thesis.

Finally, the author would like to express her very profound gratitude to her beloved family and I am eternally grateful to my parents, my grandparents, my brother and my sisters for their unconditional support, continuous encouragement and motivation throughout my years of study and through the process of researching and writing this master thesis. Without their unconditional support and believes in me, this accomplishment would not have been possible. My sincere appreciation also belongs to all those, whose unconditional support and friendship helped me to stay focused and who were understandable during the many hours spent away from them while studying and working on this master thesis. To all of you, I extend my sincere gratitude.

Lastly, I am thankful for the opportunity to be part of this Banking and Finance Master's program in English. It has been an enormous learning experience, with continuous improvements and full of demanding challenges of expanding my knowledge and moving out of my comfort zone.

Management Summary

Financial analysts and their work have attracted the interest of numerous researchers. As the banking sector employs thousands of (mostly sell-side) analysts to cover corporations and to write „independent" research reports in order to issue *'Buy'*, *'Hold'* or *'Sell'* recommendations, one can expect to generate excess returns by trading according to analysts recommendation revisions. This means their activities are expected to have value and also banks argue that their equity analysts, who are known as experts within their industries they follow, increase market efficiency. So far, the results of previously conducted research on the United States equity market examined the impact of analysts' recommendations on stock prices and their publications showed remarkably that analysts add value to the market. Those findings contradict the efficient market hypothesis which states that if the semi-strong and strong form of the hypothesis holds, no excess returns can be achieved by action on fundamental analysis such as analyst reports.

The main purpose of this master thesis *"Do Analysts' Recommendations have Investment Value",* was to investigate if analysts' recommendations issued on corporations included in the Dow Jones Industrial Average during the time period ranging from 2000 to 2017, have investment value. Specifically, it was examined whether it was worthwhile to act upon analysts' recommendations, issued on the 30 largest and mainly publicly owned companies in the United States. In this context to answer the quoted research question, it was required to answer hypotheses which cover the behavior of analysts' recommendations, analysts' preferences regarding coverage of a particular sector, the impact of recommendation upgrades and downgrades on the respective security prices, the relationship between analysts' recommendations and market sentiments, the impact of analyst coverage and brokerage coverage on security prices.

The methodology used in this study in order to analyze analysts' recommendations issued from brokerage firms on the respective securities included in the DJIA is primarily quantitative. The quantitative analysis was conducted through descriptive statistics, the abnormal returns were calculated via regression analysis, security price reactions were analyzed around the reported recommendation event date by applying the event study methodology and lastly the price performance of recommendation revisions were analyzed by applying a cross-sectional regression analysis.

The results on analysts' recommendations frequency distribution showed evidently that analysts are firstly issuing more optimistic recommendations, secondly issuing less frequently sell recommendations and thirdly have a clear preference to cover a certain sector, namely the attractive technology sector. The event study aimed at analyzing security price reactions in form of abnormal returns in the pre-event window before the event *'recommendation announcement'* happened and after the event in the post-event window. The results of abnormal returns for upgrades showed that investors are not able to gain excess returns by trading according to analysts revised recommendation direction and investors are therefore not able to obtain a value from analysts work. Contrarily, recommendation downgrades are associated with negative abnormal returns and are moving towards analysts' forecasted directions. The empirical results of the cross-sectional regression analysis have evidently rejected analysts' ability to be able to discover stocks which are undervalued or overvalued. Overall, for recommendation upgrades and downgrades this thesis found significant volume reactions around and before the event date, which imply analysts' recommendations have a significant effect on the volume traded of the respective securities, centered around the recommendation event date.

In conclusion, the empirical findings of this research showed that analysts are predominantly issuing optimistic recommendations and have a tendency to revise their previous recommendations. Investors have not a value in form of positive abnormal returns and following that one could reasonably ask what real value analysts have.

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List of Abbreviations

AAR	Average Abnormal Returns
AMSE	American Stock Exchange
AR	Abnormal Returns
Bps	Basis Points
CAAR	Cumulative Average Abnormal Returns
CAGR	Compounded annual growth rate
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Returns
DJIA	Dow Jones Industrial Average
EP	Earnings-to-price
GBM	Geometric Brownian Motion
NR	Normal Returns
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PB	Price-to-book
R	Return
VIX	Volatility Index

1 Introduction

This chapter presents an introduction to the topic and provides an overview of this master thesis. As a starting point the background and the situation in analyzing the investment value of analysts are presented. This section also describes the research question and the subsequent hypotheses.

1.1 Background and Situation

Extant literature has explored analysts stock recommendations extensively and the interest in analyzing analysts for financial researchers is of significant interest as their activities affect capital market efficiency.

Analysts are seen as an important agent between investors and companies they follow and their main tasks are forecasting earnings, writing stock recommendations reports and assisting with their opinions indirectly investment banking trading volumes. Based on their intensive analytical research process, analysts provide buy, hold or sell recommendations to clients, potential investors or to their own asset management departments. Their activities leave space for fundamental questions, for example are analysts able to predict winner stocks and loser stocks? If so, how quickly are information's provided by analysts incorporated in market prices, do analysts have the ability to predict market movements and are analysts assisting markets to move towards efficiency?

According to Grossman and Stiglitz (1980) observations the market does not perfectly incorporate all information's and investors need analysts as market agent, who are able to find overvalued and undervalued securities and keep the markets efficient. Whereas advocates for efficient market hypothesis claim that markets and stock prices reflect all publicly information analysts' recommendations do not result in any value to investors as stock price movements are unpredictable and they follow a random walk. This view is kind of naive, as the banking sector employs thousands of analysts whose job is to follow corporations in order to collect data, analyze data, and publish reports about earnings,

growth potential, management quality, and to give, based on the analyzing process; buy, hold or sell recommendations; otherwise the huge effort would not be compensated.

Further previous literature, like Sahut (2011) and Mola (2012) confirmed analysts are reducing information asymmetries and their actively monitoring activities tend to reduce the principal-agent problem between managers and outside investors. Sahut (2011) confirms the more analysts are following a corporation, the lower is the information asymmetry and the less volatile are stock returns.

Furthermore, it is common known that sell-side analysts are more reluctant to issue negative recommendations, which is confirmed by several statistical analyses like Stickel (1995), Womack (1996) and Barber, Lehavy, McNichols and Trueman (2001). Reasons for the rareness of negative recommendations is the risk to hurt the investment banking relationship with the subsequent downgraded company and the risk for incorrect sell recommendation is much higher than for an incorrect buy recommendation. Due to the less frequency of negative recommendations, the attention and therefore the after-effect is much higher.

One part of my research is to address the question if analysts' recommendations have investment value? If the information can be used systematically then it would be possible for investors to get an added value in form of higher performance returns (generate alpha) and analysts must have the ability to find underpriced and overpriced stocks.

My analysis has shown there is a gap in the research in analyzing the performance of recommendations and their investment value, as the most research papers are based on the time period prior to 2000.

1.2 Objective and Research Aim

The aim of this broad area is manifold and throughout the scope of this research study, therefore the author seeks to identify empirically, the market impact of analysts' recommendation upgrades and downgrades on the 30 stocks listed in the U.S. Dow Jones Industrial Average Index (DJIA).

The main motivation of this study is to answer the question whether, it is it worth to follow the analysts in the US stock market and if these recommendations are valuable to investors.

In this context, the sample data should provide answers to the following hypotheses:

Hypothesis 1: Analysts are issuing mostly optimistic recommendations and are more reluctant to issue sell recommendations.

Hypothesis 2: Analysts are following large capitalized corporations and are largely covering certain attractive sectors.

Hypothesis 3: Change in recommendations for stocks with low analyst coverage have a greater positive impact on prices compared to stocks with high analyst coverage.

Hypothesis 4: Analysts are able to add value through finding overpriced and underpriced securities.

Hypothesis 5: Analysts do more upgrades in recommendations when investor sentiment is high and more downgrades when investor sentiment is low.

Hypothesis 6: Change in recommendations for stocks with high brokerage coverage have a greater impact on prices than stocks with lower brokerage coverage.

1.3 Research Question

This master thesis is based on assessing if sell-side analysts employed by investment banks and brokerage houses have investment value for investors.

Thus, the addressed research question is:

Do Analysts' Recommendations have Investment Value?

In order to be able to answer the research question of this master thesis, it is imperative to design a clear and structured methodology which is being explained in section three *Research Methodology*.

1.4 Overview

The remainder of this empirical master thesis is organized as follows.

Chapter two provides a review of relevant literature on the research areas - analyzing the investment value and the profitability of sell-side security analysts. The selected review contains the most useful approaches in assessing the investment value and profitability of analysts' recommendations.

Chapter three presents the primary data, the rating scale classification and the applied research methodology and its specification in order to conduct the descriptive analysis, to analyze the impact of recommendation revisions on stock prices and the cross-sectional regression analysis.

The **fourth chapter** aims to response the questioned hypothesis, shows and evaluates the results of the research and **chapter five** summarizes the findings and discusses some of their implications.

2 Literature Review

This chapter presents in chronological order a review of relevant literature, as well as the most important findings regarding how analysts stock recommendations affect stock returns and to which extend investors are able to achieve abnormal returns. Previous research, for example Stickel (1995), Womack (1996), Barber et al. (1998), Barber et al. (2001) and Jegadeesh, Kim, Krische and Lee (2004) have demonstrated in their studies that consensus analysts' recommendations can beat the market and carry investment value.

The content of each summary is based on each academic publication and the quotations are declared underneath each summary.

2.1 Recommendation Research before and during 1980s

The first academic research paper with the title "Can Stock Market Forecasters Forecast?" in assessing if security analysts can beat the market with their recommendations was conducted by Alfred Cowles in 1933.

The paper is divided into two parts, the first part analyses the forecasting ability regarding superior returns of 20 fire insurance companies and 16 financial services during the sample period ranging from 1928 to July 1932, while the second part deals with the ability to predict future stock price levels, forecasted by 24 financial publications. Cowles finding was that some 7500 recommendations on stocks did not outperform the market and neither achieved abnormal returns and no specific investment skills were present. The same poor performance was confirmed for the forecasting ability of the future stock market movements from publications like the *Wall Street Journal*. A significant impact for the underperformance can be related due to the exogenous effect of the great crash in 1929 and their after-effect. According to Michaely and Womack (2002a) the underperformance could be a result of Cowles incorrect computation and a misstated understanding of benchmark investing during this time.

(Cowles, Alfred, 1933)

No further research was in the field of analysts' recommendations forecasting ability existent until the 1970s.

In 1986 Elton, Gruber and Grossman examined with a first comprehensive database the period from 1981 to 1983 consisting of 720 analysts from 33 brokerage firms. The paper titled, "Discrete Expectational Data and Portfolio Performance" focus was mainly on large capitalized corporations, which had a minimum coverage of three analysts. The study analyzed the monthly impact of recommendation changes, upgrades (from a lower to a higher rating) and downgrades (from a higher to a lower rating). Descriptive summary statistic for the sample shows a recommendation distribution of 48.00% buy and just 2.00% of sell recommendations. Beta-adjusted returns delivered for both scenarios insignificant excess returns. Upgrades, accumulated in the month after the recommendation release abnormal returns of 3.43%, while downgrades resulted in negative excess returns of -2.26%.

Drawback of the study is, that the calculation of beta-adjusted returns is based on a monthly basis one month after the recommendation announcement and therefore the real impact of the recommendation change on returns is unclear.
(Elton, et. al., 1986)

2.2 Publications 1994 - 1999

Following publications differ to Elton et. al., (1986) approach, as these studies are based on a larger scale database and the calculation of abnormal returns is based on a daily basis, to capture the immediately impact of recommendation announcements on stock prices and their returns.

"The Anatomy of the Performance of Buy and Sell Recommendations" analyzed the short-term and long-term price performance of 8,790 buy and 8,167 sell recommendations from the financial data source Zack, which obtained written recommendation reports from brokerage research departments. This research was based on a unique database covering the period 1988-1991, on 1,179 covered stocks, made by 1,510 security analysts from 80 security firms.

Stickel's (1995) study contributes to the existing literature, as the focus is on the determinants of stock performance on those stock recommendations and by the use of a cross-sectional analysis. With a cross-sectional regression analysis, six hypotheses were tested in order to identify which factors contribute most to the stock price performance of those buy and sell recommendations.

Following factors were in the multiple regression analysis included:

- The recommendation strength
- The size of the recommendation change, by how much it skips ranks
- Analyst reputation
- Number of employed analysts per brokerage firm and
- The difference in the market capitalization of those covered equities.

The uncertainty if a recommendation was announced before or after entering Zacks database was taken into account through ±5-day time window. In total, Stickel (1995) observed 21,387 recommendation changes, with a frequency distribution of 55% buy, 33% hold and 12% sell recommendations.
Buy recommendations contributed with a mean of 1.16% to a price increase, while sell recommendations led to an average decline of -1.28% in the time window ±5 day, centred on the recorded recommendation date by Zacks.

(Stickel, Scott E., 1995)

Womack's (1996) research with the title "Do Brokerage Analysts Recommendations Have Investment Value?" contributes to the academic literature as the paper examines how stock prices and volumes react to changes in analysts' recommendations.
In order to examine his analysis Womack collected the data from First Call, a database, which collected real-time recommendations directly from the majority of US and international security firms and provided access to this data to investors through an on-line PC system. Years ranging from 1989-1991 were studied in the research with a focus on a narrow sample by examining the recommendations of the fourteen major U.S. brokerage firms. With the focus in analyzing the stock recommendations of 14 brokerage research departments, the author aimed to control the immediately availability of their research reports to institutional investors and investment managers.

Womack's study is based on a database of 1,573 changes in analyst recommendations from strong buy to strong sell, or from strong sell to strong buy, made on 822 different companies. Womack examined analyst's recommendation changes by dividing the sample of 1,573 recommendation changes into four categories: added or removed stocks from the most favorable category buy or added or removed stocks from the least favorable category sell.

The remarkable result to emerge out of the authors sample data is that the majority of the analysts' recommendations were issued on large-capitalization companies, while just 10% of the recommendations are recommended on small-capitalization companies. Further was examined the category added to buy contains significantly most of the recommendations, than added to sell category. Which also is a significant evidence that analysts are more reluctant to issue sell recommendations. Womack's results show significant price reactions for stocks added to buy and for stocks added to sell. The price for stocks added to the buy list increased on average in the 3-day time window by 3.00%, while the stocks added to the sell category declined on average by -4.70%. The results are adjusted for size, industry and by using the Fama-French three factor model. Further, he provides evidence that stock prices after recommendation changes move significantly towards analysts forecasted recommendation direction. After the recommendation release, upgraded stocks added to buy drift on average by 2.4% which holds up to three months, while downgraded stocks added to sell drift over a six-month period on average by -9.1%. Similarly, to Barber et. al. (1998), recommendation changes on small-capitalized companies caused a larger market movement, compared to recommendation changes on large-capitalized companies. Decomposition of the post-recommendation drift shows excess returns are not mean reverting and the market movement towards analyst's recommendation direction does not appear to be short lifted.

Womack's findings give compelling evidence that analysts recommendation changes significantly influenced stock prices.

(Womack, Kent L., 1996)

The published academic paper by Barber, Lehavy, McNichols and Trueman, "Can investors profit from the prophets? Consensus analyst recommendations and stock returns" build the fundamental basis in the question of the profitability of recommendations issued by security analysts.

This analysis is based on a unique database provided by the Research Investment database Zack, which encompasses over 360,000 recommendations, issued from 269 brokerage houses, provided from 4,340 analysts over the time period 1986 to 1996. The recommendation frequency of the database excluding recommendations with termination of coverage showed a distribution of 54.0% of *buy* recommendations, 39.5% of *hold* and the minority of 6.3% of *sell* recommendations respectively.

By building calendar time portfolios and classifying the covered firms according to their average ratings into five portfolios, where the first portfolio consists of the most highly recommended stocks, for which the rating $A_{i,t-1}$ is in the scale $1 \leq A_{i,\,t-1} \leq 1.5$ and the fifth portfolio with a rating scale $A_{i,\,t-1} \geq 3$ contains the least recommended stocks. This approach follows the rating scale, rating (1) a strong buy, (2) a buy, (3) a hold, (4) a sell and (5) a strong sell recommendation. The returns are then calculated for each portfolio after the close of the trading day. The daily value-weighted returns $R_{p,t}$ for each portfolio p on each day t, are then further compounded to a monthly return. The next step involves the calculation of market adjusted-returns by taking the difference of the monthly portfolio return and the monthly return on a value-weighted market index. As the portfolio classification technique rebalances the portfolio after the close of the trading day, the return calculation uses the similar approach and calculates monthly-adjusted returns by excluding first-day return to analysts' recommendations. This approach takes into account that investors cannot act before any research reports are made public.

The results showed over the sample period a significant outperformance of the most highly recommended portfolio by an annualized geometric mean of 18.8% while the least recommended portfolio returned on average just 5.78%. The outperformance of the most favorably recommended stocks is even persistent after controlling for Fama-French factors and momentum factors, were a positive excess return of 4% per year was achieved, while a negative annually excess return of 5% was earned by the least favorably recommended stocks. In the end, the results are most pronounced for small and medium sized companies. This strong evidence justified the ability of research departments to transfer the costs of intensive security analysis into superior returns for their investors.

Limitation of the paper is that the calculation of the outperformance in based before deducting transaction costs.

(Barber et al., 1998)

"How Do Stock Markets Process Analysts' Recommendations?" by Juergens (1999) provides evidence to the question whether analysts' recommendations have investment value. The primary data used was gathered from the same data source as Womack's (1996) research is based on. 3,679 recommendations for over 208 firms in the sector computer or computer-related firms were analyzed in the sample period 1993 to 1996.
The author contributes to the literature as the analysis is based on all types of recommendations, while Stickel (1995) Womack (1996) analyzed only changes from the most highly recommended stocks and changes from the least recommended stocks. Further it differs by analyzing the impact of analysts' recommendations and public announcements on daily and on intraday returns.

Summary statistic shows for the period ranging from 1993-1996 a dramatically increase in the number of firms covered by analysts and an increase in the total number of recommendations. In line with findings from Stickel (1995) and Womack (1999) her sample contains the similar recommendation frequency distribution, as the sample exits of 56% positive recommendations and 3% of sell recommendations. These findings provide again evidence that analysts are more reluctant to issue sell recommendations. The same can be concluded from a 5 x 5 recommendation change matrix, as most of the recommendations are centered in the upper part. Looking on abnormal returns confirm the ability to outperform the market by following analysts' recommendations. Remarkable cumulative abnormal returns (CAR) were achieved by recommendation changes from hold to strong buy upgrade which resulted into a 3-day CAR of 4.14%, which is of greater magnitude then found in previous studies.[1] In contrast a downgrade change from strong buy to hold earned on average a negative CAR rate of -5.39%. All positive recommendations have earned on average a 3-day CAR of 1.91%, while all negative recommendations garnered a negative return of -3.14%. Significantly return

[1] Stickel (1995) achieved abnormal returns of 1.16% in a 11-day time window, while Womack (1996) achieved in a 3-day time window returns of 3.0%.

difference was further confirmed with a mean difference test. The market impact of analysts' recommendations was further assessed by intraday return calculation. Intraday returns were calculated for 15-minute intervals in the time frame, two hours before and two hours after the recommendation announcement. The results were significant at the 1% significance level for positive recommendations (0.55%) and negative recommendations earned -1.27%.

To conclude Juergens analysis confirmed, it is possible to earn significant intraday returns with analysts' recommendations and those reports provide investment value around the recommendation announcement time.

(Juergens, 1999)

2.3 Publications 2000 - 2010

Barber et. al. research paper "Prophets and losses: Reassessing the returns to analysts' stock recommendations" continues on his previous research (1998) where analyst's recommendation has significantly outperformed those recommendations of the least recommended stocks throughout the time period 1986-1996.

His subsequent paper aims to validate if the outperformance is still present during the narrow time frame from 1996 to 2000, where it was widely spread analysts were working in favor of investment banking activities and writing research reports in favor for companies which are having a client relationship with the investment bank. A total of 160,000 recommendations were collected from Thomson Financial' s database First Call, made by 299 securities firms, covering 9,621 companies. Breaking down the total number of recommendations, the sample contains overall of 67.9% of strong buy/ buy, 29.1% of hold and 3.0% of sell/ strong sell recommendations.

The analysis follows the approach of Barber et al (1998), where the covered firms are based on their average ratings, placed into five portfolios on a calendar time basis.
Analysts buy recommendations have on average significantly outperformed those of least favorable recommendations during 1996-99, while on the contrary this outperformance

vanished in the year 2000 regardless of the market phase and of the sectors of those recommended stocks. The most highly recommended stocks returned on average annualized excess return of -31.20%, while the market-adjusted return for the least recommended stocks averaged an annualized return of 48.66%. This unpredicted pattern and the huge dispersion between both portfolio performance raises questions over the usefulness of the investment value of analyst's stock recommendations in the long-term. There is still considerable uncertainty if the year 2000 is a turning point in the usefulness of analysts' accuracy and if this is caused by increasing incentives to forecasting towards investment banking benefits.

(Barber et. al., 2001)

In 2004 Barber et. al. expanded his analysis of security analyst's investment value by, investigating in his publication "Comparing the stock recommendation performance of investment banks and independent research firms", the profitability of security recommendations issued from independent research firms and investment banks, for a narrow sample window during the period 1996 to 2003.

The conducted study collected the data from Thomson Financial' s First Call database and the data sample encompassed 335,000 recommendations issued by 409 securities firms.

This paper divides analysts' recommendations into two samples, issued by independent research firms (without any investment banking activities) and issued by investment banks. It further divides the sub samples, according to their ratings into two sub portfolios, first portfolio with *buy* recommendations and second portfolio with *hold* and *sell* recommendations.

By using the Fama-French Method and controlling for market risk, size, book-to-market and price momentum effects, the daily abnormal returns were calculated for each portfolio respectively.

A further analysis was conducted by splitting the time period into two market phases, time frame until March 10, 2000 refers as the bull market and following to that date as the bear market.

The sample of investment banks buy recommendation is further broken down into three investment banking categories in order to investigate if a performance difference exists between sanctioned and non-sanctioned investment banks.

The results confirm the hypothesis that investment banks are more reluctant to downgrade stocks, as the findings showed investment banks are not able to outperform buy recommendations of independent research firms. The *buy* portfolio of independent research firms has outperformed by 3.1 basis points (bps) on a daily basis or by 8% yearly. On the other hand, the hold and sell portfolio of investment banks has outperformed by -1.8 bps per day and annualized by -4.5%, those recommendations of independent research firms. These results conclude by following the sell recommendations of investment banking research, investors are able to minimize their financial losses.
Investment banking buy recommendations have on average outreached those of independent research firms, by a statistically insignificant 0.4 bps in the bull market. While in the bear market independent research firms buy recommendations have exceeded significantly those of investment banks by 6.9 bps on a daily basis and more than 17% annually. The market phase analysis further confirms, investment banking hold and sell recommendations are able to outperform independent research firms, as the results showed the majority of their hold and sell recommendations are concentrated in the bear market and outperformed those of independent research firms by 3.5 bps per day.

The performance analysis between the three investment banking categories, with the group sanctioned investment banks[2] (containing of 10 banks), non-sanctioned investment banks (which are lead underwriter like the 10 sanctioned banks) and non-sanctioned banks (with no active lead underwriter role, which are syndicate members) showed, there is no difference among the performance of sanctioned and non-sanctioned investment banks compared to independent research firms. All three categories were not able to outperform those buy recommendations of independent research firms and do not show evidence that non-sanctioned banks provide independent research reports to investors. Conflict of interest claims of sell side analysts are supported by Barber et. al. results.

[2] 10 Investment banks were sanctioned in 2003 in the SECs Global Research Analyst Settlement.

(Barber et. al., 2005)

Years ranging from 1985-1998 were studied in the research published by Jegadeesh, Kim, Krische and Lee in “Analyzing the Analysts: When do Recommendations Add Value?” with a focus finding out the source of investment value those recommendations provide. As a primary data source Zacks Investment Research database was used.

Recommendation level and changes in recommendations were analyzed by using twelve characteristic variables, which have the ability to predict returns as confirmed by previous literature and previous studies.

These twelve explanatory variables are categorized into five categories:

(1) Momentum and Trading Volume;
(2) Valuation Multiples;
(3) Growth Indicators;
(4) Firm Size and
(5) Fundamental Indicators.

As these twelve variables are correlated with future returns, Jegadeesh et. al. expected, a correlation towards the same way with recommendation level and changes.
The hypothesis of this study is, if analysts are paying attention to these variables in the above-mentioned categories, then most recommended stocks must be based on following characteristic:

- High momentum stocks and / or low volume stocks;
- High valuation with a high earnings-to-price ratio (EP) and high book-to-price ratio (PB);
- Low past growth and low expected future growth or
- Low accruals ratio and low capital expenditure ratio.

Recommendation level is calculated as an average of all outstanding recommendations within one calendar year, while the recommendation change is calculated as the difference between the current calendar quarter and the prior calendar quarter, which results either in an increase or decrease in the consensus level of analyst recommendation.

This study used descriptive statistic, by analyzing on a firm level the sample distribution across years. The results show a remarkable increase in firm observations over time and yields over 56 quarters an average of 971.4 firm observations per quarter. A further descriptive analysis was conducted on the analyst's sample recommendations. Consensus recommendation levels and recommendation changes were grouped into quintiles, where the quintile 0.00 contains the least recommended stocks and the quintile 1.00 contains the most recommended stocks. The outcome of the five consensus recommendation level quintiles, are in line with other studies and confirm clearly, analysts are more reluctant to issue sell recommendations. On the other hand, the results of the recommendation changes quintiles, show firms were more likely to be downgraded than upgraded by analysts.

Positive correlation between future market-adjusted returns and recommendation level and changes was examined by using the Spearman rank correlation method and the results give evidence for analyst's predictive ability in stock recommendations. The Spearman rank correlation was further used for assessing the correlation between future returns and the twelve investment variables. The findings confirmed a correlation between the explanatory variables and future returns. The variables positive price momentum, positive earnings momentum, and total accrual ratio were in 75% of the quarters presents and were identified as the most predictive variables with the ability of causing positive future returns. The Spearman correlation analysis between consensus recommendation level and changes in recommendation with the twelve defined investment variables, demonstrated a strong positive correlation with momentum factors. This implies analysts most favorably recommendations are based on securities with momentum factors. Further analysts prefer high turnover stocks, low PB, high EP, high past growth and high expected future growth as well stocks with a high accruals and high capital expenditure ratios. Analysts preference for momentum stocks, was further confirmed by using a multivariate regression analysis, with analyst's recommendation as the dependent variable and the twelve investment variables as explanatory variables.

Summarizing up Jegadeesh et al. examined analysts' recommendations as well the twelve considered investment variables, have the ability to predict future returns. A positive

relation exists for analysts' recommendations and explanatory variables, where the most striking focus is on momentum stocks with a strong past performance which is expected to continue in the future. Although the authors showed that most recommended stocks have outperformed least recommended stocks.

(Jegadeesh et. al., 2004)

2.4 Publications 2011 - 2016

Souček and Wasserek (2014) study uses as a primary data source Thomson Reuters *I/B/E/S* database and the analyzed period ranging from 2000-2012, with a focus on the German DAX 30 Index. Based on a sample of 12,998 observations, made by 1,446 from 126 security firms, the aim of the paper is to study the impact of analysts' recommendation upgrades, downgrades and reiterations on the stock returns and if investors are able to profit from those recommendations.

Souček et. al. contribute to the academic literature as this study is the first research on analysts' recommendations on the German DAX and for a more recent time frame. In addition, the paper analyses compared to Stickel (1995) and Womack (1996) the price reactions of all recommendations.

Excess return calculation is based on the approach of the famous theoretical Capital Asset Pricing Model (CAPM) and controlling of other factors and to test the robustness, the Fama-French (1997) three factor model, as well the Carhart (1997) four factor extension model was applied.

The recommendation sample contains 41.7% of buy recommendations, 39.1% of hold and surprisingly a large amount of 19.2% sell recommendations. This gives evidence that the analysts' recommendations frequency distribution is compared to the US findings less biased. Recommendation change, 5 x 5 transition matrix shows the bulk of recommendations are in the upper 3 x 3 part and illustrates clearly that sell recommendations are less frequent than buy recommendations.

Recommendation changes to upgrades accumulated significantly positive abnormal returns around the recommendation release date, while recommendation downgrades accumulated significantly negative returns. The same return patterns apply for initial recommendations, a new buy recommendation gains significantly positive returns, whereas significantly negative returns hold and sell recommendations accumulate. No statistically significant returns and market reactions were obtained by recommendation reiterations. Further as confirmed from previous papers, the paper provides evidence that the stock market reaction on recommendation revisions is most powerful at the announcement day and the post-recommendation drift in stock prices last up to six months for upgrades and four months for downgrades. Due to the findings that the stock market reaction is strongest at the recommendation release date, the analysis give further evidence that investors are able to gain the highest profit from analysts' recommendations by trading on the event day in a timely manner.

(Souček et al, 2014)

Years ranging from 1996 to 2012 were analyzed by Boulland, Ornthanalai and Womack in the research paper "Speed and Expertise in Stock Picking: Older, Slower and Wiser?" with the aim to examine how the speed of recommendation changes have investment value. The study contributes to the literature as it is one of the first study that examines the impact of analyst's decision speed-style on the stocks, analysts are following and by looking on the investment value by classifying analysts into two types according to their speed.

The final sample for the period 1993 to 2012 uses I/B/E/S database, which contained 240,957 observations. Overall the sample contains solely recommendation changes, upgrades (44.54%) and downgrades (55.46%).

Descriptive statistic for the sample shows an average of a recommendation stay without a change is 12.36 months and analysts are following on average 6.91 stocks.
The paper calls the time or the speed it takes to revise analyst's recommendation as turnover. Further analysts can be classified into two categories, fast-turnover analysts, who change their recommendations on average every 6 months and slow-turnover analysts who typically change their opinion approximately every 20 months. The study

uses Barber et. al. (2001) famous real-calendar time portfolio approach, which is in the academic literature the standard approach in assessing abnormal returns of buy vs. sell recommendations. Boulland et. al. found that recommendation changes made by slow-turnover analysts have significantly outperformed by 1.93% in the first five months after the recommendation change, relative to fast-turnover analysts. While risk-adjusted returns of downgrades are by 1.23% relatively lower. A multivariate regression analysis, with analysts' recommendation speed-style as the dependent variable and various analyst's characteristics as independent variables delivered strong evidence for the relation between analyst's ability to make better recommendations and their decision-speed. The coefficients of analyst's characteristic variables top brokerage house, experience and analyst's all-star category have significantly negatively effects on the dependent variable fast-turnover group, further indicates slow-turnover analyst's ability to make more careful and better decisions. In summary, the paper demonstrates better recommendations are made by slow-turnover analysts and those add value for investors through their prudent decision style.

(Boulland et. al., 2016)

3 Research Methodology

This section provides information about the methodology by explaining the database, the time period of the analysis, the selected equity index, the rating scale classification and the research design.

3.1 The Data Selection

The analyst recommendations used in this study were obtained from the financial data provider Bloomberg. The recommendation time frame encompasses the period 2000 to 2017 with a solely focus on the Dow Jones Industrial Average Index (DJIA). One of the significant reason for choosing the DJIA, is as it shows the performance of the industrial sector within the American economy and contains the 30 largest and mainly important publicly owned companies based in the United States. The companies listed in the DJIA, are attached in table 10 in the Appendix.

The recommendations had to fulfil some criteria to be included in the entire data sample:[3]

- At least one analyst who has issued a recommendation on a specific stock and reconsidered the opinion within 365 days. If a recommendation exceeds the time window of 365 days, it will be seen as a new recommendation, in order to avoid outdated recommendations with no reference to previous one.
- Recommendations issued when the American Stock Exchange (AMSE) and the New York Stock Exchange (NYSE) is closed are eliminated to ensure availability of stock returns on all trading days, as the DJIA is quoted at the end of every US trading day.

Consequently, to create the sample of recommendation upgrades and downgrades the following criteria were additionally imposed for the sample to be used in the event study and cross-sectional regression analysis:

- Recommendations are excluded if an analyst makes only one recommendation, as those recommendations have no reference to change in recommendations.

[3] Criteria selection follows the approach by Stickel (1995), Jegadeesh et al (2010) and Souček et al (2014).

- Recommendation revisions of previous recommendations are excluded, since recommendations on securities issued by the same analysts are classified as upgrades or downgrades compared to the previous announced recommendations.

In the event study and cross-sectional regression analysis, buy recommendations are defined as all rating upgrades to a strong buy and buy coming from a recommendation of hold, sell or strong sell. Sell recommendations are defined as all downgrades in recommendation revision to strong sell and sell, coming from a rating of strong buy, buy or hold. Including recommendation downward revisions to hold from a strong buy or a buy recommendation.

All recommendations which are present the first time in the data sample, are treated as recommendation initiation. This might be not the true initiation of coverage. This assumption is relevant in order to start with the analysis.

The stock prices data will be looked up on Bloomberg. For all 30 DJIA securities the official daily closing price is chosen, after the adjustment of capital market events like stock-dividends, dividend pay-out and mergers and acquisitions. For each security, the corresponding stock price return is calculated as the natural logarithm difference in the closing price over the one day period as follow:

$$R_t = Ln\left[\frac{P_t}{P_{t-1}}\right]$$

This approach is the most acceptable method in finance to model asset prices and the main benefit of using log-returns instead of arithmetic returns in modeling assets prices is to avoid the occurrence of negative assets prices, as asset prices never take prices less than zero. Since in academic finance the process of a stock price S_t at time t is modelled as a stochastic process, which is called geometric Brownian motion (GBM), a further advantage is the assumption of normally distributed log-returns. This can be opposed as the price of a security follows a GBM (Hilber, 2017).

3.2 Rating Scale

‘Buy’, ‘hold’ and ‘sell’ are the most commonly used and known expressions by security analysts. However, from broker to broker houses analysts use slightly different expressions for the same meaning, for example ‘attractive’, ‘neutral’, ‘market-perform’ or ‘underweight’, see table 11 in Appendix.

As the sample consists of 131 different rating expressions as the individual brokerage firms use a variety of different rating phrases for their stock recommendations, all expressions have to be analyzed and standardized and coded into a common rating system.

To ensure comparability of recommendations across brokerage firms, the study make use of the common 5-point scale rating system. The different analyst’s recommendations were classified into a common rating scale from 1 to 5. Where rating 1 is a ‘*Strong buy’*, 2 is a ‘*Buy’*, 3 is a ‘*Hold’*, 4 is a ‘*Sell’* and 5 is a ‘*Strong sell’*. Rating 6 *‘No coverage’* was attached when the analyst coverage was terminated.

Some expressions contain two rating phrases, a firm and an industry recommendation separated by a slash. The used rating expression in this analysis, is solely the firm recommendation, which is the text before the slash.

3.3 Research Design

It is imperative that this study requires mainly quantitative analysis in extent to answer the addressed research question. The methodology of this master thesis will consist of different steps.

The first step will be the review of all recommendations in the sample period and standardizing the expressions into a common rating scale, by attaching numerical numbers to all recommendation expressions. Subsequently, the data sample will be analyzed by applying descriptive statistics on all recorded recommendations exported from Bloomberg. Proceeding with the analysis, only changes in recommendations are

used, which means any revisions of previous recommendations are excluded. Continuing the impact of recommendation changes on stock prices will be analyzed by applying the methodological concept of an event study. The last step conducts a cross-sectional regression analysis to determine the performance of recommendation revisions.

3.3.1 Descriptive Statistics

To begin with the quantitative analysis, the entire data sample will be analyzed by using descriptive statistics.

As a first step, a table with annual descriptive statistics which include per year the number of firms covered, number of analysts and number of brokerages, which should give information's about the annually average number of analysts covering firms and average number of analysts employed at a brokerage house, as well the average number over the entire sample period.

Secondly, I will analyze the frequency distribution of the recommendations classified among three rating categories buy, hold and sell. Whereas category buy encompasses strong buy and buy recommendations and the category sell encompasses sell and strong sell recommendations.

Thirdly descriptive statistics of analysts' recommendations is going to be conducted for each DJIA firm separately. Descriptive statistics for each firm aims to break down the number of analysts following a company, number of brokerages per company and the average rating for each firm and their median respectively. The motivation is to find out, if brokerage houses tend to cover the top level of large capitalized firms, if a specific sector is attractive to follow and for which firm analysts are issuing most highly (least) recommendations.

Finally, all possible changes in analysts' recommendations are going to be examined with a 5 x 5 recommendation change matrix. The purpose of the matrix is to show where the bulk of recommendations are clustered and to deliver the number of upgrades and

downgrades. The matrix will give insight if more upgrades or downgrades occurred in the encompassing sample period.

3.3.2 Event Study and Cross-Sectional Regression Analysis

The quantitative analysis in assessing the price performance of analysts' recommendations will be examined by the usage of the commonly known event study concept and a cross-sectional regression analysis. This master thesis builds upon the event study methodology, which is widely accepted and was applied in previous literature, like Fama, Fisher, Jensen and Roll (1969), Stickel (1995), Womack (1996) and Souček et al. (2014).

The event study methodology is used to investigate the share price reaction following the recommendation changes. The methodological approach used in this master thesis follows the event study methodology described by Bowman (1983). This methodological concept is also known under the names such as residual analysis and abnormal performance index tests.

To start with an event study, the structure of an event study involves the following steps, according to Bowman (1983) and De Jong (2007) described structure of an event study:

I. Identify the event of interest and precisely the timing of the event.

The event of interest in this master thesis is the investigation of recommendation revisions, which occur for different securities at different calendar dates. To begin with, the timing of the event has to be identified. The timing of the event equals to the exact announcement day of the recommendation as recorded by the Bloomberg database. Consequently, all different calendar dates of all single events need to be standardized to event time zero ($t = 0$), as the aim is to bring all single events together into a single sample. This event time procedure allows to describe time periods in event time relative to the zero time when the event, the recommendation revisions occurred. The figure below shows the time line of an event study.

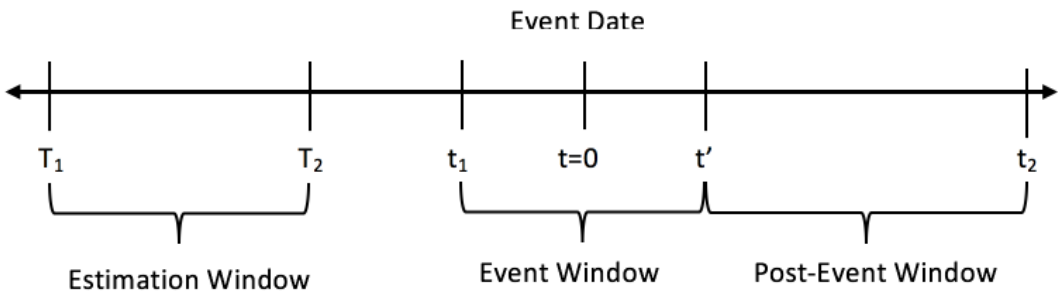

Figure 1: Time Line of an Event Study.

In this study, the time period of the estimation window right before the event window ranges from $T_1 = -180\ to\ T_2 = -40$, following the length of the estimation window from Brown and Warner (1980) classical event study paper. The information content event window in the analysis was expanded to include days before the announcement date, due to the uncertainty of the announcement date of the analysts' recommendations. This encounters the likelihood that an investment bank or brokerage house research departments informs specific target clients on any recommendation changes prior to the date of the research report and prior to the announcement date in the Bloomberg database. According to the Ethical and Professional Investment Standards of the CFA Institute (2017) all clients of an investment bank or brokerage house must have a fair chance to act on every recommendation, nevertheless following the guidance it is acceptable to communicate any recommendations to clients first who pay for a different service level. Therefore, it is useful to extend the event window around the event date to capture a pre-event drift before the actual announcement date. The chosen event period ranges from $t_1 = -20\ to\ t_2 = +120$ and follows the time line structure of two event studies, as Stickel (1995) showed, a pre-event drift occur twenty days before the event and Womack (1996) findings showed the post-event drift might last up to 6 months after the event.

II. Calculate normal returns based on a specified benchmark model for normal share price behavior in order to assume the event had not taken place.

The second step requires the specification of an appropriate benchmark to calculate and model normal stock return behavior. The S&P 500 Index is used as a benchmark index,

since the S&P 500 includes all stocks tracked in the DJIA index and the S&P 500 is one of the broadest benchmark index which tracks the 500 largest US corporations. The selection of the S&P 500 as a broad index in this study to represent the market portfolio aligns with Womack and Zhang (2003) suggestions to select either the S&P 500 or the Russell 2000 index.

Next step requires the selection of a statistical model to calculate the residuals of the process generating returns. Referring to Bowman (1983) the correct model is a critical element in event studies to be able to find security price reactions. In this study, the widely accepted single factor model, called market model is chosen:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where the parameters are as follow, R_{it} is the return on security i in period t, R_{mt} is the return on the market portfolio, the selected market benchmark in period t, coefficients α and β are constants for security i. The coefficient beta β_i or slope of the regression, measures the sensitivity of return R_{it} with the reference market and returns have to be adjusted for differences in beta, since the market sensitivity for each stock is not equal to one. The parameter ε_{it} is the error term or residual of the market model, which is completely a random part of the model.

The calculation of normal returns is performed over the estimation period ranging from the start $T_1 = -180$ up to the end $T_2 = -40$. From the above model, normal returns can be mathematically derived as follows:

$$NR_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{mt}$$

Subsequently the parameters of the model are estimated by using Ordinary Least Squares (OLS) regression method. The next step involves the calculation of residuals based on the estimated parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$. This means abnormal returns can be expressed as residuals or error terms of the market model:

$$\hat{\varepsilon}_{it} = R_{it} - \left(\hat{\alpha}_{it} + \hat{\beta}_{it} R_{mt}\right)$$

According to Bachmann (2015a) and (2015b) residuals expectation and OLS estimation assumptions are the following:

$$E(\varepsilon_{it}) = 0 \;\; for\ i = 1, \dots, N$$

This means on average the expected value of abnormal (excess returns) has to be zero and holds in an efficient market environment, where no excess returns can be achieved. This means any non-zero value in residuals is termed as abnormal (excess) returns, since the expected value of the residuals is assumed to be zero on average, according to the above equation.

The second property states a zero correlation, as it is assumed the error term is not correlated with the market return R_m and security return R_{it} is uncorrelated with security return R_{jt}. This property is also referred as no autocorrelation in residuals, see Bachmann (2015f).

$$\sigma\left(\varepsilon_{it}, \varepsilon_{jt}\right) = 0\ for\ i, j = 1, \dots, N\ and\ i \neq j$$

Last required OLS estimation assumption is homoscedasticity, which means all error terms have the same variance.

$$V(\varepsilon_i) = \sigma^2\ for\ i = 1, \dots, N$$

This assumption is violated if the variance of the error terms is not constant and depends on the values of the independent variables used in the regression model, referred as heteroscedasticity. Consequently, a violation of the assumption means that the OLS standard errors $s_{bo}, \dots, s_{bk}$ are incorrect and could be either too low or too high.

A graphical inspection, by the usage of residual plot helps to detect whether outliers and heteroscedasticity is present. This approach is of limited use as these residual plots do not provide evidence of that problem. Therefore, it is necessary to conduct statistical tests.

Statistically, heteroscedasticity can be assessed by running a Breusch-Pagan test or a White test. The Breusch-Pagan test runs under the following hypothesis:

$$H_0: constant\ error\ variance\ \sigma^2$$

$$H_1: error\ variance\ depends\ on\ population\ regression\ function\ E(\langle y_i | x_{i1}, \dots, x_{ik} \rangle)$$

The Breusch-Pagan test requires the estimation of the so-called auxiliary regression $e_i^2 = a_0 + a_1 \hat{y}_i + u_i$. Consequently, by the use of a chi-squared test statistic it can be decided whether to reject the null hypothesis or not if:

$$n * R^2{}_{e^2} > \chi^2{}_{1,\alpha}$$

where $\chi^2{}_{1,\alpha}$ is the critical value of a chi-square distribution with 1 degree of freedom and confidence level α. (Bachmann, 2015e)

III. Calculate abnormal (excess) returns in the determined event window.

Step three involves the calculation of abnormal returns, where abnormal returns *(AR)* are calculated as actual returns *(R)* minus normal returns *(NR)* in the event window ranging from t_1 to t_2.

$$AR_{it} = R_{it} - NR_{it}$$

Where R_{it} is the return on stock *i* on day *t* and NR_{it} is defined as the expected return in the estimation period. The determination of abnormal returns is performed over the event window ranging from $t_1 = -20$ to $t_2 = 120$ and the event date is labelled in event time as $t = 0$, as outlined in the first step. Therefore, AR_{i0} represents abnormal return on the event date and AR_{it} represents abnormal return on *t* periods (days) after the event.

Due to the fact that there are multiple events[4] for each firm present, the relative events are treated as if they belong to separate firms. Assuming the used sample is of size *N*, a matrix of abnormal returns can be constructed in the following form:

$$\begin{bmatrix} AR_{i,t1} & \dots & AR_{N,t1} \\ \vdots & \dots & \vdots \\ AR_{1,-1} & \dots & AR_{N,-1} \\ AR_{1,0} & \dots & AR_{N,0} \\ AR_{1,1} & \dots & AR_{N,1} \\ \vdots & \dots & \vdots \\ AR_{i,t2} & \dots & AR_{N,t2} \end{bmatrix}$$

Each matrix column presents a time series of abnormal returns for stock *i*, where the time index *t* is counted from the event date *(t=0)*. Each row builds a cross-section of abnormal returns for each time period.

Proceeding with the analysis, abnormal returns need to be organized and grouped into two portfolios, either buy or sell portfolio according to the relative event if it is either an upgrade or downgrade in the recommendation revision.

Subsequently the abnormal returns are averaged to improve the information content of the analysis over the observations together. Below equation expresses average abnormal returns *(AAR*) at time *t* across all observations under studies.

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}$$

[4] For illustration table 12- Event Counts per Company - included in Appendix stores the total number of events for each firm.

The total impact of an event, measured during the event period t_1 to t_2 is examined through cumulating individual abnormal returns to obtain cumulative abnormal returns *(CAR)* from the start of the event period t_1 up to time t_2, as follows:

$$CAR_i = AR_{i,t1} + \cdots + AR_{i,t2} = \sum_{t=t_1}^{t_2} AR_{it}$$

The last step involves the calculation of cumulative average abnormal returns *(CAAR)*, which means the *CARs* are aggregated over the cross-section of events.

$$CAAR_t = \frac{1}{N}\sum_{i=1}^{N} CAR_{it} = \sum_{t=t_1}^{t_2} AAR$$

Where *N* equals the number of observations in the respective buy or sell portfolio and *t* refers to the number of aggregated time periods.

IV. Use significance tests to test if abnormal (excess) returns are statistically significant. Analyze the results.

The final step requires to test whether the abnormal returns, CAAR are statistically significant from zero with a given significance level. The stated null hypothesis to be tested is the following:

$$H_0: E\left(AR_{i,t}\right) = 0$$

the null hypothesis of no abnormal return is tested by using the most common and simple t-test. This test assumes the t-test statistics follows a Student-t distribution with $N - 1$ degrees of freedom and builds on a normally distribution. To achieve a reliable t-test statistic it is important to check whether the residuals (abnormal returns) are normally distributed. As the Central Limit Theorem states, large samples will follow approximately a standard normal distribution, abnormal returns used in this study are expected to follow a standard normal distribution, since the number of cross-section events is quite large.

Hence, abnormal returns need to be checked and a histogram of the abnormal returns is drawn. Figure 6 shows the residuals are fairly normally distributed and this was verified by using the Stata command *sktest*, which is a normally distribution test based on skewness and on kurtosis. Then the computed t-test statistic is compared to a critical t-value with the appropriate degrees of freedom to check whether the results are significant at less than 0.10, 0.05 or 0.01 significant level. Lastly, the results need to be analyzed and interpreted.

Defining independent variables

After calculating the impact of change in recommendations on the share price performance a cross-sectional regression analysis is used to investigate the determinants of the stock price performance of recommendations and to test the imposed hypothesis. As outlined the regression model uses cumulative abnormal returns (CAR) as dependent variable and the returns are regressed on selected independent variables. The applied regression analysis to describe the cumulative abnormal returns orientates itself on the different addressed hypothesis.

Hypothesis 3: Change in recommendations for corporations with low coverage have a greater positive impact on prices compared to corporations with high analyst coverage.

The third hypothesis aims to answer the effect of analyst coverage on returns. The literature stated the negative relation between coverage and returns exists for small firms. While Sahut (2011) observed returns for firms covered by more analysts are less volatile, whereas when the number of analysts is decreasing the volatility on returns are increasing, respectively. The question arises if this relation as a result of information asymmetry also holds for large capitalized stocks. One would expect revisions in recommendations have a similar effect likewise for small firms, which means a company with a low analyst's coverage experience a larger price reaction and a company with a high analyst coverage a lower price reaction.

The regression model incorporates analyst coverage ($COVER_{ANALYST}$) as independent variable. This explanatory variable equals the mean number of analysts who made a recommendation change during the sample period. The coefficient on $COVER_{ANALYST}$ was hypothesized to be negative for buys and positive for sells as a higher coverage, leads in return to lower positive and negative abnormal returns.

Hypothesis 4: Analysts are able to add value through finding overpriced and underpriced securities.

Issued buy recommendations by analysts come a long with analyst believes that the assessed company is undervalued by the market and a sell recommendation that the company is overvalued in the market. According to Stickel (1995) prices should react more to strong buy and strong sell, as those securities are considered to be even more undervalued and overvalued respectively.

To test this hypothesis, the regression model includes the dummy variable STRONG to assess the strength in recommendation revisions on prices. The coefficient STRONG takes the value one if recommendations are upgraded to strong buy and zero for upgrades to buy. Due to the limited amount of strong sell recommendations, the dummy variable STRONG equals one for recommendation downgrades to strong sell or sell and zero for downgrades to hold. The coefficient on the dummy variable STRONG for upgrades to strong buy is expected to be positive and the dummy variable STRONG for downgrades is expected to be negative, as it is predicted that changes to strong buy and strong sell should have a greater positive and a greater negative impact on prices, respectively.

When analysts revise their recommendations in a way that recommendation skip a rank, the revision is expected to have a greater impact on the price of a security. Referring to Stickel (1995) a change from hold to strong buy incorporates a greater change in expectation compared to a change from buy to strong buy. The revision from hold to strong buy means that the analyst is believing the security is even more undervalued.

To test this hypothesis, the regression model includes as independent variable, the dummy variable SKIPRANK, which equals one if the characteristic the revision in recommendations skips a rank is observed. If the revision of recommendations does not skip a rank, the dummy variable takes the value zero otherwise. It can be expected that the coefficient on the dummy variable SKIPRANK should be positive for buy recommendations and negative for sell recommendations.

Hypothesis 5: Analysts do more upgrades in recommendations when investor sentiment is high and more downgrades when investor sentiment is low.

The purpose of the fifth hypothesis is to investigate the relation between stock recommendations upgrades and downgrades with investor sentiment. Prior literature, like Hilary and Shon (2007) and Bagnoli, Clement and Crawley (2009) confirmed a positive relation between stock recommendations and market sentiment exists. Bagnoli et al. (2009) found in their research, recommendations issued by analysts are more favorable on average in bullish markets when investor sentiment is high.[5] This correlation is also supported by Kaplanski and Levy (2010) findings, their time series analysis confirmed analysts issue more optimistic recommendations when investor sentiment is positive[6], while the contrary takes place when investor sentiment is negative. Further researchers, Corredor, Ferrer and Santamaría (2011) have confirmed the robustness of the correlation between analysts' recommendations and investor sentiment, as those researchers have shown it is not only in the US market present it also holds across four main European stock markets.

[5] Bagnolli et al. (2009) further finding is that those recommendations which are positively correlated with investor sentiment are less profitable. The sources of lower profitability can be either (1) by a smaller impact of investor sentiment on stock prices or (2) by analysts missing capability to correctly incorporate investor sentiment into their recommendations. This result is a strong signal for analysts to focus on fundamental analysis (cash flows, earnings and discount rates), rather than trying to capture investor sentiment to make profitable recommendations.

[6] Kaplanski et al. (2010) additionally found a correlation between investor sentiment and herding among analysts. This means analysts' recommendations are not only positive with high investor sentiment, further they are also more homogenous during this market environment. The opposite holds true when sentiment is negative.

To test if this hypothesis is valid throughout the sample period and to assess herewith the impact on the stock price, the regression analysis incorporates the dummy variables $MARKET_{TYPE}$ and $TRADING_{SIGNAL}$. $MARKET_{TYPE}$, equals one if the characteristic change in recommendation occurred in an upward moving market referred as bull market and takes the value zero if the change in recommendation occurred in a downward moving market referred as bear market. The dummy variable $TRADING_{SIGNAL}$ signal captures market sentiment by the usage of a technical trading strategy over the volatility index (VIX). When a recommendation was revised during times where the short-term moving average crossed the long-term moving average the dummy variable equals one (buy signal) and zero (sell signal) otherwise, when the long-term moving average crossed the short-term moving average. This means when it takes the value one, the market is in an upward moving trend, investors are bullish and market sentiment is expected to be high and zero otherwise when the market is in a downward moving trend and market sentiment is expected to be low, respectively.

Hypothesis 6: Change in recommendations for stocks with high brokerage coverage have a greater impact on prices than stocks with lower brokerage coverage.

To test if this designated hypothesis is valid, the regression analysis includes $COVER_{BROKER}$ as independent variable, which equals the mean number of brokers who covered a stock. The coefficient is expected to be positive for buys and negative for sells.

4 Empirical Results

This chapter provides empirical results for all statistical analysis as described in the previous chapter. The first section of this chapter, starts with the results of the descriptive statistics on the entire recommendation sample. The following sections show the event study and the cross-sectional regression results to answer the imposed hypothesis three to five and the addressed research question. Finally, in the last section, an additional test will be conducted in order to analyze if the trading volume differ significantly at the event date.

4.1 Descriptive Statistics

To begin, table 1 provides annual descriptive statistics on analyst recommendations for the years 2000 through 2017. Column (3) shows the number of analysts providing recommendations has increased from 269 in 2000 to 537 in 2017. In this data sample, the DJIA was on average by 499 analysts covered during the sample period. The same development applies for the number of brokerage houses in column (4), since the number of brokerage houses has increased consistently from 58 brokerage firms in 2000 to a high of 100 brokerage firms in 2017. The entire sample period records on average 96 brokerage firms. Column (5) shows the mean number of analysts employed per brokerage house. As the number of brokerage firms were increasing, the mean number of analysts per brokerage has increased subsequently. Since the mean number can be distorted from larger institutions like J.P. Morgan, Credit Suisse, Barclays, UBS, Morning Star and Morgan Stanley who employ on average between 20 to 30 analysts, the median provides better information on analysts per brokerage house. Column (6) indicates the median number of analysts has increased from two per brokerage in 2000 to three analysts per brokerage in 2017. Over the entire period the median number shows three analysts were working in a brokerage house. Column (7) shows the mean number of analysts following a firm has increased across the time period from 12 analysts to almost 30 analysts and the median number of analysts from 11 to 28, respectively. These numbers are in line with the findings of Welch (2000) and Michaely et al. (2002a) who observed in their research that a firm is followed on average by 20 to 30 analysts. In contrast to these results, Souček

et al. (2014) found in their descriptive statistics firms in the German Dax are on average covered by 16.85 analysts during the period 2000-2012.

Year	Number of Firms	Number of Analysts	Number of Brokerages	Analysts per Brokerage		Analysts per covered firm	
				Mean	Median	Mean	Median
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2000	29	269	58	4.64	2	12.14	11
2001	29	389	72	5.4	2	17.28	15
2002	29	435	96	4.53	2	19.90	19
2003	29	463	99	4.68	2	20.48	18
2004	29	446	91	4.90	2	19.59	18
2005	29	473	88	5.38	3	21.55	21
2006	29	437	92	4.91	3	19.66	19
2007	29	415	83	5.00	2	19.34	18
2008	30	428	88	4.86	2.5	19.43	18
2009	30	527	103	5.12	3	25.41	23
2010	30	554	111	4.99	3	25.93	24
2011	30	584	108	5.41	3	28.03	27
2012	30	615	111	5.49	3	29.57	27
2013	30	598	110	5.49	3	29.10	27
2014	30	625	103	5.95	3	31-34	30
2015	30	603	99	5.97	3	29.50	27
2016	30	589	107	5.45	3	29.77	28
2017	30	537	100	5.37	3	27.47	28
Overall average		499.28	95.50	5.20	3.00	23.64	22

Table 1: Annual Descriptive Statistics on the DJIA Analysts' Recommendations sample

Hypothesis 1:

The first designated hypothesis stated analysts are more reluctant to issue sell recommendations. To check whether this hypothesis is valid, the distribution of analysts' recommendations was analyzed and descriptive statistic was used across the sample period.

Figure 2 demonstrates graphically the distribution of analysts' recommendations over the examined time frame from 2000 to 2017. It can be clearly seen that analysts tend to provide mostly buy and hold recommendations rather than a sell or a strong sell recommendation. Strong buy recommendations decreased surprisingly in 2000 from 15% to 5% in year 2002 and make up a minority amount as the recommendation percentages per year is in line with a strong sell recommendation. The extensive decline in strong buy

recommendation by 66.67% is the result of NASD 2711[7] and NYSE 472[8] rules on brokerage houses to disclose their recommendation distributions. This further disclosure requirements also contributed to a shift in recommendations, where the percentage of buy recommendations increased from 2002 onwards. The graph shows a pattern between buy recommendations and hold recommendations, the graph clearly indicates over time, when buy recommendations are increasing, hold recommendations are decreasing. The opposite is true when hold recommendations are increasing, buy recommendations are decreasing, respectively. Referring to chapter three *Research Methodology*, this development can be caused by the positive relation between market sentiment (investors mood) and analysts' recommendations. Ample research reports showed over time, analysts' recommendations are more opportunistic when investor sentiment is high, as quoted in the previous chapter three *Research Methodology*. Surprisingly this graph contradicts partially with the positive correlation, just by viewing on the below graph, as it shows in years ranging 2000-2001 where investor sentiment was high, a decrease in buy recommendations started already. This does not mean that the positive correlation, which is reported by the literature, is rejected.

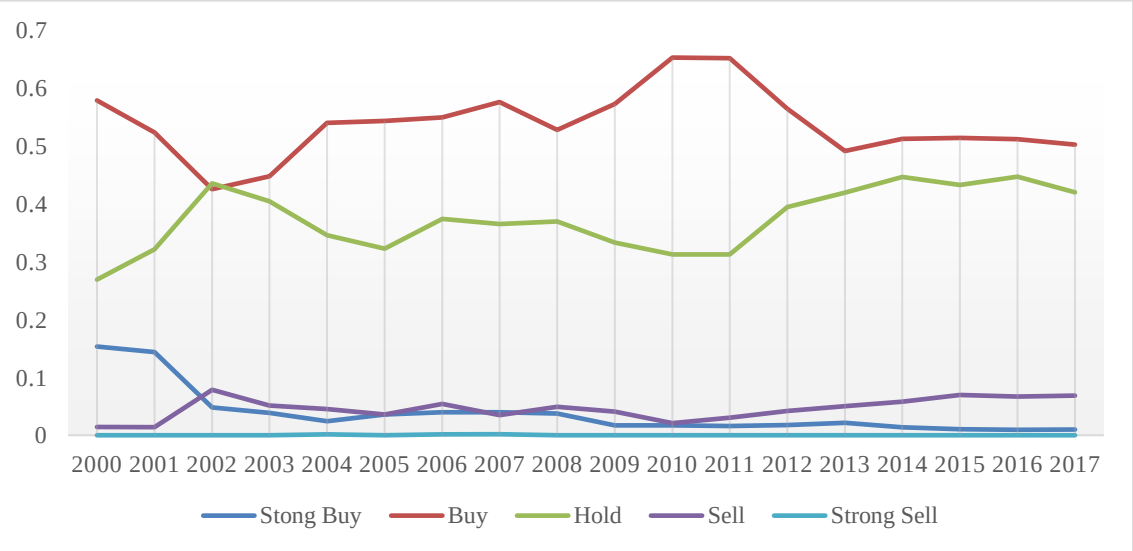

Figure 2: Distribution of Analysts' Recommendations over time period 2000 to 2017

Each line presents the corresponding recommendation's weight in relation to the total amount of recommendations.

[7] See http://finra.complinet.com/en/display/display_main.html?rbid=2403\&element_id=3675 for further detailed information.
[8] See http://finra.complinet.com/en/display/display_main.html?rbid=2403\&record_id=16349 for further detailed information.

Table 2 provides statistics on the recommendations included in this research study. Per year the number of recommendations, the number of covered firms, the number of brokerage houses issuing recommendation reports and the average rating. The average rating follows the rating scale from 1 to 5, where rating 1 is a *'Strong buy'* and rating 5 means a *'Strong sell'*, respectively. Additionally, the ratings are composed into three categories Strong Buy/ Buy, Hold and Sell/ Strong Sell. The absolute amount of observations per category and the percentage of total recommendations by years are presented. The number of covered firms is constant across the sample period, since the focus is solely on all recommendations on the DJIA. For the entire period covered by this research the sample includes 12,389 recommendations, where a rating from 1 to 5 was issued, made by 270 different brokerage houses. Remarkable is how the amount of analysts' recommendations has doubled from 351 in 2000 to 806 in 2017. It can be seen that analysts have provided more positive recommendations in the early 2000s, where category Strong Buy/ Buy make more than 60% of the recommendations. This pattern normalized after the implied new rules on research in connection with investment banking activities, whereas as a result Hold recommendations increased by a compounded annual growth rate (CAGR) of 29.03%, precisely from 26.50% to 44.12% in 2002. Overall Sell/ Strong Sell increased from 1.42% and remained stable at a lower level of 6.82% in 2017.

Year	Number of Recommendations	Number of Firms	Number of Brokerage Houses	Average Rating	Median	Recommendation Frequency					
						Strong Buy/Buy		Hold		Sell/Strong Sell	
						N	% of Total	N	% of Total	N	% of Total
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2000	351	29	58	2.14	2	253	72.08%	93	26.50%	5	1.42%
2001	502	29	72	2.21	2	334	66.53%	161	32.07%	7	1.39%
2002	578	29	96	2.55	3	277	47.92%	255	44.12%	46	7.96%
2003	587	29	99	2.50	2	303	51.62%	252	42.93%	32	5.45%
2004	548	29	91	2.44	2	323	58.94%	198	36.13%	27	4.93%
2005	604	29	88	2.38	2	373	61.75%	208	34.44%	23	3.81%
2006	563	29	92	2.44	2	326	57.90%	207	36.77%	30	5.33%
2007	560	29	83	2.39	2	339	60.54%	201	35.89%	20	3.57%
2008	581	30	88	2.44	2	333	57.31%	218	37.52%	30	5.16%
2009	732	30	103	2.41	2	448	61.20%	253	34.56%	31	4.23%
2010	764	30	111	2.34	2	510	66.75%	238	31.15%	16	2.09%
2011	825	30	108	2.35	2	545	66.06%	255	30.91%	25	3.03%
2012	870	30	111	2.45	2	497	57.13%	337	38.74%	36	4.14%
2013	862	30	110	2.51	2	450	52.20%	368	42.69%	44	5.10%
2014	905	30	103	2.53	2	462	51.05%	392	43.31%	51	5.64%
2015	871	30	99	2.55	2	445	51.09%	367	42.14%	59	6.77%
2016	880	30	107	2.55	2	443	50.34%	380	43.18%	57	6.48%
2017	806	30	100	2.55	2	413	51.24%	338	41.94%	55	6.82%
Overall	**12,389**	**29.56**	**270**	**2.43**	**2**	**7,074**	**57.10%**	**4,721**	**38.11%**	594	**4.79%**

Table 2: Annual Descriptive Statistics on the DJIA Analysts' Recommendations by category

In total on average 57.10% Strong Buy/ Buy, 38.11% Hold and 4.79% Sell/ Strong Sell recommendations were issued on the securities included in the DJIA. Those numbers are in line with most research studies, where all U.S. outstanding recommendations on securities were examined. As expected and in consistent with prior literature, Elton et al. (1986)[9], Stickel (1995)[10], Barber et al. (1998)[11], Willis (2004)[12] and further literature, the number of Sell/ Strong Sell recommendations, category Sell/ Strong Sell (designated rating 4 and 5), building a minority in comparison to the total amount of analysts' recommendations. In contrast to the prior mentioned literature which deliver similar results is Souček et al. (2014) findings where sell recommendations make up 19.20% of the total recommendation sample on securities included in the German Dax.

The sample in my study showed that strong buy and buy recommendations make the majority of recommendations and occur more frequently than sell and strong sell recommendations. This observation clearly confirms hypothesis one that analysts are issuing predominantly optimistic recommendations and analysts hesitance to issue more negative recommendations in form of a strong sell or a sell recommendation is evidently reflected in the data.

Michaley et al. (2002a) explain these biases in recommendations by the fact that analysts are facing pressure to report and reiterate positive recommendations on covered firms with which the investment bank has either an existing client relationship or intents to build a relationship with a potential client. Further both researchers state the impact of negative recommendations hits an investment banking business activities in the future, as the company where a negative recommendation is issued will most likely switch to another investment bank. Moreover, the risk of an incorrect sell recommendation is much higher than an incorrect buy recommendation for an analysts and investment banks

[9] Elton et al. (1986) examined in their research during the time period 1981-1983 a distribution of 48% of Strong Buy/ Buy and 2% of Strong Sell/ Sell recommendations.
[10] Stickel (1995) research showed for the analyzed time frame 1988-1991 a recommendation frequency distribution 55% in category Strong Buy/ Buy, 33% of Hold and 12% of Sell/ Strong Sell recommendations.
[11] Barber et al. (1998) Research examined in the time frame from 1986-1996 a recommendation frequency distribution of 55% of Strong Buy/ Buy, 33% of Hold and 6.3% of Sell/ Strong Sell recommendations.
[12] Distribution of recommendations included in Willis et al. (2004) research for the time frame 1993-1999 shows 58.2% Strong buy/ buy; 35.6% are hold and 6.2% of the recommendations are Sell/ Strong Sell.

reputation. Therefore, due to the higher risk of a wrong anticipated outcome of a recommendation, it is expected according to Souček et al. (2014) that sell recommendations are issued less frequently.

According to Michaley et al. (2002a) the bias of analysts to issue sell recommendations is called *"optimism bias"* and both researchers have observed in their study a ratio of 10 buy recommendations to 1 sell recommendation throughout their sample period. In this research on average a ratio of 13 Strong Buy/ Buy recommendations to 1 Sell/ Strong sell recommendation throughout the time frame 2000-2017 is observed.

Hypothesis 2:

The second hypothesis stated that analysts are following large capitalized corporations and largely covering certain attractive sectors. In comparison to most academic research papers, this empirical research is able to provide descriptive statistics on analyst's recommendation separately to all firms included in the study as the focus is solely on recommendations of securities included in the DJIA index and not on all outstanding U.S. recommendations, which can be easily obtained from the I/B/E/S Thomson Reuters recommendation database.

Table 3 shows descriptive statistics on all securities included in the DJIA, total number of observations per security, weighted average rating and median rating for the years ranging from 2000 to 2017. Average rating, mean is based on the rating scale where a rating 1 follows a *'Strong buy'*, 2 a *'Buy'*, 3 a *'Hold'*, 4 a *'Sell'* and rating 5 a *'Strong sell'*, respectively. From a view on the amount of recommendations for each firm, the table demonstrates a preference of analysts to cover firms in the information technology sector. The highest amount of recommendations was made on securities for instance Intel, Microsoft and Apple, whereas the least amount of recommendations is issued on industrial, material and consumer discretion sectors. Analysts made the most favorable recommendation on firms like United Health Group where an average rating of 2.21 was issued, Visa with a reported consensus average rating of 2.22, Apple with a rating of 2.24 and a rating of 2.27 for United Technologies. The median rating, which is the midpoint

of the data, also confirms a clear buy for all above mentioned firms. The highest consensus average rating was reported for Merck & Co. and Travellers Company with a rating of 2.59, DuPont with a rating of 2.60, Caterpillar and Exxon Mobile with a rating of 2.65 and American Express with an average rating of 2.66, which almost corresponds to a hold. For all six firms the median rating, which separates half of the observations below the median and half above, corresponds to a rating of 3, which is a hold.

Firms	**Industry**	**Number of Recommnedations**	Rating per Security **Mean**	**Median**
(1)	(2)	(3)	(4)	(5)
Apple	INFORMATION TECHNOLOGY	618	2.24	2
American Express	FINANCIALS	420	2.66	3
Boing	INDUSTRIALS	389	2.52	2
Caterpillar	INDUSTRIALS	349	2.65	3
Cisco Systems	INFORMATION TECHNOLOGY	665	2.38	2
Chevron	ENERGY	377	2.46	2
DuPont	MATERIALS	271	2.60	3
Disney World	CONSUMER DISCRETION	479	2.46	2
General Electric	INDUSTRIALS	320	2.37	2
Goldman Sachs	FINANCIALS	386	2.56	3
Home Depot	CONSUMER DISCRETION	432	2.41	2
IBM	INFORMATION TECHNOLOGY	407	2.52	2
Intel	INFORMATION TECHNOLOGY	685	2.50	2
Johnson & Johnson	HEALTHCARE	371	2.40	2
JP Morgan	FINANCIALS	443	2.36	2
Coca Cola	CONSUMER STAPLES	313	2.49	2
McDonalds	CONSUMER DISCRETION	358	2.50	2
3M	INDUSTRIALS	269	2.46	2
Merck & Co.	HEALTHCARE	389	2.59	3
Microsoft	INFORMATION TECHNOLOGY	632	2.32	2
Nike	CONSUMER DISCRETION	344	2.35	2
Pfizer	HEALTHCARE	400	2.30	2
P&G	CONSUMER STAPLES	342	2.51	2
Travellers Company	FINANCIALS	364	2.59	3
United Health Group	HEALTHCARE	356	2.21	2
United Technologies	INDUSTRIALS	324	2.27	2
Visa	INFORMATION TECHNOLOGY	343	2.22	2
Verizon	TELECOMMUNICATIONS	545	2.53	3
Wal Mart	CONSUMER STAPLES	487	2.46	2
Exxon Mobile	ENERGY	358	2.65	3

Table 3: Descriptive Statistics on all Firms included in the DJIA

Table 4 reports information on analyst's coverage and brokerage coverage per firm included in the DJIA. Column (4) represents the average number of analysts covering a security and column (6) represents the average number of brokerage houses per firm. The table shows evidently a preference of analysts to follow a certain attractive sector, since Apple is covered on average by 34.94 analysts, Cisco Systems by 37.22 analysts on average, Microsoft by 35.55 analysts on average and Intel by 38.50 analysts respectively. The information technology sector is overall on average by 33.79 analysts followed during the sample period. Whereas the coverage on the industrial sector is considerably lower, as General Electric is on average covered by 17.83 analysts, United Technology on average by 18.33 analysts and 3M with an average coverage of 15.11 analysts. Generally, the industrial sector is covered by 18.51 analysts during the sample period. Further least preferred sector is the material sector, as DuPont with an average coverage of 15.11 amounts the lowest average coverage of analysts. Additionally, the sector information technology is on average covered by a higher number of brokerage firms in contrast to other sectors, see column (6).

These summary statistics are in line with the observations in table 3, where based on the total amount of recommendations a preference of analysts to follow a certain attractive sector was obviously seen.

		Number of Analysts		Number of Brokerage	
Firms	**Industry**	**Number**	**Mean**	**Number**	**Mean**
(1)	(2)	(3)	(4)	(5)	(6)
Apple	INFORMATION TECHNOLOGY	159	34.94	117	34.94
American Express	FINANCIALS	100	22.89	65	23.44
Boing	INDUSTRIALS	92	21.67	62	21.67
Caterpillar	INDUSTRIALS	79	19.56	55	19.56
Cisco Systems	INFORMATION TECHNOLOGY	167	37.22	122	37.39
Chevron	ENERGY	96	20.94	57	20.94
DuPont	MATERIALS	64	15.11	47	15.11
Disney World	CONSUMER DISCRETION	100	27.56	81	27.56
General Electric	INDUSTRIALS	86	17.83	58	17.94
Goldman Sachs	FINANCIALS	87	21.33	61	21.33
Home Depot	CONSUMER DISCRETION	82	24.5	67	24.50
IBM	INFORMATION TECHNOLOGY	102	23.00	78	23.00
Intel	INFORMATION TECHNOLOGY	166	38.5	117	38.67
Johnson & Johnson	HEALTHCARE	100	21.06	59	21.06
JP Morgan	FINANCIALS	98	24.5	71	24.50
Coca Cola	CONSUMER STAPLES	74	17.39	48	17.39
McDonalds	CONSUMER DISCRETION	83	21.41	62	21.41
3M	INDUSTRIALS	69	15.11	40	15.11
Merck & Co.	HEALTHCARE	93	21.83	61	21.83
Microsoft	INFORMATION TECHNOLOGY	195	35.5	115	35.50
Nike	CONSUMER DISCRETION	88	29.22	63	19.22
Pfizer	HEALTHCARE	111	24.24	74	24.24
P&G	CONSUMER STAPLES	81	19.00	54	19.00
Travellers Company	FINANCIALS	90	20.22	59	20.22
United Health Group	HEALTHCARE	74	20.17	50	20.17
United Technologies	INDUSTRIALS	78	18.39	52	18.39
Visa	INFORMATION TECHNOLOGY	85	33.60	64	34.40
Verizon	TELECOMMUNICATIONS	127	20.89	92	31.17
Wal Mart	CONSUMER STAPLES	110	27.87	73	27.78
Exxon Mobile	ENERGY	97	19.78	62	19.83

Table 4: Statistics on all Firms included in the DJIA: Analyst and brokerage coverage

Descriptive statistics on all DJIA securities confirmed hypothesis 2 that analysts follow large capitalized firms and have a preference to follow a certain attractive sector. The sample data reflects, all securities have on average an analyst coverage of at least 15 analysts. Further, there is a preference to cover the information technology sector, as this sector had the highest analyst coverage, the highest brokerage coverage and as this sector recorded the highest amount of recommendations.

Table 5 shows a 5 x 5 transition matrix of analysts' recommendations, where each cell shows the number of recommendations revisions from an initial rating to a new rating. The diagonal cells of the matrix are recommendations reiterations, whereas the off-diagonal cells present recommendation revisions. According to the imposed criteria in chapter three *Research Methodology*, this table excludes analysts' recommendations, where only an initial recommendation was issued, without a revision in the sample period.

It can be observed that the recommendations are clustered at the rating buy in the upper 2 x 2 cells, which means analysts tend mostly to revise their previous announced buy recommendations. When a previous recommendation is a hold, analysts tend to upgrade a recommendation to buy, rather than to downgrade the rating of a corporation to sell.

	To Recommendation of:						
From Recommendation of:	(1) Strong Buy	(2) Buy	(3) Hold	(4) Sell	(5) Strong Sell	Total	Percent
(1) Strong Buy	**179**	109	65	9	0	362	3.31%
(2) Buy	98	**4,661**	1,107	94	2	5,962	54.44%
(3) Hold	44	1,096	**2,786**	180	1	4,107	37.50%
(4) Sell	5	86	187	**241**	0	519	4.74%
(5) Strong Sell	1	0	1	0	**0**	2	0.02%
Total	327	5,952	4,146	524	3	10,952	-
Percent of Total	2.99%	54.35%	37.86%	4.78%	0.03%	-	100%

Table 5: 5x5 Transition Matrix of Analysts' Recommendations

The tendency of analysts to revise their previous opinions which occur more frequently as observed in the above table, can be explained by various research studies which address the herding behavior of security analysts. Agreeing with Welch (2000) there is no surprise why security analysts exhibit herding behavior, as all analysts have the same information and therefore act all in similar way. Further his findings give insight into the direction of recommendation revisions, since Welch (2000) observed a tendency of analysts to revise their recommendations towards previous recommendations than away from them. Herding effect investigated by Jegadeesh and Kim (2010) confirms analysts' reluctance to stand out from the crowd, as their findings indicate recommendation revisions are partly based by analysts' aspiration to follow the crowd.

4.2 Event Study Results

Table 13 and table 14 attached in the appendix stores calculated average abnormal returns (AAR) for single event days ranging from $t = -20$ to $t = +120$ for upgrades and downgrades and their respective t-statistics.

Table 13 reports average abnormal returns of upgrades which are throughout the time period positive, negative and statistically significant from zero at different significance levels and across different event days. Moreover, the table shows no pattern in the size of abnormal return and a variation at a lower marginal percentage level across the event days. One-tailed hypothesis test, which tested the hypothesis if AAR are significantly larger than zero, resulted in significant coefficients in the pre-event window at event days $t = -17$, $t = -9$ to $t = -8$, $t = -5$ before the event date and in the post-event window at event days $t = +11$, $t = +33$, $t = +63$, $t = +79$ and $t = +96$. The coefficients of negative abnormal returns resulted in various statistically significant coefficients by computing an additional two-tailed hypothesis test. Abnormal returns from $t = -1$ to $t = +1$, which includes the event day $t = 0$ resulted in positive abnormal returns which are not statistically different from zero. To conclude the hypothesis of no abnormal returns cannot be rejected before and immediately after the event happened. This means days before and after a recommendation announcement have not an impact on security prices and investors do not profit from trading according to analysts' recommendation direction.

Average abnormal returns of downgrades in table 14 points out abnormal returns are generally negative and statistically significant across various single event days in the pre-event window and in the post-event window. Further one can see the coefficients of negative abnormal returns differ in the size across the event days and no obvious pattern in the magnitude is apparent. In the pre-event window before day $t = -1$ there are barely any significant abnormal returns, besides the significant coefficient at event days $t = -18$, $t = -10$ and $t = -8$. Compared to upgrades, the coefficients of abnormal returns of downgrades are as expected, statistically significant in the event-window from $t = -1$ to $t = +1$ around the event date and the hypothesis of no abnormal returns can be rejected at less than 0.05 and 0.01 level for both one-tailed and two-tailed hypothesis test. Negative abnormal returns are more negative on the event date $t = 0$ compared to one day after

the event. The results imply recommendation announcements in the 3-day event period centered on the recommendation event date have an impact on security prices, nevertheless a less economically meaningful effect as can be seen by the lower marginal percentage level. To conclude the alternative hypothesis of abnormal returns cannot be rejected before and immediately after the event happened.

Table 6 reports cumulative average abnormal returns (CAAR) with t-statistics over different event windows in ten day intervals separately for recommendation upgrades and downgrades.

Recommendations which were upgraded are generally statistically significant in various time periods starting from day $t = +21$ until day $t = +120$. By looking on the numbers one can see CAAR are mostly negative across different time interval periods likewise table 13 showed a negative pattern in average abnormal returns. Barely three-time intervals $t = -10$ to $t = -1$, $t = -1$ to $t = +1$ and $t = +61$ to $t = +70$ resulted in positive cumulative average abnormal returns, whereas CAAR of the last-mentioned time interval is statistically significant at the 0.01 significance level. In the long-term interval which ranges from $t = -5$ to $t = +120$ a significant negative post-recommendation drift of -3.18% is found. Comparing the observed post event drift with the reported recommendation drift observed by Womack (1996), the drift in this empirical research is surprisingly negative and not moving towards the direction of analysts' forecasts. Overall in this research, no positive significant pre-event drift and no positive long-term post-event recommendation drift is observed.

Recommendation revisions which were downgraded had generally as predicted negative returns and abnormal returns were in most time intervals in the pre-event and post-event window highly statistically significant at less than 0.01 significance level. Compared to downgrades the coefficient of the short-term time period $t = -1$ to $t = +1$ which includes the event date $t = 0$, differ significantly from zero and the null hypothesis of no abnormal performance can be evidently rejected based on the high t-statistic value of *t-Stat*= -5.01. To conclude in this research, the drift in the pre-event recommendation

window and post-event recommendation window are both negative and statistically significant different from zero. Moreover, the magnitude of abnormal returns is increasing as the event window is extended. These findings align with Womack's (1996) findings, who observed a significant post-recommendation drift.

Summarizing the results, barely a significant pre-event recommendation drift is observed for recommendation downgrades and sign of the coefficients are towards analysts forecasted direction. CAAR in the long-term post-event recommendation window ranging from $t = -5$ to $t = +120$ are equally for upgrades and downgrades highly statistically significant as can be seen by the high t-statistic value of -7.34 for buys and -6.10 for sells respectively.

Upgrades			**Downgrades**		
Event Day (t)	Mean (%)	t-Statistic	Event Day (t)	Mean (%)	t-Statistic
(-20, -11)	-0.1093	-0.79	(-20, -11)	-0.0915	-0.80
(-10, -1)	0.1227	0.89	(-10, -1)	-0.2113*	-1.69
(-1, +1)	0.1043	1.00	(-1, +1)	-0.5229***	-5.01
(0, +10)	-0.1724	-1.31	(0, +10)	-0.2621**	-2.04
(+11, +20)	-0.5402	-0.48	(+11, +20)	-0.1522	-1.58
(+21, +30)	-0.3327***	-2.73	(+21, +30)	-0.3075***	-2.61
(+31, +40)	-0.3870***	-3.07	(+31, +40)	0.1393	1.20
(+41, 50)	-0.2821**	-2.50	(+41, 50)	-0.4050***	-3.42
(+51, 60)	-0.3739***	-2.88	(+51, 60)	-0.3477***	-2.98
(+61, +70)	0.4268***	-3.20	(+61, +70)	-0.2747**	-2.11
(+71, +80)	-0.1932*	-1.88	(+71, +80)	0.0531	0.52
(+81, +90)	-0.4253***	-3.53	(+81, +90)	-0.1845*	-1.67
(+91, +100)	-0.0547	-0.45	(+91, +100)	0.0230	0.21
(+101, +110)	-0.1240	-1.02	(+101, +110)	0.1845*	-1.67
(+111, +120)	-0.4116***	-3.85	(+111, +120)	-0.4426***	-4.33
(-5, +120)	-3.1834***	-7.34	(-5, +120)	-2.3425***	-6.10

Table 6: Cumulative Average Abnormal Returns

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

Figure 3 and figure 4 plots the average stock price reaction in form of cumulative abnormal returns (CAR) over the event period ranging from t_1=-20 to t_2=+20 centered on the recommendation event date.

The CAR graph of recommendation upgrades shows a volatile pattern in abnormal returns, one can see that abnormal returns were increasing in the pre-event period from event-window $t = -10$ to $t = -5$ and two days before event day $t = 0$ until event day $t = +4$ and then it reversed. Moreover, the graph shows two maximum drawdowns occurred during the 20-day period. The most remarkable price adjustments occur within the 20-day period immediately following day zero. Comparing this CAR price-drift with the price movement found in the literature, by surprise the upgrades CAR graph is not moving towards analysts revised recommendation direction in the post-estimation window. Further the observed increase in average excess returns before event day zero, is not statistically significant from zero, as can be viewed in table 15 attached in the appendix.

To conclude, the graph clearly implies investors are not able to achieve excess returns (Alpha) by trading according to analysts' recommendations and investors cannot gain a value from analysts.

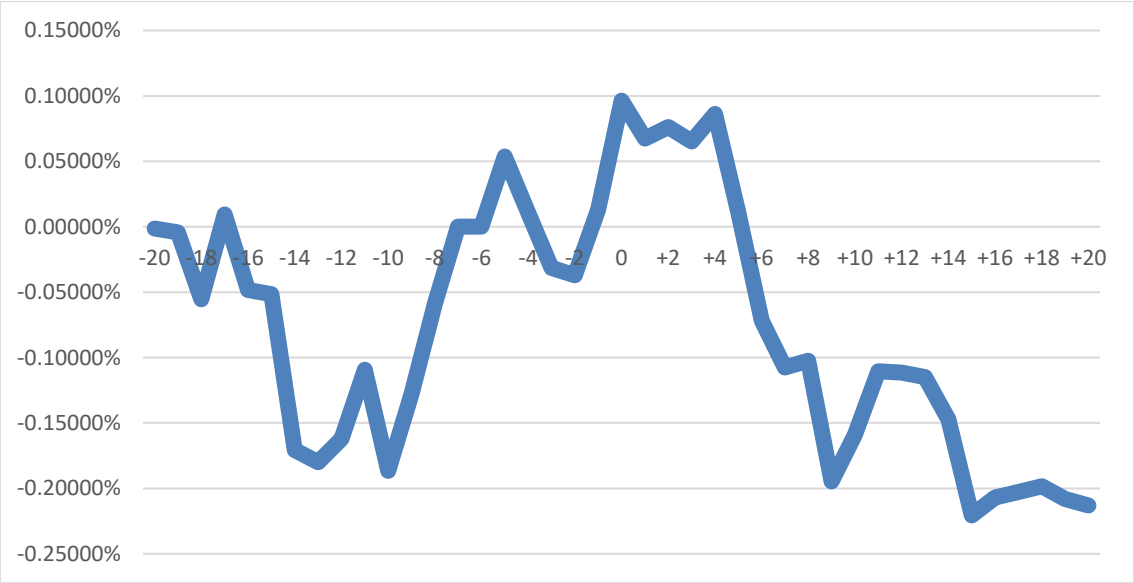

Figure 3: Cumulative Abnormal Returns (CAR) of Recommendation Upgrades

CAR graph of recommendation downgrades shows abnormal returns are negative in the pre-event period before the event day $t = 0$ and are continuing to decrease sharply from event day $t = -3$ forwards. This CAR pattern is highly statistically significant from zero at less than 0.01 significance level over then event period ranging from $t = -1$ to $t = +20$, as can be seen in table 15 in the appendix where the corresponding CAR and t-statistics are stored.

The figure CAR of downgrades clearly indicates that recommendation revisions of downgrades are moving towards analysts revised recommendation direction before the event occurred and the post-event drift is highly statistically significant at less than 0.01 significance level. Overall, the price reaction of sell recommendations is in line with the findings of Stickel (1995), who observed the pre-event drift starts in the 20-day period before the event.

To conclude, the graph clearly implies sell recommendations are associated with negative abnormal returns, and abnormal returns start to decrease before the recommendation event date.

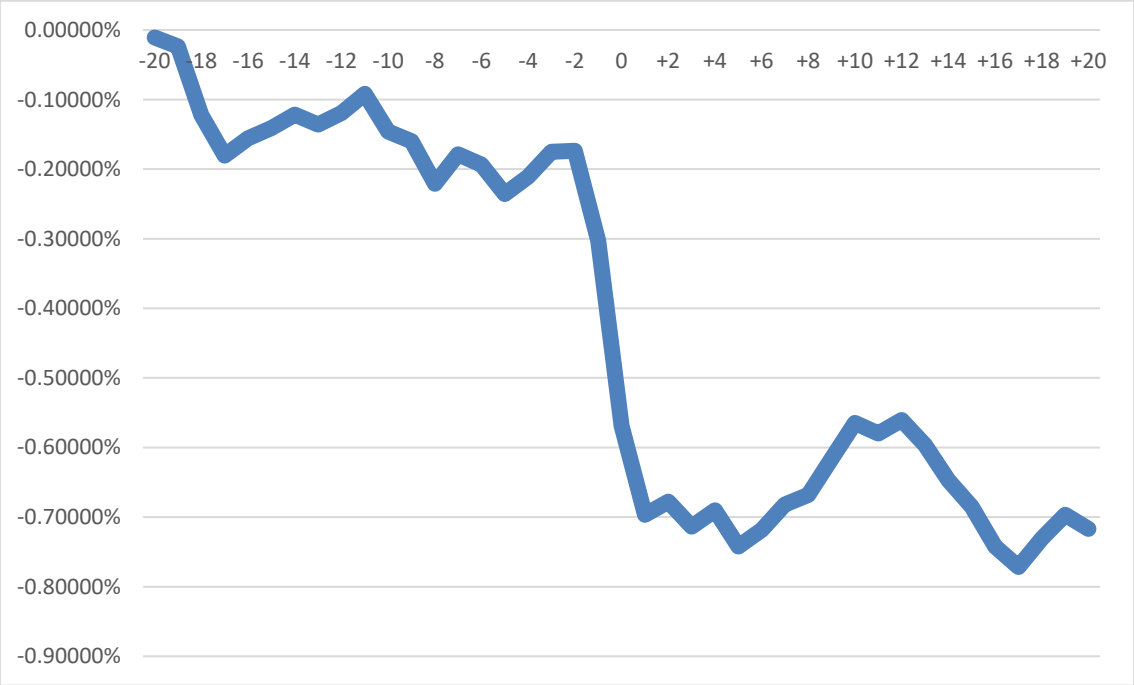

Figure 4:Cumulative Abnormal Returns (CAR) of Recommendation Downgrades

4.3 Regression Analysis

In the following cross-sectional regression analysis, buy recommendations are defined as all rating upgrades to a strong buy and buy coming from a recommendation of hold, sell or strong sell. Sell recommendations are defined as all downgrades in recommendation revision to strong sell and sell, coming from a rating of strong buy, buy or hold. Including recommendation downward revisions to hold from a strong buy or a buy recommendation.

The following multivariate OLS regression was estimated separately for recommendation revisions combined in the buy portfolio and recommendation revisions included in the sell portfolio. The hypotheses were tested on the below cross-sectional regression equation, which regresses cumulative abnormal return of stocks in the event window $[t_1\,, t_2]$ as dependent variable against selected independent variables as explained in section three *Research Methodology*.

$$CAR_{t1,t2} = \alpha_0 + \beta_1 COVER_{ANALYST} + \beta_2 STRONG + \beta_3 SKIPRANK + \beta_4 MARKET_{TYPE} + \beta_5 TRADING_{SIGNAL} + \beta_6 COVER_{BROKER} + \varepsilon$$

The results are reported for short information content window $[-5, +5]$ and for long information content window $[-5, +120]$ whereas the respective selection aims to capture the short-term and long-term price performance. As discussed in section three *Research Methodology* days before the event date need to be included to account for the likelihood of earlier dissemination. The regression equation is also conducted across different event windows ranging from $[-10, -1]$, $[-1, +1]$ and $[0, +10]$, to capture if the results holds across varying time periods which include the event date.

Table 6 reports descriptive statistics for the dependent variables used in the buy and sell regressions. For buy recommendations the means of CAR are surprisingly negative in most event periods and not statistically significant. The means of CAR are only positive for $CAR_{(-10, -1)}$ $CAR_{(-1, +1)}$, at a lower percentage level. For sells, the means of $CAR_{(-5, +5)}$ $CAR_{(-5, +120)}$, $CAR_{(-10, -1)}$ $CAR_{(-1, +1)}$ and $CAR_{(0, +10)}$ are -0.60%, -2.30%, -0.30%, -0.48%

and -0.24%. All means are significantly different from zero at less than 0.05 and 0.01 level and increasing in the magnitude from short-term to long-term event window. As stated in the table, abnormal returns for buys was calculated based on 1,002 observations and based on 1,188 observations for sells.

Variable	Number of Observations	Mean	t-Statistics	p-value	Minimum	Fisrt Quarter	Median	Third Quarter	Maximum
Buy recommendations									
CAR (-5, +5)	1,002	-0.0012%	-0.0081	0.5032	-18.18%	-2.42%	0.13%	2.48%	18.92%
CAR (-5, +120)	950	-3.0576%	-6.8267	1.0000	-63.41%	-10.36%	-3.16%	5.18%	10.81%
CAR (-10, -1)	1,002	0.0638%	0.3908	0.348	-46.81%	-2.29%	-0.08%	2.30%	54.24%
CAR (-1, +1)	1,002	0.0904%	0.8547	0.1965	-20.00%	-1.25%	0.10%	1.58%	16.54%
CAR (0, +10)	1,002	-0.1611%	-1.2104	0.8868	-19.43%	-2.34%	-0.26%	2.07%	22.04%
Sell recommendations									
CAR (-5, +5)	1,188	-0.6028%	-3.8751***	0.0001	-56.84%	-3.00%	-0.38%	2.27%	21.68%
CAR (-5, +120)	1,127	-2.2967%	-6.0055***	0.0000	-63.65%	-9.30%	-2.43%	5.27%	6.71%
CAR (-10, -1)	1,188	-0.2981%	-2.1800**	0.0147	-52.10%	-2.52%	-0.21%	2.08%	19.83%
CAR (-1, +1)	1,188	-0.4779%	-4.2937***	0.0000	-17.38%	-1.96%	-0.28%	1.15%	43.10%
CAR (0, +10)	1,188	-0.2416%	-1.8720**	0.0307	-23.41%	-2.36%	-0.10%	1.99%	21.88%

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Distributions of dependent variables used in the regression analysis

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

Table 7 shows the distribution of independent dummy variables used in the cross-sectional regression analysis. Barely 11% of the buy recommendations were strong buy recommendations, whereas almost 18% of the sell recommendations were downgraded to either strong sell or sell. The percentage amount of recommendations that skipped a rating rank is for buy recommendations 8.18% and for sell recommendations 10.27%, respectively. As expected more recommendations were upgraded in the bull market phase and remarkably the similar applies for recommendation downgrades. The dummy variable $TRADING_{SIGNAL}$ shows a balanced distribution for both recommendation upgrades and downgrades across upward moving and downward moving market trends.

	Upgrades		Downgrades	
	0	1	0	1
STRONG	89.03%	10.97%	82.24%	17.76%
SKIPRANK	91.82%	8.18%	89.73%	10.27%
MARKET TYPE	16.35%	83.65%	14.98%	85.02%
TRADING SIGNAL	56.23%	43.77%	53.54%	46.46%

Table 8: Distributions of independent dummy variables

Definitions of variables:

The dummy variable STRONG takes the value one if a recommendation is either revised to strong buy for upgrades and zero otherwise (buy). For sell recommendations the dummy equals one if the recommendation is a strong sell or sell and zero otherwise (hold). SKIPRANK takes the value one if the change in recommendation skipped a rank and zero otherwise (do not change a rank).

For upgrades and downgrades in recommendations, the dummy $\text{MARKET}_{\text{TYPE}}$ equals one if recommendation was revised in the bull market phase and zero otherwise (bear market).

$\text{TRADING}_{\text{SIGNAL}}$, equals one if the change in recommendation happened when the short and long-term moving average cross showed a buy signal and zero otherwise, when the cross of both moving averages signaled sell. Buy signal is often viewed as an indicator of an emerging upward moving market and sell signal as a downward moving market.

In order to determine whether the data meets the regression assumptions and to ensure the validity of the regression model, several regression diagnostics were conducted. One important diagnostic is to detect the presence of heteroscedasticity in residuals. Consequences of the problem are biased standard errors, which in turn leads to bias test statistics and impacts the consequent significance values (Williams, 2015).

The following figure 5 for the buy regression which uses $\text{CAR}_{(-5,\,+120)}$ over the long-term event window $[-5, +120]$, points out the variance of residuals exhibits heteroscedasticity, which means the variance of the error term is not uniformly distributed and a non-random pattern in residuals is apparent. The width for some x_i values is for some residuals considerably larger than for others.

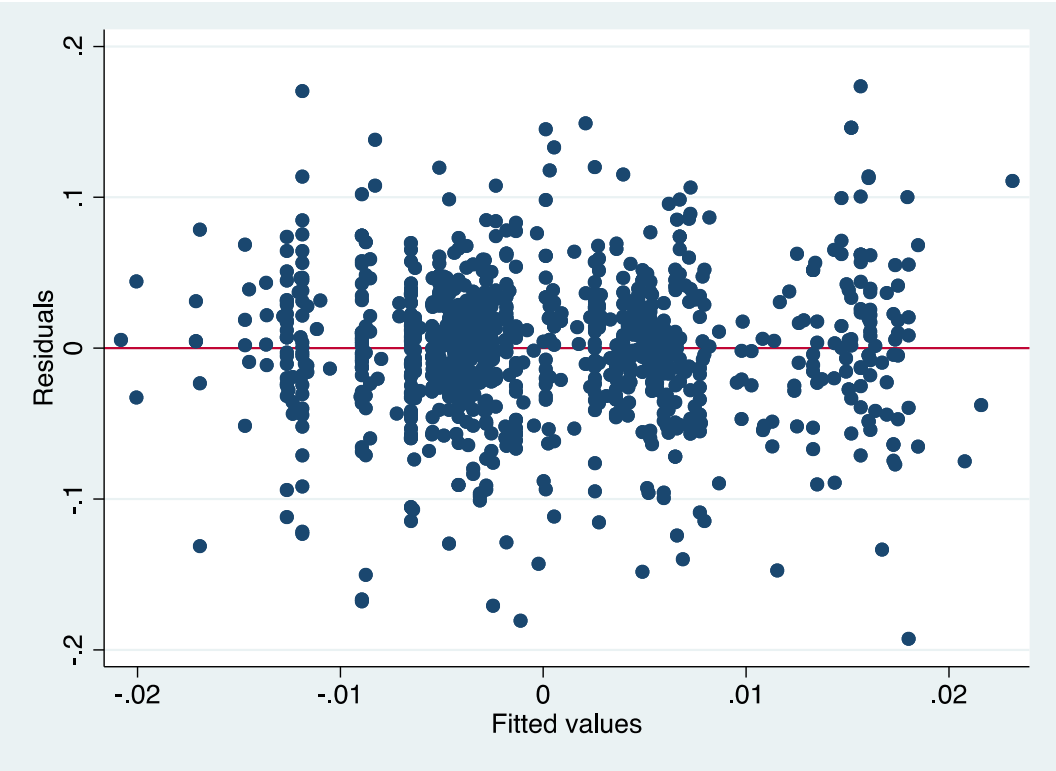

Figure 5: Residuals versus fitted values of the regression model using $CAR_{(-5,\,+120)}$

The similar pattern is present in four different regression models which use different event window, ranging from $[t_1, t_2]$ as mentioned earlier. Graphical inspection for buy and sell regressions is pointed out in figure 7 and figure 9 attached in the appendix. Figure 8 and figure 10 which plotted residuals squared against fitted values, further indicates the presence of heteroscedasticity as the squared residuals increase in magnitude as the fitted values increases. To verify whether the variance of error terms is not homoscedasticity a formal test is computed, namely the Breusch-Pagan/Cook-Weissberg heteroscedasticity test. The performed specification test aims to test under the null hypothesis that error term has a constant variance. The test output confirms heteroscedasticity, as the performed test rejects the null hypothesis with 99% confidence as indicated by the large chi-square test statistic, see figure 11 in appendix. The reason for heteroscedastic error term lies in the nature of securities due to the evidence that some securities are more volatile than others and exhibit a higher variance from the higher sensitivity to the overall market. For that reason, analytic weights of abnormal returns are used, which means abnormal returns with a high variance receive a lower weight. This is easily done by the statistical software Stata by applying the *robust* command and herewith by computing robust standard errors.

Correlation matrix are used to detect any multicollinearity in independent variables, as the assumptions of an OLS regression are violated if two or more variables are perfectly correlated. The below table 9 points out the variables $COVER_{ANALYST}$ and $COVER_{BROKER}$ are highly correlated with each other. Referring to Bachmann (2015d) a correlation coefficient around 0.8 might signal problems, since it might cause multicollinearity, which in turn leads to unreliable estimators. Therefore, two separate regressions were run and one regression each excludes the variable $COVER_{BROKER}$ and the variable $COVER_{ANALYST}$. The correlation matrix of the independent variables for the regression analysis of buy and sells can be found in table 17 and 18 attached in the appendix.

	COVER ANALYST	STRONG	SKIPRANK	MARKET TYPE	TRADING SIGNAL	COVER BROKER
COVER ANALYST	1.0000					
STRONG	-0.0074	1.0000				
SKIPRANK	0.0208	0.3122	1.0000			
MARKET TYPE	0.0276	-0.0784	-0.0526	1.0000		
TRADING SIGNAL	-0.0112	0.0317	-0.0041	-0.4252	1.0000	
COVER BROKER	0.7965	-0.0151	0.0001	0.0495	-0.0187	1.0000

Table 9: Correlation matrix of explanatory variables, upgrades and downgrades sample

Subsequently no autocorrelation in residuals need to be ensured, as any correlation in errors leads to biased OLS standard errors, unreliable test statistics and unreliable significant values. As a consequence, the null hypothesis is rejected too often, even when the null hypothesis is true. The recommendation change database exhibits cross-sectional dependence in events, since the revisions of analysts' recommendations are clustered and occur mostly in the same time period. By using the *cluster* command in Stata any cross-sectional and time-sectional autocorrelation is easily corrected. The technical implication behind is an adjustment of the standard error of the OLS estimators, as Stata uses automatically robust standard errors.

Another important aspect is identifying unusual and influential data points. Figure 12 and figure 13 in the appendix indicates some potential outliers are present as in every plot some data points are far away located from the rest of the data points. To prevent any biases in the regression coefficients and overall results, observation points which deviates significantly from the average cumulative return will be excluded. After performing

regression diagnostics, verification and corrections of the OLS assumptions, the estimators are consistent, the regression results are unbiased and can be presented and interpreted. Subsequently, several regression output results are described to answer hypothesis three to five. The regression results for upgrades and downgrades are stored in tables, which are attached in the appendix.

Results Hypothesis 3

Hypothesis three indicated that change in recommendations for corporations with low analyst coverage have a greater price impact on prices compared to corporations with higher analyst coverage. In order to test this hypothesis, the regression includes the independent parameter $\text{COVER}_{\text{ANALYST}}$. So far, the negative correlation between coverage and return is known from the literature. Hence, the coefficient is expected to be negative for buys and positive for sells. This means a higher coverage leads to lower positive and lower negative abnormal returns due to the higher amount of information's is made available from analysts and the reduced information asymmetry.

Table 19 show the regression results for recommendation upgrades and table 21 for recommendation downgrades, respectively. When looking at the regression output table 19, the coefficient of $\text{COVER}_{\text{ANALYST}}$ is generally as predicted negative for upgrades in recommendations and statistically significant at the 0.10 level in the long-term model (2) and statistically significant at the 0.05 level in model (5). In model (4) the sign of the coefficient in the event period $t_1 = -1$ to $t_2 = +1$ reversed and is different compared to the other models at a much lower economically meaningful percentage level.

The coefficient of the independent variable $\text{COVER}_{\text{ANALYST}}$ is in some models' positive and in some models' negative for sell recommendation revisions, as pointed out by table 21. In contrast to upgrades, the positive coefficients of $\text{COVER}_{\text{ANALYST}}$ are neither in model (1) and model (4) significantly different from zero.

Overall the results conclude, hypothesis three can be partially accepted. This means, hypothesis three can be only accepted for upgrades and restricted to the time interval $[-5, +120]$ and $[0, +5]$. The regression output indicates lower positive CAR is predicted when a stock is upgraded, which is covered by more analysts. For downgrades the

regression output delivers no statistical evidence for lower negative abnormal returns when the stock is covered by more analysts. Hence, it is not clear if a higher analyst coverage leads to lower negative abnormal returns and hypothesis three has to be rejected for downgrades.

Results Hypothesis 4

Hypothesis four stated that analysts are able to add value through finding overpriced and underpriced securities. To test the hypothesis the regression incorporates two independent dummy variables STRONG and SKIPRANK. The hypothesized effect of the dummy variable STRONG is that recommendation revisions to strong buy or strong sell should have a greater impact on stock prices than a change to buy or sell. The dummy SKIPRANK captures the price effect of upgrades and downgrades if one rank is skipped, whereas the price effect is expected to be larger if a rank is skipped due to the larger change in expectations. Therefore, it can be expected that both estimates of these dummies to be positive for buys and negative for sells.

Table 19 and table 20 shows the coefficient of variable STRONG of recommendation upgrades are negative across all different event windows and not positive as predicted. In both regression outputs the coefficients of the long-term model (2) and model (5) are statistically significant at less than 0.05 and 0.01 significance level. These results conclude recommendation upgrades to strong buy have a negative impact on prices than upgrades to buy. In the short-term model (1), which used CAR over the event period $t = -5$ to $t = +5$, upgrades have a marginal percentage effect of -0.90 on prices and even a higher negative impact of -3.34 in the long-term model (2). The negative impact on prices is increasing in the magnitude as the event-window is increasing, as can be seen in table 19 and table 20.

The regression output tables 21 and 22 for downgraded recommendations points out downgrades to strong sell and sell have generally a greater price impact than downgrades to hold and the coefficient of the dummy variable STRONG is mostly negative as predicted. Besides in model (5), where the coefficient is positive at a lower percentage level. Comparing the coefficients of the short-term model with the coefficients of the

long-term model, the tables show the negative impact is increasing in magnitude as the event window is extended. Model (1) which uses $CAR_{(-5, +5)}$ has a marginal percentage impact of -0.12 and model (2) which uses $CAR_{(-5, +120)}$ has a marginal percentage impact of -1.59 on prices.

When looking at the coefficients of the dummy variable SKIPRANK in the regression outputs of downgrades, one can see the coefficients are predominantly negative as predicted across all models. The tables of recommendation upgrades, show positive coefficients across all models. Revised recommendations to sell that skip a rank have a marginal percentage effect of -0.46 on price over the event period $t = -5$ to $t = +5$ and buy recommendations that skip a rank have a marginal percentage effect of +0.52 on prices. In the event period $t = -5$ to $t = +120$, buy recommendations have a marginal percentage effect of +2.62 and sell recommendations have a marginal percentage effect of -0.04. The positive marginal percentage impact on prices for upgrades is increasing in magnitude when the event period is extended, as the coefficients of the short-term model (1) have an impact of +0.52 and the long-term model (2) have a marginal effect of +2.62 on prices. For downgraded recommendations that skipped a rank, the results show a negative higher effect on prices in the short-term model compared to the long-term model.

To conclude the results of downgrades are consistent with the hypothesis that analysts are able to find overvalued securities as the results showed downgrades to strong sell and sell resulted in greater negative price impact than downgrades to hold. However, the implication if a security is downgraded to strong sell need to be even more overvalued compared to a downgrade to sell and downgrades skipping a rank have a larger negative price effect, is statistically not proven by the achieved regression results.

Contrarily the hypothesis of analysts' ability to find undervalued securities is supported only by the explanatory dummy variable SKIPRANK. The results of the dummy variable STRONG do not support the implication when a stock is upgraded to strong buy, the stock is even more undervalued and should result in higher price effect compared to an upgrade to buy. As outlined by the negative coefficients and therefore resulting in lower abnormal returns. Just when a rank is skipped the implication of higher price effect is

supported and the magnitude of the price effect was increasing as the event period increased. Nevertheless, the positive coefficients are not statistically significant. To conclude, a recommendation which is upgraded to strong buy and recommendation upgrades skipping a rank, results in higher positive effect is statistically not proven by the achieved regression results. Therefore, there is not enough evidence to accept the hypothesis of analysts' stock picking ability to find undervalued securities.

Results Hypothesis 5

Hypothesis five specified analysts do more upgrades in recommendations when investor sentiment is high and more downgrades when investor sentiment is low. To test the hypothesis the regression uses two proxy dummy variables $MARKET_{TYPE}$ and $TRADING_{SIGNAL}$.

Previously table 8 gave insight whether there are more upgrades in recommendations when investor sentiment is high, when the market is in an upward trend and more downgrades in recommendations after the market is in a downward trend. Referring to the results of the table, the distribution of dummy variable $MARKET_{TYPE}$ shows 83.65% of upgrades in analyst recommendations occurred during bull markets and 16.35% during bear markets. The results of analyst recommendation downgrades reveal the same results, as most recommendations were downgraded in upward trending markets and not as predicted in downward trending markets. Just by looking on the distribution of recommendation revisions across two market types the hypothesis is only partially supported. The results of recommendation upgrades are in line with the results of Bagnoli et al. (2009) and Kaplanski et al (2010), who found a positive correlation between investor sentiment and recommendation revisions. Both researchers found analysts issue more optimistic recommendations in form of recommendation upgrades when investor sentiment is high. The negative relation between low market sentiment and higher negative recommendation changes cannot be supported by the variable $MARKET_{TYPE}$, as just 14.98% of recommendation downgrades occurred when the markets were in a downward trend. The inconsistent results for downgrades might lie in the nature of market type, as across the sample period an upward trending market (bull market) is spread over

171 months compared to a downward trending market (bear market) is spread over 47 months. In contrast to this result, the negative correlation that analysts issue more sell recommendations when investor sentiment is negative can be supported by the dummy variable $TRADING_{SIGNAL}$, as more downgrades occurred when the market is in a downward trend which counts for 53.54% of sell recommendations.
Overall, the results for upgrades and downgrades are in favor of hypothesis five by combining the results of both dummy variables which capture market sentiment in two different approaches.

Coming to the regression results of the dummy variables $MARKET_{TYPE}$ and $TRADING_{SIGNAL}$ and their respective effect on price.

As previously examined more upgrade in recommendations occurred when investor sentiment is high when the market was upward trending referred as bull markets and the coefficients of $MARKET_{TYPE}$ are throughout the table 19 and table 20 generally negative across different event periods. Moreover, the coefficients are statistically different from zero at less than 0.05 and 0.01 significance level. The marginal negative impact on prices is even increasing in the magnitude as the event period increases. In the short-model (1) upgrades have a marginal effect of -1.23 compared to a high marginal effect of -6.20 in the long-term model (2). These results are in line with Bagnoli et al. (2009) results, who found that those recommendation which are positively correlated with investor sentiment are less profitable. The implication of the received results is, too many unprofitable recommendation upgrades occurred, which might have overestimated market sentiment or incorporated market sentiment not accurately into their recommendation revisions.

Table 21 and table 22 shows the coefficient of $MARKET_{TYPE}$ for recommendation downgrades is mainly negative across all event periods and the negative impact is significantly increasing in the magnitude as the event period is increasing. The marginal percentage effect on price is -0.10 in the short-model (1) and the effect is increasing in the size to -3.01 in the long-term model (2). Furthermore, the coefficient in the long-term model is statistically different from zero at less than 0.05 significance level. These results imply the price effect of downgrades is larger and more negative when recommendations

were downgraded in upward trending market (bull market) compared to downward trending market (bear market).

To conclude, the results indicate analyst recommendation upgrades during upward trending markets are less profitable and analyst recommendation downgrades during this market phase have a larger negative effect and by following these sell recommendations investors are able to reduce the loss on a security. This imply analysts should take an anticyclical view, which means when investor sentiment is high according to bull market phase, analysts should not hesitate to downgrade stocks based on fundamental and justified research.

The results of market sentiment captured by the dummy variable $\text{TRADING}_{\text{SIGNAL}}$ shows as expected positive impact on price for upgrades and generally negative impact on price for downgrades throughout the different event periods.

For recommendation upgrades the marginal percentage effect is decreasing in the magnitude from the short-model (1) to the long-term model (2) and statistically significant at less than 0.01 significance level in the event period $t = -5$ to $t = +5$. The results show a positive impact on price, when analysts do upgrades, when the dummy variable shows a buy signal. This indicates larger positive price performance in upward trending market.

Equally table 21 and table 22 reports generally negative coefficients for the variable $\text{TRADING}_{\text{SIGNAL}}$, which means when the trading signal is buy, the impact on prices is negative in the short-term event period $t = -5$ to $t = +5$ and positive as expected in the long-term event period $t = -5$ to $t = +120$. In the long-term model (2) the coefficient confirms a positive marginal percentage effect on price when the market is in an upward trend signaled by a buy trading signal. Contrarily a larger negative marginal percentage effect on price when the market is in a downward trend and herewith signaled by a sell trading signal. This implies the performance of recommendation downgrades are greater negative in downward trending markets than in upward trending market.

These results, confirm for upgrades a larger positive price effect in upward trending markets and for downgrades a larger negative price effect in downward trending markets, as captured by the dummy variable $TRADING_{SIGNAL}$.

Hypothesis 6

Hypothesis six aims to analyze the impact of brokerage coverage on the price performance of upgrades and downgrades. The hypothesis states recommendation revisions for stocks with higher brokerage coverage have a greater impact on prices than stocks with lower brokerage coverage. The coefficients of upgrades are expected to be positive, which in turn leads to higher positive abnormal returns and the coefficients for downgrades are expected to be negative, which leads to higher negative abnormal returns.

By looking on the regression output results which include the independent variable $COVER_{BROKER}$ one can see the coefficients are throughout the tables generally negative for upgrades and downgrades. The results for sell recommendations are as predicted negative for sell recommendations and statistically different from zero at less than 0.10 significance level in the event period $t = 0$ to $t = +10$. The negative coefficients for upgrades are statistically significant in the long-term model and in model (5) at 0.10 and 0.01 significance level. To conclude, the results indicate lower abnormal returns for recommendation upgrades and greater negative abnormal returns for recommendation downgrades. Generally, a higher broker coverage for upgrades and downgrades, have a less economically meaningful effect on prices, since the coefficients vary a lot and are at a lower percentage level.

Overall regression results

The performed regressions for upgrade in recommendation revisions and downgrade in revisions, show in all different event periods a low R-squared, which indicates the used explanatory variables in the model do not explain very much in the variation of the dependent variables CAR. The R-squared which is the coefficient of determination varies in all models at a lower level between 0.002 to 0.035. The lowest and highest R-squared numbers can be viewed in tables 20 and 22. The R-squared results are consistent with prior studies like Stickel (1995) who received a R-squared of 0.01 across all used event periods.

The F-test statistics which tests if all parameters are equal to zero or not indicates in most cases that not all of the variables are equal to zero at a 0.01 and 0.10 significant level and the regression model of upgrades is significant as a whole. The statistical significant results imply the included explanatory variables make sense to be included in the model despite the low R-squared results. F-statistic values can be found in the respective regression output tables for upgrades and downgrades in recommendation.

4.4 Abnormal Trading Volume

Ample research publications found the trading volume of securities differ significantly across various announcements, which means an event has an impact on the volume of the respective securities traded.

Likewise, in the research of investment value of analysts, Womack (1996) found the trading volume around the event date differs significantly compared to the average trading volume. To test if this anomaly is present in the data sample of this empirical research, an additional test of abnormal trading volume is conducted. The formula is based on Womack's (1996) recommended formula for abnormal trading volume.

$$AV_t^i = \frac{V_t^i}{\left(\sum_{t=-2}^{-61} V_t^i + \sum_{2}^{61} V_t^i\right) * {}^{1}/_{120}}$$

Abnormal volume *(AV)* for each security in the sample of upgrades and downgrades is calculated as a ratio of the trading volume *V* of security *i* relative to each event day *t*, to the average trading volume. The average trading volume is calculated 60 trading days before and 60 trading days after the event and by excluding the event window $t = -1$ to $t = +1$. To proceed the mean of all observations *i* at time day *t* in the upgrades and downgrades sample is calculated.

Figure 6 and 7 shows abnormal trading volume surrounding event days in the event window $t = -20$ to $t = +20$, centered around the reported recommendation event date.

Both graphs show in the pre-event period and in the post-event period, trading volume is for both upgrades and downgrades at 1.0 when trading volume is normal. Similarly, for upgrades and downgrades abnormal volume is increasing in magnitude before the event and decreasing after the event. The peak in abnormal volume is reached exactly on the event day, when the recommendations were announced. The average trading volume on the recommendation event date is 170% of normal for upgrades and 175% of downgrades. Furthermore, abnormal volume is on each event day statistically significant at less than 0.01 significance level and is herewith statistically different from normal. By looking on

both graphs, one can see abnormal volume for recommendation upgrades and downgrades do not differ significantly.

To conclude the results in this research, align with Womack (1996) findings, who documented significant volume reactions and showed the average trading volume for buy recommendation is about 190% and for sell recommendation is about 300% of normal trading volume.

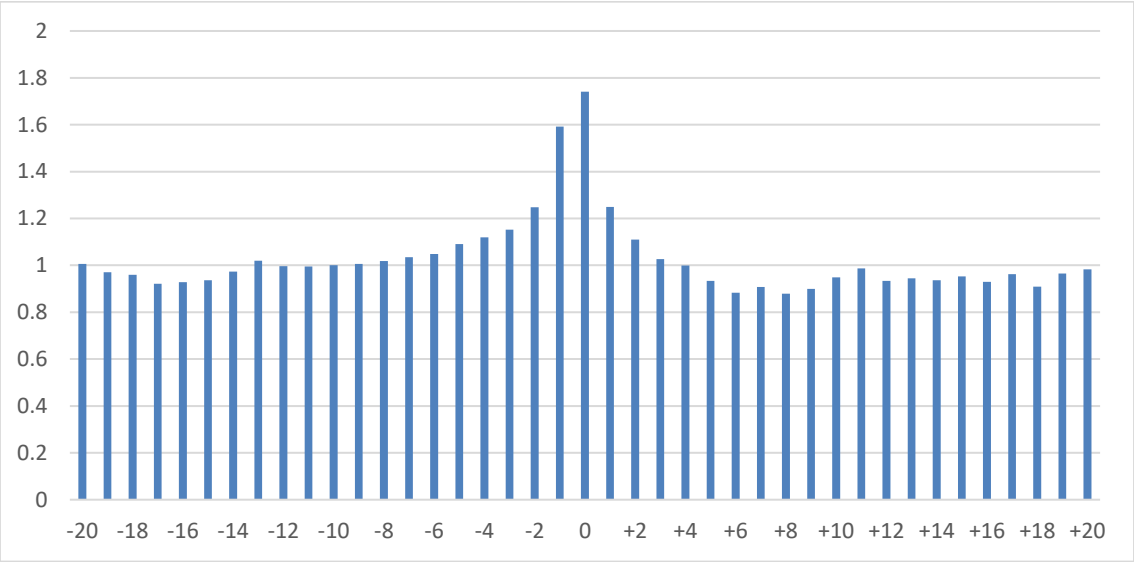

Figure 6: Abnormal Trading Volume, Upgrades

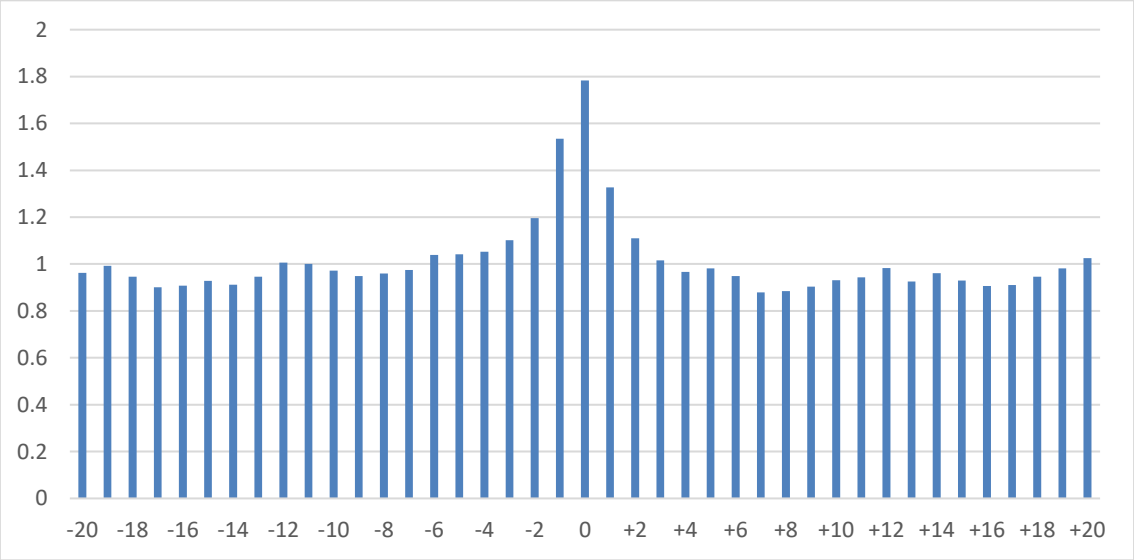

Figure 7: Abnormal Trading Volume, Downgrades

5 Conclusion and Outlook

This master thesis analyzed analysts' recommendations issued from brokerage firms on the securities included in the DJIA by performing descriptive statistics, applying the event study method to analyze security price reactions and by applying a cross-sectional regression analysis. The purpose of this research is, to analyze the imposed research question *"Do Analysts Recommendations have Investment Value"*, which questions if investors derive a value from these recommendations issued from analysts.

It is particular of interest to analyze the investment value of analysts during the time period ranging from 2000 to 2017, as previously conducted research publications have shown that analysts add value. These results are evidently contradicting with the efficient market hypothesis, which states if the semi-strong and the strong form hypothesis holds that no excess return can be achieved by fundamental analysis since all the information is already priced in. Since share prices immediately incorporate all public and private information, neither technical nor fundamental analysis has any value in stock selection ability to investors.

Therefore, this empirical research analyzed in the main part of this master thesis, the impact of recommendation revisions on stock prices, which means only changes in recommendations from a previous recommendation to a new recommendation are analyzed, issued from the same analyst on the same security. This approach excludes any recommendation reiterations, since recommendations issued are classified as either recommendation upgrades or recommendation downgrades. Referring to the literature this approach allows to determine analysts' ability to detect the extend of mispricing in securities.

Looking at the frequency distribution of all recommendations, which fulfilled the criteria to be included in the entire data sample, it could be derived that analysts are issuing more optimistic recommendations and less frequently sell recommendations. This bias of analysts to issue more positive recommendations is referred to as „optimistic bias". The data resulted in a ratio of thirteen "*Strong buy*/ *Buy"* recommendations over one "*Sell/ Strong sell"* recommendation. Further a preference of analysts to cover large-capitalized

companies is observed, as all companies are on average covered by at least 15 analysts. Moreover, the sample showed analysts have a preference to cover a certain attractive sector, namely the information technology sector, as this sector is covered on average by 33.79 analysts and further has the highest coverage by brokerage firms, compared to other sectors.

A 5 x 5 transition matrix of analysts' recommendations revealed the previous observed results of optimistic recommendations, as a large amount of recommendations are clustered at the rating buy, which gave insights that analysts often tend to revise their previously issued recommendation. Further the matrix showed a tendency of analysts to upgrade a recommendation rather than to downgrade a recommendation, coming from a hold rating. This behavior is not a surprising pattern, as it is commonly known that analysts exhibit a herding behavior, due to the fact that all analysts have the same information and therefore act in a similar way as it appears to be less risky to follow the crowd than to behave differently.

The results of the event study aimed to analyze the security price reactions in form of abnormal returns before the recommendation announcement, which is the event date, and after the event date. Excess returns were calculated by using the market model, which is commonly applied in the analysis of security price performance. Recommendation upgrades resulted in neither a significant positive pre-event drift, nor in a positive and significant post-recommendation drift. Further in a short event interval $[-1, +1]$, which includes the event date, showed no significant abnormal returns and therefore the announcement is not impacting security prices. Contrarily recommendation downgrades showed negative and significant abnormal returns in the event window $[-1, +1]$ centered on the event date. Further recommendation revisions, which were downgraded had generally predicted negative returns and resulted in significant pre-event recommendation and post-recommendation drift. Recommendation downgrades are associated with a -2.31% post recommendation drift over the long-term event window $[-5, +120]$.

To conclude, the results of abnormal returns for upgrades showed that investors are not able to achieve excess returns by trading according to analysts' recommendations and investors cannot gain a value from analysts. Further the long-term post-recommendation drift is negative and not moving towards analysts' forecasts. Recommendation

downgrades are associated with negative abnormal returns and are moving towards analysts forecasted direction, as abnormal returns start to decrease two days before the recommendation event date.

By looking on the results, the findings confirm investors are able to minimize their loss on securities by trading according to analysts' forecasts. Nevertheless, the real value of sell recommendations is questionable, due to the low frequency of strong sell and sell recommendations.

The cross-sectional regression analysis analyzed factors that contribute to the stock price performance of recommendation revisions, by looking on the short-term and long-term performance and across different event windows. The final recommendation revisions sample included 1,002 buy recommendations and 1,188 sell recommendations, covering 30 securities included in the DJIA, made by 886 analysts from 180 brokerage houses. Cumulative abnormal returns for buy recommendations are associated with an average decrease of -3.06% and sell recommendations with an average decrease of -2.30% in the long-term event window.

The impact of different explanatory variables on price performance of recommendation revisions were analyzed, namely the strength of the recommendation revision, the magnitude of the recommendation revision by whether the recommendation revision skips a rank, the impact of recommendation upgrades and downgrades during a market type (bull market vs. bear market) and the impact on performance when recommendations are either upgraded or downgraded during upward or downward moving markets according to a technical trading strategy.

The results showed a positive correlation between market sentiments, as more recommendation upgrades occurred during a market phase, when the market sentiment was high. Furthermore, more recommendation downgrades occurred during downward trending markets, according to the technical trading approach. The hypothesis of analysts' stock picking ability to detect underpriced and overpriced securities, imposed any changes to strong buy or strong sell and recommendation upgrades and downgrades skipping a rank, should result in higher positive and higher negative abnormal returns, respectively. The findings showed that downgrades to strong sell or sell have a greater impact than downgrades to hold, but the results are not statistically significant.

Furthermore, the results of changes in recommendations that skip a rank have a larger price effect than changes that do not skip a rank, both for upgrades and downgrades in recommendations. Nevertheless, there is no statistical evidence. To conclude based on the statistical results, there is no evidence to accept the hypothesis of analysts' stock picking ability, in order to pick stocks which are undervalued and should result in higher abnormal returns and stocks which are overvalued, which should result in higher negative abnormal returns.

Overall, the results of the event study which analyzed security price reactions and the results of the cross-sectional regression analysis come to the result that analysts do not have investment value for investors. There is no evidence that investors can have an added value by trading towards analysts' recommendations, as shown by the event study and the cross-sectional regression analysis which exhibited neither evidence for greater positive price performance when recommendations were revised to strong buy, nor a greater negative price performance when recommendations were revised to strong sell. Consequently, the question arises why the financial sector employs thousands of analysts whose job is to track corporations and issue recommendation opinions on their securities, based on a fundamental and pro-found research. As this research showed that investors do not gain an added value in form of positive abnormal returns, one needs to ask why analysts are still present and what is their real output.

Moreover, the results of the analysis of abnormal trading volume, resulted in significant above average trading volume before and after the event date, for upgrades and downgrades. which imply analysts have a significant effect on the volume traded of the respective securities, centered around the recommendation event date.

An assumption why banks still employ analysts, is connected to their investment banking activities. Analysts are involved in the process to position a potential corporation in the initial public offering (IPO) process on capital markets. Despite the fact that a Chinese wall is between the equity research team and the investment banking team, analysts are needed to analyze independently the equity story of a potential IPO candidate and its respective equity story. Furthermore, equity analysts do not have data from the investment

banking team and have only access to publicly available information, which allows them to propose an independent book building range based on an outside valuation view, which is not based on data received from the respective corporation. Moreover, a bank's investment banking business needs equity analysts, as those analysts are viewed as an independent channel to speak with investors. Proceeding in an IPO process, equity analysts are the front people who start to speak with potential investors and are supporting market equities of the equity sales team in the trading division of an investment bank. When a corporation was successfully listed on a stock exchange, an analysts' task is to conduct ongoing research for the corporation and their respective industry. Due to the fact, that the investment bank aims to keep the relationship with the respective corporations and to avoid any decline in future investment banking business activities, it is no surprise why analysts face pressure to issue optimistic recommendations and show herding behavior, to avoid damage on their reputation and on the reputation of the investment banking business of their bank.

As the results of this empirical study showed a preference of analysts to follow corporations in the information technology sector, it would be motivating to build up on my research and to analyze why this sector has a much higher analysts' coverage compared to other sectors. In my point of view, it would be interesting to analyze if this sector needs a higher analysts' coverage in order to increase the efficiency as the technology industry is more difficult to understand than industrials sector.

Further it might be interesting to extend this study, by analyzing price and volume reactions of analysts' recommendation revisions separately for small-capitalized, mid-capitalized and large-capitalized companies. In order to identify if significant price and volume reactions between small and large companies might exists. Due to the fact, that large companies have a higher analysts' and brokerage coverage, which in turn leads to a larger extend of information available to investors. Therefore, it can be expected to investigate significantly larger price reactions for smaller companies, due to the higher information asymmetry and the higher risk and return differences between small-capitalized and large-capitalized companies.

Additionally, it might be interesting to conduct this research on the main European equity markets, to investigate if there are differences within Europe and if there are differences between the European and the US equity market, with regard to analysts' behavior, market and volume reactions.

For further research, I would recommend investigating whether analysts' behavior can positively influence an investment banks underwriting business. And to what extend the relation between an analyst and the respective followed companies, contributes to the investment banking business.

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MASTER THESIS

ZURICH UNIVERSITY OF APPLIED SCIENCES

Do Analysts' Recommendations have Investment Value?

Appendix

Tables and Figures

written at the

School of Management and Law

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Program:	Master of Science in Banking and Finance
Department:	Banking and Finance
Supervisor:	Prof. Dr. Hans Brunner
Co-Supervisor:	Anita Sigg
Defense Date:	July 9, 2018

Winterthur, June 15, 2018

1) 3 M (MMM)
2) American Express (AXP)
3) Apple (AAPL)
4) Boeing BA)
5) Caterpillar (CAT)
6) Chevron (CVX)
7) Cisco Systems (CSCO)
8) Coca-Cola (KO)
9) DuPont (DD)
10) Exxon Mobil (XOM)
11) General Electric (GE)
12) Goldman Sachs (GS)
13) Home Depot (HD)
14) IBM (IBM)
15) Intel (INTC)
16) Johnson & Johnson (JNJ)
17) JP Morgan (JP)
18) MC Donalds (MCD)
19) Merck & Co. (MRK)
20) Microsoft (MSFT)
21) Nike (NKI)
22) Pfizer (PFE)
23) Procter & Gamble (PG)
24) Travellers Companies (TRV)
25) United Technologies (UTX)
26) United Health Group (UNH)
27) Verizon (VZ)
28) Visa (V)
29) Wal-Mart (WMT)
30) Walt Disney (DIS)

Table 10: Companies included in the DJIA

Recommendation	Rating
Strong buy	1
Long-term buy	1
above average	1
aggressive buy	1
long-term attractive	1
short-term strong buy	1
top pick	1
Overwt/Attractive	2
overwt/positive	2
buy 1	2
Outperform	2
Overweight	2
Sector Outperform	2
market outperform	2
buy	2
Attractive	2
Positive	2
Accumulate	2
buy/attractive	2
Buy/Neutral	2
overwt/neutral	2
Trading buy	2
Add	2
buy 2	2
moderate outperform	2
recommend list	2
focus list	2
gradually accumulate	2
industry outperform	2
market outperform	2
outperf/attractive	2
positive	2
short-term accumulate	2
short-term buy	2
short-term market outperform	2
short-term outperform	2
speculative buy	2
speculative outperform	2
Near-term buy	2
overwt/in-line	2
outperf/cautious	2
outperf/neutral	2

overwt/cautious	2
overwt/in-line	2
overwt/negative	2
buy/cautious	2
sector perform	3
Market Perform	3
Hold	3
Equalweight	3
Neutral	3
In-line	3
Market Weight	3
Peer Perform	3
Maintain Position	3
Fairly Valued	3
Equalwt/In-Line	3
peerperform	3
equalwt/neutral	3
in-line/neutral	3
equalwt/positive	3
Equalwt/attractive	3
neutral weight	3
neutral 2	3
in-line/attractive	3
neutral/neutral	3
average	3
neutral 1	3
below average	3
equalwt/negative	3
industry perform	3
in-line/cautious	3
long-term hold	3
maintain	3
market neutral	3
moderate underperformer	3
neutral 2	3
neutral rate	3
neutral/attractive	3
neutral/cautious	3
neutral/neutral	3
perform in line	3
performer	3
sector weight	3
short-term market perform	3

Equalwt/Cautious	3
Short-term Hold	3
corporate	3
cautious	4
underwt/positive	4
sell/neutral	4
sell/attractive	4
Unattractive	4
underperf/attractive	4
underperf/neutral	4
underwt/attractive	4
underwt/in-line	4
underwt/neutral	4
underwt/positive	4
Underweight	4
Sell	4
Negative	4
Reduce	4
Sector Underperform	4
Underperform	4
underwt/cautious	4
short sell	4
sell/cautious	4
industry underperform	4
market underperform	4
reduce 1	4
reduce 2	4
short-term underperform	4
underperf/cautious	4
underwt/cautious	4
underwt/negative	4
avoid	5
Strong Sell	5
swap	5
susp/positive	6
Not Rated	6
No Rating System	6
suspended coverage	6
restricted	6
source of funds	6
susp/negative	6
susp/neutral	6
susp/positive	6

Rating Suspended	6
under review	6

Table 11: Rating definitions and their attached Rating according to the 5-point Rating Scale

Company	Eventcounts
AAPL UW Equity	91
AXP UN Equity	85
BA UN Equity	82
CAT UN Equity	77
CSCO UW Equity	125
CVX UN Equity	63
DD UN Equity	58
DIS UN Equity	82
GE UN Equity	51
GS UN Equity	91
HD UN Equity	72
IBM UN Equity	56
INTC UW Equity	140
JNJ UN Equity	67
JPM UN Equity	89
KO UN Equity	56
MCD UN Equity	66
MMM UN Equity	42
MRK UN Equity	61
MSFT UW Equity	81
NKE UN Equity	58
PFE UN Equity	67
PG UN Equity	58
TRV UN Equity	79
UNH UN Equity	48
UTX UN Equity	45
V UN Equity	31
VZ UN Equity	113
WMT UN Equity	86
XOM UN Equity	72
Total	2,192

Table 12: Event-counts per Company

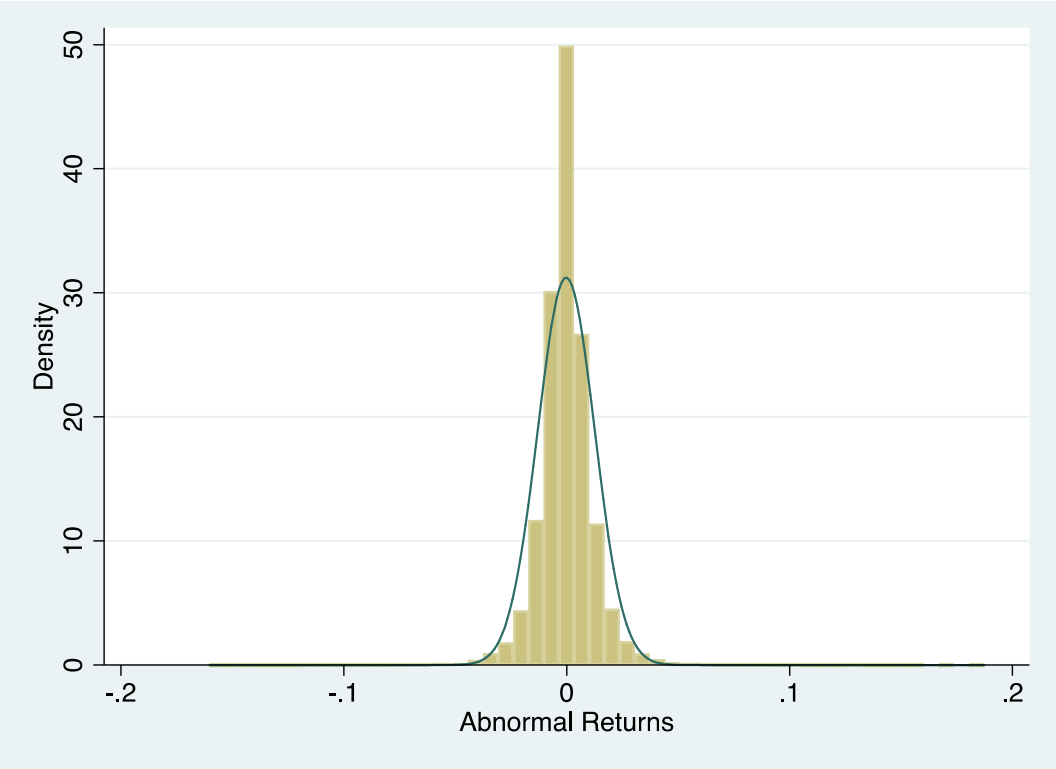

Figure 8: Histogram Abnormal Returns with Normal Density Curve

Upgrades					
Event Day (t)	Mean (%)	t-Statistic	Event Day (t)	Mean (%)	t-Statistic
-20	-0.0026	-0.06	+22	-0.0488	-1.21
-19	-0.0074	-0.02	+23	-0.0303	-0.08
-18	-0.0531	-1.20	+24	-0.0175	-0.43
-17	0.0685*	1.49	+25	-0.1046**	-2.44
-16	-0.0612	-1.34	+26	-0.0495	-1.17
-15	-0.0080	-0.16	+27	-0.0071	-0.18
-14	-0.1158**	-2.34	+28	-0.1011**	-2.14
-13	-0.1339	-0.30	+29	-0.0142	-0.36
-12	0.1646	0.37	+30	0.0445	1.11
-11	0.0570	1.27	+31	-0.1148***	-2.67
-10	-0.0752*	-1.67	+32	-0.0819	-1.59
-9	0.0626*	1.53	+33	0.0524*	1.32
-8	0.0659*	1.44	+34	-0.0163	-0.41
-7	0.0572	1.28	+35	-0.0053	-0.11
-6	0.0026	0.06	+36	-0.0794**	-2.06
-5	0.0631*	1.51	+37	-0.0045	-1.12
-4	-0.0395	-0.10	+38	0.1262	0.66
-3	-0.0380	-0.81	+39	-0,1049**	-2.50
-2	-0.0092	-0.02	+40	-0.0201	-0.55
-1	0.0626	1.04	+41	-0.0039	-0.23
0	0.0844	1.26	+42	0.0221	0.60
+1	-0.0339	-0.08	+43	-0.0398	-1.09
+2	0.0016	0.04	+44	-0.0339	-0.91
+3	-0.0115	-0.03	+45	0.0022	0.06
+4	0.0247	0.69	+46	-0.0759**	-2.03
+5	-0.0786**	-2.01	+47	-0.0148	-0.41
+6	-0.0816**	-2.37	+48	-0.1513	-1.40
+7	-0.0380	-1.13	+49	0.0008	0.02
+8	0.0037	0.10	+50	-0.0742*	-1.91
+9	-0.0886***	-2.73	+51	-0.0308	-0.74
+10	0.0385	1.11	+52	-0.1102***	-2.78
+11	0.0532*	1.44	+53	0.0083	0.23
+12	-0.0014	-0.04	+54	-0.0433	-1.09
+13	-0.0033	-0.08	+55	-0.0373	-0.97
+14	-0.0318	-0.09	+56	-0.0242	-0.65
+15	-0.0737*	-1.81	+57	-0.0499	-1.19
+16	0.0180	0.44	+58	0.0056	0.13
+17	-0.0048	-0.12	+59	-0.0646*	-1.68
+18	0.0016	0.05	+60	-0.0174	-0.45
+19	-0.0180	-0.53	+61	-0.0937**	-2.56
+20	-0.0066	-0.17	+62	-0.0143	-0.33
+21	-0.0054	-0.14	+63	0.0652*	1.43

Table 13: Average Abnormal Returns of Upgrades over Event Days t= -20 to t= +120

Upgrades - *Continued*					
Event day (t)	Mean (%)	t-Statistic	Event day (t)	Mean (%)	t-Statistic
+64	-0.0129	-0.33	+93	0.0419	0.96
+65	-0.0930	-1.59	+94	0.0049	0.12
+66	-0.0469	-1.07	+95	-0.0353	-0.93
+67	-0.1208***	-2.62	+96	0.3450***	2.63
+68	-0.0143	-0.38	+97	0.0325	0.86
+69	-0.0586	-1.55	+98	-0.0312	-0.73
+70	-0.0414	-1.09	+99	0.0036	0.09
+71	-0.0077	-0.20	+100	-0.0816	-2.09
+72	-0.0576*	-1.68	+101	0.0362	0.09
+73	-0.0872**	-2.40	+102	0.0010	0.02
+74	0.0012	0.03	+103	-0.0028	-0.70
+75	0.0244	0.63	+104	-0.0379	-0.97
+76	-0.0080	-0.23	+105	-0.0039	-0.24
+77	-0.0143	-0.40	+106	-0.0883**	-1.99
+78	-0.0748**	-2.06	+107	-0.0463	-1.32
+79	0.0553*	1.44	+108	0.0084	0.18
+80	-0.0340	-0.99	+109	0.0098	0.23
+81	-0.0640*	-1.89	+110	0.0487	1.27
+82	-0.0021	-0.05	+111	-0.0255	-0.72
+83	-0.0435	-1.18	+112	-0.0119***	-3.19
+84	-0.0098**	-2.50	+113	0.0134	0.32
+85	-0.0476	-1.40	+114	0.0236	0.65
+86	-0.0534	-1.35	+115	-0.0957**	-2.55
+87	-0.0720*	-1.87	+116	-0.0955***	-2.74
+88	0.0381	0.97	+117	-0.0507	-1.50
+89	-0.0275	-0.72	+118	-0.0488	-1.43
+90	-0.0496	-1.28	+119	0.0145	0.38
+91	-0.0130	-0.33	+120	-0.0249	-0.74
+92	0.0279	0.63			

Table 13: Average Abnormal Returns of Upgrades over Event Days t= -20 to t= +120

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

T-statistics with an absolute value of 1.28, 1.65 and 2.33 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level for one-tailed significance test.

Downgrades					
Event Day (t)	Mean (%)	t-Statistic	Event Day (t)	Mean (%)	t-Statistic
-20	-0.1679	-0.43	+22	0.0110	0.29
-19	-0.0120	-0.33	+23	-0.1024***,***	2.73
-18	-0.1024**,***	-2.52	+24	-0.0426	-1.13
-17	-0.0471	-1.08	+25	-0.0591*	-1.39
-16	0.0206	0.44	+26	0.0272	0.63
-15	0.0148	0.34	+27	-0.0162	-0.42
-14	0.0177	0.48	+28	-0.0091	-0.25
-13	-0.0139	-0.37	+29	-0.0274	-0.76
-12	0.0272	0.66	+30	-0.0576*	-1.46
-11	0.0342	0.78	+31	0.0204	0.49
-10	-0.0562*	-1.33	+32	-0.0410	-1.04
-9	-0.0202	-0.52	+33	0.0121	0.30
-8	-0.0616*	-1.64	+34	0.0113	0.31
-7	0.0521	1.32	+35	0.0626*	1.68
-6	-0.0212	-0.52	+36	0.0185	0.48
-5	-0.0434	-0.18	+37	0.0105	0.30
-4	0.0326	0.78	+38	-0.0048	-0.13
-3	0.0365	0.81	+39	0.0631*	1.72
-2	0.0022	0.05	+40	0.0023	0.06
-1	-0.1299**,**	-2.30	+41	-0.0137	-0.40
0	-0.2621***,***	-3.65	+42	-0.0358	-0.85
+1	-0.1217***,***	-2.80	+43	-0.0395	-1.02
+2	0.0247	0.67	+44	-0.0340	-1.06
+3	-0.0426	-1.21	+45	-0.0520*	-1.48
+4	0.0361	0.97	+46	-0.0715*,**	-1.78
+5	-0.0465*	-1.35	+47	-0.0841**,***	-2.38
+6	0.0242	0.74	+48	-0.0530*	-1.53
+7	0.0343	1.05	+49	-0.0214	-0.55
+8	0.0123	0.41	+50	0.0038	0.10
+9	0.0464	1.40	+51	-0.0289	-0.78
+10	0.0535	1.51	+52	-0.0235	-0.64
+11	-0.0153	-0.49	+53	-0.0737**,**	-2.17
+12	0.0184	0.57	+54	-0.0616*	-1.63
+13	-0.0389	-1.14	+55	0.0140	0.36
+14	-0.0488*	-1.50	+56	0.0589*	1.74
+15	-0.0398	-1.21	+57	-0.0755*,**	-1.88
+16	-0.0581**,*	-1.78	+58	-0.0447	-1.03
+17	-0.0295	-0.97	+59	-0.1078***,***	-2.63
+18	0.0373	1.08	+60	0.0107	0.25
+19	0.0311	0.88	+61	-0.0380	-0.09
+20	-0.0197	-0.52	+62	0.0461	1.22
+21	-0.0068	-0.18	+63	0.0204	0.51

Table 14: Average Abnormal Returns of Downgrades over Event Days t= -20 to t= +120

Downgrades - *Continued*					
Event Day (t)	Mean (%)	t-Stat	Event Day (t)	Mean (%)	t-Stat
+64	-0.0237	-0.55	+93	-0.0367	-0.90
+65	-0.0967*,**	-1.76	+94	-0.0395	-1.09
+66	0.0364	0.81	+95	-0.0513*	1.36
+67	-0.1098**,***	-2.35	+96	0.1217***	3.30
+68	-0.0179	-0.46	+97	-0.0741**,**	-2.09
+69	-0.0144	-0.37	+98	0.0418	0.99
+70	-0.0627*	-1.63	+99	-0.0500*	-1.32
+71	0.0181	0.52	+100	0,1012***	2.76
+72	-0.0600*,**	-1.76	+101	-0.0484*	-1.36
+73	-0.0065	-0.19	+102	-0.0638*	-1.57
+74	0,0606*	1.74	+103	0.0249	0.71
+75	0.0353	1.01	+104	0.0376	1.02
+76	-0.0227	-0.64	+105	-0.0888***,***	-2.56
+77	0.0065	0.17	+106	-0.0036	-0.10
+78	-0.0125	-0.34	+107	-0.0311	-0.89
+79	-0.0079	-0.23	+108	-0.0050	-0.14
+80	0.0301	0.81	+109	0.0245	0.64
+81	-0.0684*,**	-1.82	+110	-0.0414	-1.14
+82	-0.0460	-1.27	+111	-0.0710**,**	-2.03
+83	0.0200	0.57	+112	0.0159	0.48
+84	-0.0103	-0.27	+113	-0.0197	-0.57
+85	-0.0149	-0.39	+114	-0.0480*	-1.30
+86	0.0356	0.98	+115	-0.0809**,**	-2.30
+87	-0.0132	-0.34	+116	-0.0533*,**	-1.80
+88	-0.0257	-0.67	+117	-0.0405	-1.16
+89	0.0098	0.27	+118	-0.0760**,**	-2.06
+90	-0.0747**,**	-2.03	+119	-0.0635*,**	-1.91
+91	0.0430	1.10	+120	-0.0096	-0.29
+92	-0.0242	-0.65			

Table 14: Average Abnormal Returns of Downgrades over Event Days t= -20 to t= +120

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

T-statistics with an absolute value of 1.28, 1.65 and 2.33 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level for one-tailed significance test.

Upgrades			Downgrades		
Event Day (t)	Mean (%)	t-Statistic	Event Day (t)	Mean (%)	t-Statistic
-20	-0.0013	-0.03	-20	-0.0107	-0.27
-19	-0.0044	-0.07	-19	-0.0234	-0.43
-18	-0.0555	-0.72	-18	-0.1223*	-1.82
-17	0.0095	0.11	-17	-0.1803**	-2.38
-16	-0.0483	-0.48	-16	-0.1559*	-1.83
-15	-0.0515	-0.47	-15	-0.1408	-1.50
-14	-0.1706	-1.45	-14	-0.1215	-1.21
-13	-0.1801	-1.44	-13	-0.1360	-1.31
-12	-0.1621	-1.22	-12	-0.1195	-1.08
-11	-0.1093	-0.79	-11	-0.0915	-0.80
-10	-0.1867	-1.32	-10	-0.1460	-1.26
-9	-0.1277	-0.91	-9	-0.1597	-1.32
-8	-0.0587	-0.40	-8	-0.2212*	-1.74
-7	0.0000	0.00	-7	-0.1784	-1.37
-6	0.0001	0.00	-6	-0.1932	-1.42
-5	0.0537	0.33	-5	-0.2358*	-1.70
-4	0.0108	0.06	-4	-0.2109	-1.47
-3	-0.0314	-0.18	-3	-0.1752	-1.17
-2	-0.0370	-0.21	-2	-0.1737	-1.14
-1	0.0134	0.07	-1	-0.3028*	-1.86
0	0.0964	0.50	0	-0.5690***	-3.16
+1	0.0673	0.34	+1	-0.6966***	-3.77
+2	0.0761	0.38	+2	-0.6779***	-3.62
+3	0.0652	0.32	+3	-0.7137***	-3.70
+4	0.0862	0.41	+4	-0.6904***	-3.57
+5	0.0106	0.05	+5	-0.7421***	-3.76
+6	-0.0719	-0.33	+6	-0.7184***	-3.61
+7	-0.1076	-0.49	+7	-0.6818***	-3.40
+8	-0.1025	-0.46	+8	-0.66814***	-3.33
+9	-0.1946	-0.86	+9	-0.6163***	-3.04
+10	-0.1590	-0.69	+10	-0.5649***	-2.72
+11	-0.1105	-0.47	+11	-0.5800***	-2.78
+12	-0.1115	-0.47	+12	-0.5606	-2.68
+13	-0.1148	-0.48	+13	-0.5963***	2.81
+14	-0.1473	-0.62	+14	-0.6471***	-3.02
+15	-0.2207	-0.09	+15	-0.6850***	-3.17
+16	-0.2069	-0.85	+16	-0.7421***	-3.41
+17	-0.2027	-0.82	+17	-0.7717***	-3.53
+18	-0.1983	-0.79	+18	-0.7308***	-3.33
+19	-0.2082	-0.83	+19	-0.6967***	-3.13
+20	-0.2130	-0.84	+20	-0.7170**	-3.20

Table 15: Cumulative Abnormal Returns over Event Days t= -20 to t= +20

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

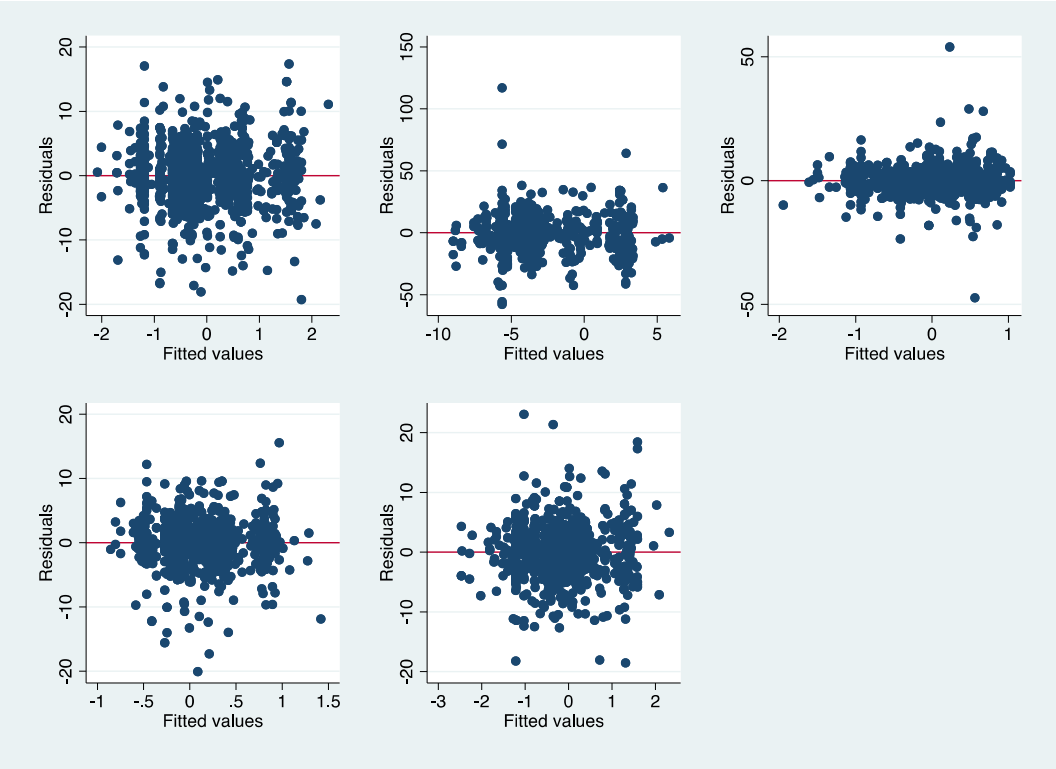

Figure 9: Scatterplot of Residuals against Fitted Values Model 1 to 5 of Buy sample

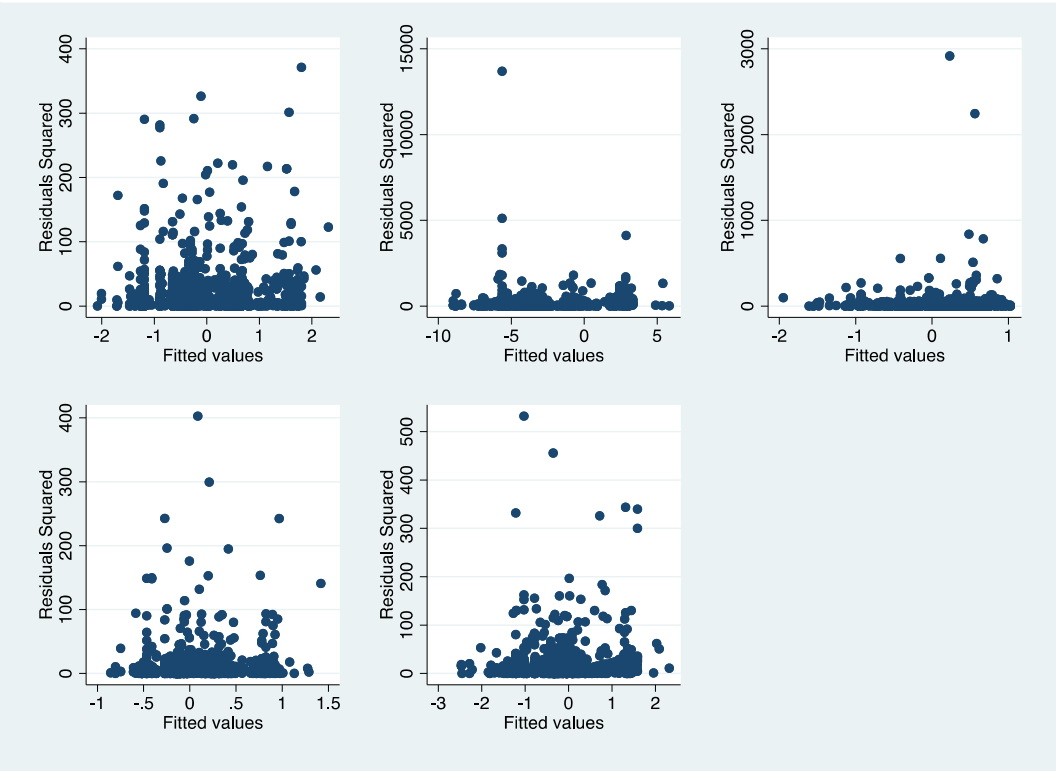

Figure 10: Scatterplot of Residuals squared against Fitted Values Model 1 to 5 of Buy sample

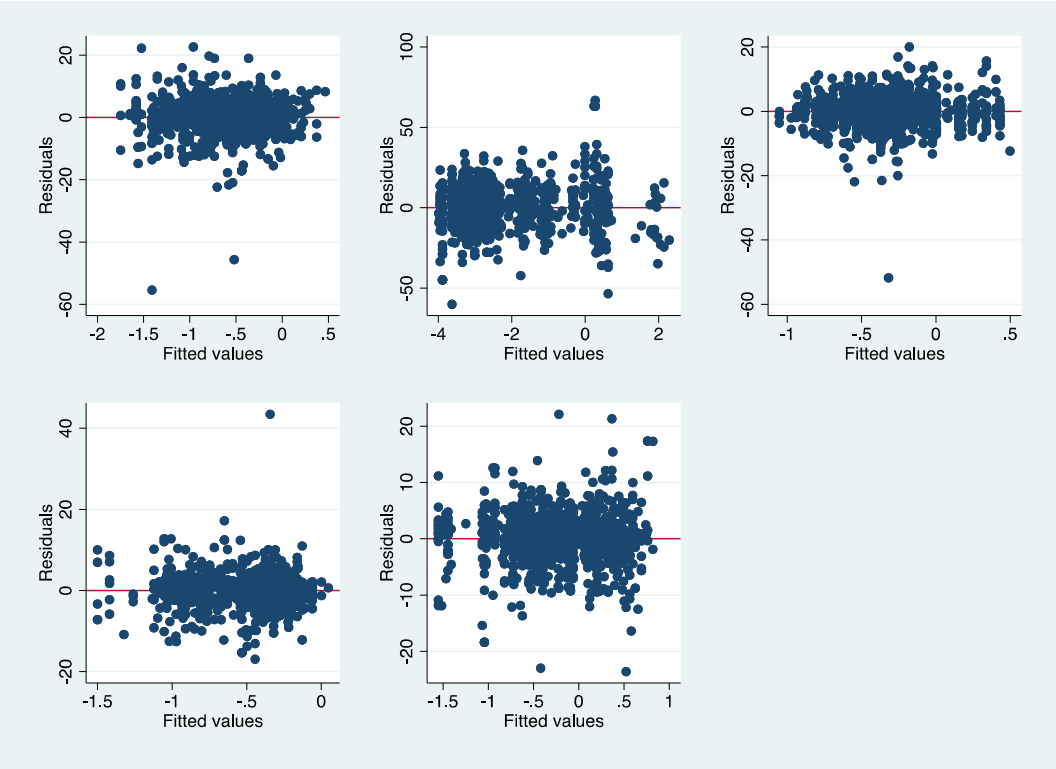

Figure 11: Scatterplot of Residuals against Fitted Values Model 1 to 5 of Sell sample

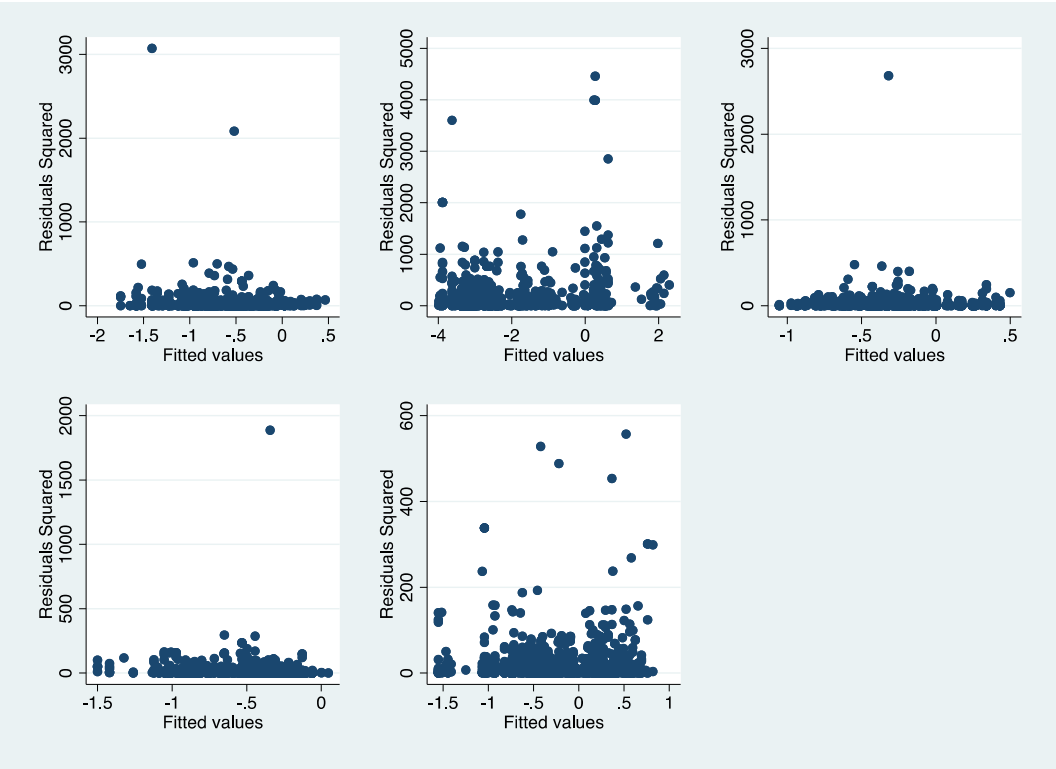

Figure 12: Scatterplot of Residuals squared against Fitted Values Model 1 to 5 of Sell sample

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7 . estat hettest

  Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
           Ho: Constant variance
           Variables: fitted values of CAR_long

           chi2(1)      =    82.30
           Prob > chi2  =   0.0000
```

Figure 13: Breusch-Pagan / Cook-Weisberg test output model which uses CAR (-5, +120)

	COVER ANALYST	STRONG	SKIPRANK	MARKET TYPE	TRADING SIGNAL	COVER BROKER
COVER ANALYST	1.0000					
STRONG	-0.0074	1.0000				
SKIPRANK	0.0208	0.3122	1.0000			
MARKET TYPE	0.0276	-0.0784	-0.0526	1.0000		
TRADING SIGNAL	-0.0112	0.0317	-0.0041	-0.4252	1.0000	
COVER BROKER	0.7965	-0.0151	0.0001	0.0495	-0.0187	1.0000

Table 16: Correlation Matrix of the Independent Variables, Buy and Sell combined

	COVER ANALYST	STRONG	SKIPRANK	MARKET TYPE	TRADING SIGNAL	COVER BROKER
COVER ANALYST	1.0000					
STRONG	-0.0345	1.0000				
SKIPRANK	0.0040	0.2816	1.0000			
MARKET TYPE	0.0401	-0.2959	-0.0647	1.0000		
TRADING SIGNAL	-0.0526	0.1114	0.0079	-0.4412	1.0000	
COVER BROKER	0.7986	0.0019	-0.0189	0.0695	-0.0761	1.0000

Table 17: Correlation Matrix of the Independent Variables of Upgrades

	COVER ANALYST	STRONG	SKIPRANK	MARKET TYPE	TRADING SIGNAL	COVER BROKER
COVER ANALYST	1.0000					
STRONG	0.0115	1.0000				
SKIPRANK	0.0339	0.3289	1.0000			
MARKET TYPE	0.0162	0.0717	-0.0444	1.0000		
TRADING SIGNAL	0.0246	-0.0267	-0.0149	-0.4128	1.0000	
COVER BROKER	0.7984	-0.0251	0.0156	0.0322	0.0308	1.0000

Table 18: Correlation Matrix of the Independent Variables of Downgrades

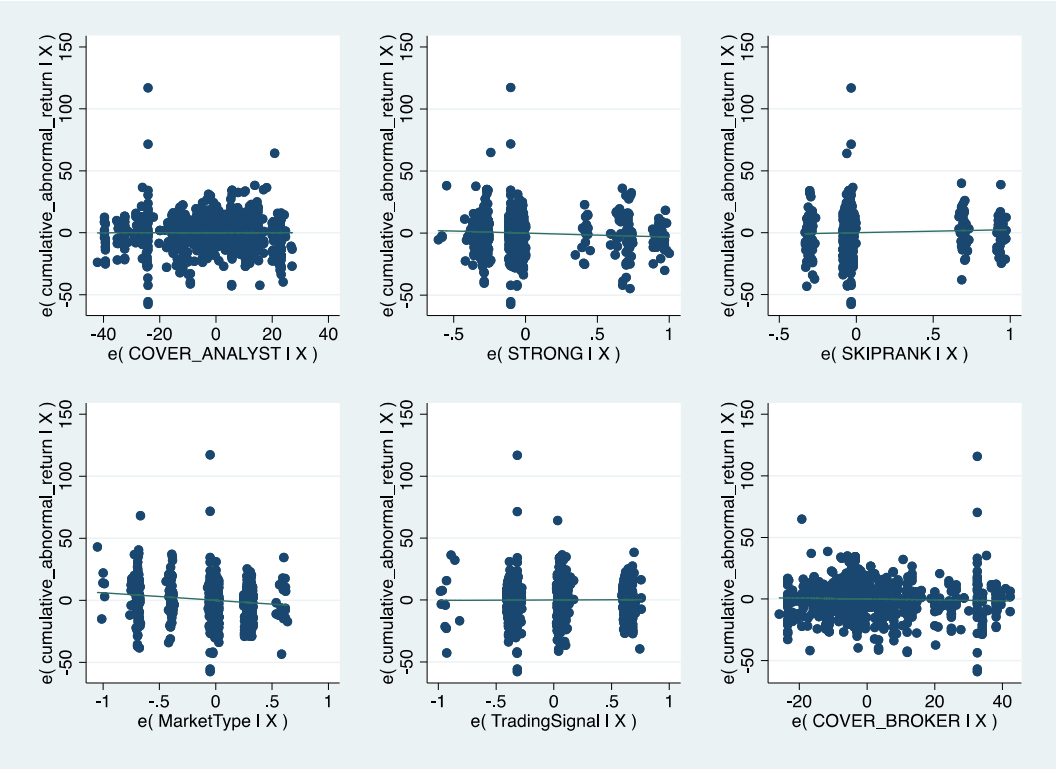

Figure 14: Graphical inspection of Outliers of Upgrades

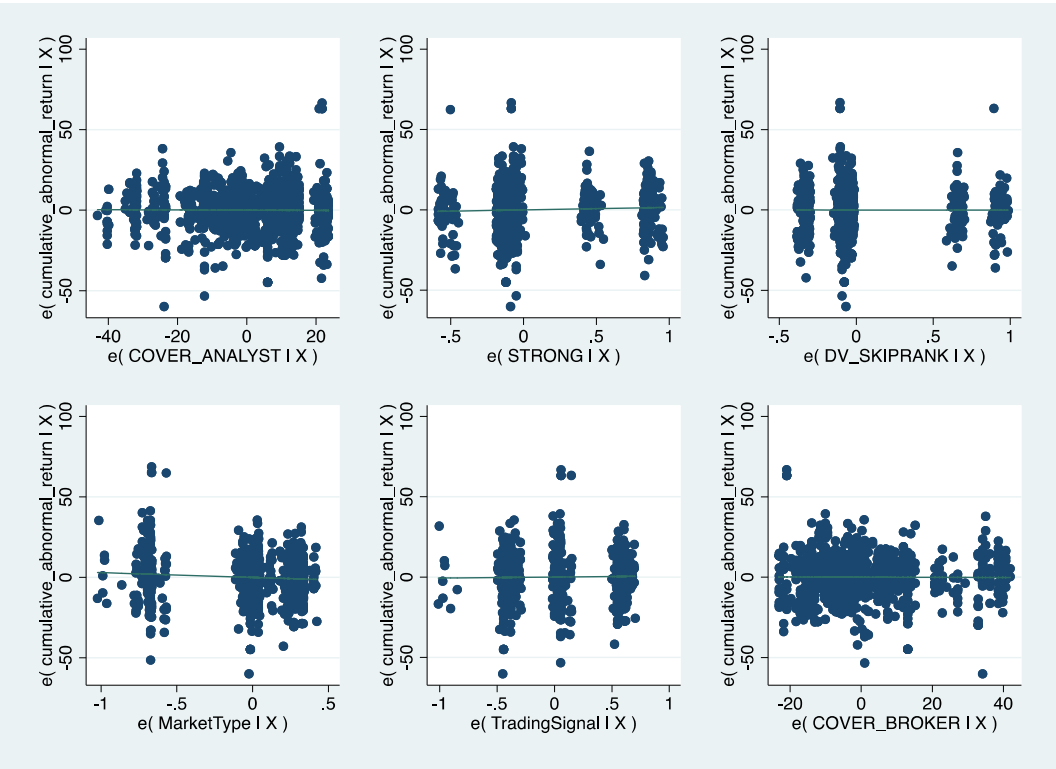

Figure 15: Graphical inspection of Outliers of Downgrades

VARIABLES	(1) CAR (-5, +5)	(2) CAR (-5, +120)	(3) CAR (-10, -1)	(4) CAR (-1, +1)	(5) CAR (0, +10)
COVER ANALYST	-0.00287	-0.0266*	-0.000460	0.000201	-0.0131**
	(0.00596)	(0.0159)	(0.00685)	(0.00431)	(0.00545)
STRONG	-0.897	-3.343**	-0.521	-0.376	-1.305***
	(0.569)	-1.622	(0.551)	(0.408)	(0.480)
SKIPRANK	0.523	2.620	-0.466	0.479	0.775
	(0.579)	-1.611	(0.511)	(0.368)	(0.587)
MarketType	-1.127**	-6.201***	-0.00995	-0.578	-1.230**
	(0.574)	-1.607	(0.670)	(0.442)	(0.499)
TradingSignal	0.926***	0.416	0.552*	0.384	0.445
	(0.329)	(0.931)	(0.323)	(0.251)	(0.285)
Constant	0.821	4.173*	-0.0380	0.391	1.800***
	(0.773)	-2.175	(0.964)	(0.571)	(0.681)
Observations	1,002	950	1,002	1,002	1,002
Prob > F	0.0002	0.0011	0.3988	0.0906	0.0006
R-squared	0.025	0.034	0.004	0.011	0.029

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Determinants of Stock Price Performance of Upgrades

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

CAR = Cumulative abnormal return from event day t_1 to event day t_2.

Definitions of variables:

$COVER_{ANALAYST}$, equals the mean number of analysts' coverage for a stock.

STRONG, for upgrades, equals one if the recommendation is a strong buy and zero otherwise (buy). For downgrades, equals one if the recommendation is a strong sell or sell and zero otherwise (hold).

SKIPRANK takes the value one if the change in recommendation skipped a rank and zero otherwise (do not change a rank).

$MARKET_{TYPE}$ equals one if the recommendation was revised in the bull market phase and zero otherwise (bear market).

$TRADING_{SIGNAL}$ equals one if the change in recommendation happened when the short and long-term moving average cross showed a buy signal and zero otherwise, when the cross of both moving averages signalled sell. Buy signal is often viewed as an indicator of an emerging upward moving market and sell signal as an indicator of an emerging downward moving market.

VARIABLES	(1) CAR (-5, +5)	(2) CAR (-5, +120)	(3) CAR (-10, -1)	(4) CAR (-1, +1)	(5) CAR (0, +10)
STRONG	-0.868	-3.20**	-0.497	-0.369	-1.24***
	(0.570)	(1.613)	(0.551)	(0.408)	(0.478)
SKIPRANK	0.500	2.52	-0.487	0.473	0.726
	(0.575)	(1.599)	(0.507)	(0.367)	(0.586)
MarketType	-1.10*	-6.10***	0.0223	-0.567	-1.19**
	(0.00574)	(1.605)	(0.667)	(0.444)	(0.498)
TradingSignal	0.908***	0.364	0.527	0.375	0.432
	(0.327)	(0.918)	(0.324)	(0.249)	(0.285)
COVER BROKER	-0.0092	-0.0356*	-0.0096	-0.0031	-0.0155***
	(0.00676)	(0.0202)	(0.00740)	(0.0047)	(0.0059)
Constant	1.26*	4.66**	0.627	0.634	1.88***
	(0.00743)	(2.205)	(0.977)	(0.534)	(0.668)
Observations	1,002	950	1,002	1,002	1,002
Prob > F	0.0007	0.0002	0.1872	0.0829	0.0006
R-squared	0.027	0.035	0.006	0.012	0.030

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Determinants of Stock Price Performance of Upgrades

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level

CAR = Cumulative abnormal return from event day t_1 to event day t_2.

Definitions of variables:

STRONG, for upgrades, equals one if the recommendation is a strong buy and zero otherwise (buy). For downgrades, equals one if the recommendation is a strong sell or sell and zero otherwise (hold).

SKIPRANK takes the value one if the change in recommendation skipped a rank and zero otherwise (do not change a rank).

$\text{MARKET}_{\text{TYPE}}$ equals one if the recommendation was revised in the bull market phase and zero otherwise (bear market).

$\text{TRADING}_{\text{SIGNAL}}$ equals one if the change in recommendation happened when the short and long-term moving average cross showed a buy signal and zero otherwise, when the cross of both moving averages signalled sell. Buy signal is often viewed as an indicator of an emerging upward moving market and sell signal as an indicator of an emerging downward moving market.

$\text{COVER}_{\text{BROKER}}$, equals the mean number of brokerage coverage for a stock.

VARIABLES	(1) CAR (-5, +5)	(2) CAR (-5, +120)	(3) CAR (-10, -1)	(4) CAR (-1, +1)	(5) CAR (0, +10)
COVER ANALYST	-0.00620	-0.0107	-0.000138	0.000227	-0,00347
	(0.00670)	(0.0154)	(0.00320)	(0.00449)	(0.00580)
STRONG	-0.123	1.585	-0.173	-0.0148	0,0352
	(0.448)	-1.086	(0.219)	(0.304)	(0.366)
SKIPRANK	-0.437	-0.0352	-0.360	0.104	0,053
	(0.570)	-1.414	(0.276)	(0.373)	(0.499)
MarketType	-0.0985	-3.009**	0.443*	0.464	-0.250
	(0.592)	-1.482	(0.244)	(0.397)	(0.511)
TradingSignal	-0.375	0.614	-0.283	-0.112	0.598**
	(0.332)	(0.750)	(0.174)	(0.236)	(0.261)
Constant	-0.865	0.529	-0.564	-0.846	-0,0404
	(0.780)	-1.906	(0.362)	(0.529)	(0.666)
Observations	1,188	1,127	1,188	1,188	1,188
Prob > F	0.7099	0.1218	0.0417	0.8006	0.2491
R-squared	0.002	0.012	0.010	0.003	0.006
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Table 21: Determinants of Stock Price Performance of Downgrades

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level.

CAR = Cumulative abnormal return from event day t_1 to event day t_2.

Definitions of variables:

COVER$_{ANALAYST}$, equals the mean number of analysts' coverage for a stock.

STRONG, for upgrades, equals one if the recommendation is a strong buy and zero otherwise (buy). For downgrades, equals one if the recommendation is a strong sell or sell and zero otherwise (hold).

SKIPRANK takes the value one if the change in recommendation skipped a rank and zero otherwise (do not change a rank).

MARKET$_{TYPE}$ equals one if the recommendation was revised in the bull market phase and zero otherwise (bear market).

TRADING$_{SIGNAL}$ equals one if the change in recommendation happened when the short and long-term moving average cross showed a buy signal and zero otherwise, when the cross of both moving averages signalled sell. Buy signal is often viewed as an indicator of an emerging upward moving market and sell signal as an indicator of an emerging downward moving market.

VARIABLES	(1) CAR (-5, +5)	(2) CAR (-5, +120)	(3) CAR (-10, -1)	(4) CAR (-1, +1)	(5) CAR (0, +10)
STRONG	-0.129	-1.561	-0.383	-0.0264	0.00711
	(0.449)	-1.088	(0.375)	(0.306)	(0.366)
SKIPRANK	-0.461	-0,0412	-0,0126	0.117	0.0724
	(0.572)	-1.414	(0.530)	(0.374)	(0.498)
MarketType	-0.0760	-2.992**	-0.148	0.483	-0.212
	(0.593)	-1.474	(0.525)	(0.397)	(0.510)
TradingSignal	-0.358	0.624	-0.183	-0.0990	0.622**
	(0.328)	(0.752)	(0.269)	(0.237)	(0.261)
COVER BROKER	-0.00200	-0,0107	0,00514	-0.00487	-0.0120*
	(0.00794)	(0.0174)	(0.00625)	(0.00514)	(0.00622)
Constant	-0.248	0.450	-0.401	-0.487	0.531
	(0.823)	-2.027	(0.678)	(0.539)	(0.672)
Observations	1,188	1,127	1,188	1,188	1,188
Prob > F	0.8586	0.1298	0.7768	0.6483	0.0869
R-squared	0.002	0.011	0.002	0.004	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: Determinants of Stock Price Performance of Downgrades

T-statistics with an absolute value of 1.65, 1.96 and 2.58 indicate significance at the 0.10, 0.05 and 0.01 levels, respectively * indicates statistical significance at less than the 0.10 level, ** at less than the 0.05 level and *** indicates statistical significance at less than the 0.01 level

CAR = Cumulative abnormal return from event day t_1 to event day t_2.

Definitions of variables:

STRONG, for upgrades, equals one if the recommendation is a strong buy and zero otherwise (buy). For downgrades, equals one if the recommendation is a strong sell or sell and zero otherwise (hold).

SKIPRANK takes the value one if the change in recommendation skipped a rank and zero otherwise (do not change a rank).

$MARKET_{TYPE}$ equals one if the recommendation was revised in the bull market phase and zero otherwise (bear market).

$TRADING_{SIGNAL}$ equals one if the change in recommendation happened when the short and long-term moving average cross showed a buy signal and zero otherwise, when the cross of both moving averages signalled sell. Buy signal is often viewed as an indicator of an emerging upward moving market and sell signal as an indicator of an emerging downward moving market.

$COVER_{BROKER}$, equals the mean number of brokerage coverage for a stock.

	Upgrades		Downgrades	
	0	1	0	1
STRONG	89.03%	10.97%	82.24%	17.76%
SKIPRANK	91.82%	8.18%	89.73%	10.27%
MARKET TYPE	16.35%	83.65%	14.98%	85.02%
TRADING SIGNAL	56.23%	43.77%	53.54%	46.46%

Table 23: Distribution of Explanatory Dummy Variables

Definitions of variables:

STRONG, for upgrades, equals one if the recommendation is a strong buy and zero otherwise (buy). For downgrades, equals one if the recommendation is a strong sell or sell and zero otherwise (hold).

SKIPRANK takes the value one if the change in recommendation skipped a rank and zero otherwise (do not change a rank).

$MARKET_{TYPE}$ equals one if the recommendation was revised in the bull market phase and zero otherwise (bear market).

$TRADING_{SIGNAL}$ equals one if the change in recommendation happened when the short and long-term moving average cross showed a buy signal and zero otherwise, when the cross of both moving averages signalled sell. Buy signal is often viewed as an indicator of an emerging upward moving market and sell signal as an indicator of an emerging downward moving market.