



BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science

Final Master thesis – Counts 80% of total grade

Do Analysts' Price Targets Change Stock Prices? The Impact of Price Targets on Stocks with Different Characteristics.

Navn: Agneta Karin Elisabeth Zelmin,
Alexander Klamroth

Start: 02.03.2018 09.00

Finish: 03.09.2018 12.00

Do Analysts' Price Targets Change Stock Prices? The Impact of Price Targets on Stocks with Different Characteristics

Alexander Klamroth and Agneta Zelmin

September 2018

This thesis is a part of the MSc in Business with major in Finance at BI Norwegian Business School. The school takes no responsibility for the methods used, results found and conclusions drawn.

Acknowledgment

We want to thank Professor Ilan Cooper for his support, engagement and excellent guidance throughout the process of writing this thesis.

Abstract

This thesis analyzes the impact of financial analysts' price targets on stock prices. According to the efficient market hypothesis, all information should be incorporated in the stock price, meaning that financial analysts' price targets should not influence the stock price. Further, we investigate if volatility or tangibility have an impact on the extend of the stock price changes. Using the event study methodology, we analyze if any abnormal returns occur the days surrounding the event date. We define an event as consensus stock price target change of more than three percent. Our most important results are: First, when a new price target is released, on average stock prices move in the same direction as the analysts' price targets. Second, downgrades lead to a stronger price reaction than upgrades. Third, both tangibility and volatility influence how strongly a stock responds to the price target. We see that low volatile stocks and high tangible stocks respond to a lower degree than their counterparts. Our paper also includes suggestions for further research on this topic and concludes that financial analysts' price targets do impact stock prices.

Contents

1	Introduction	1
2	Theoretical Background and Literature	2
2.1	Efficient Market Hypothesis	2
2.2	Financial Analysts	4
2.3	Stock Characteristics	6
3	Data	7
3.1	Sample Selection	7
3.2	Data Handling	7
3.3	Weaknesses of the Data	9
4	Methodology	11
4.1	Event Study	12
4.2	Limitations of the Methodology	17
5	Empirical Results and Discussion	17
5.1	Do Analysts' Price Targets Influence Stock Prices?	19
5.2	The Impact of Volatility	20
5.3	The Impact of Tangibility	20
5.4	Comparing the Results and Additional Remarks	21
6	Conclusion and Further Research	22

List of Figures

1	Distribution of events over the data period.	10
2	Number of events per stock.	11
3	Event study timeline.	14
4	Event study timeline with multiple events (τ_i).	15
5	Average abnormal returns for the whole event list.	19
6	Average abnormal returns for highly and less volatile companies.	20
7	Average abnormal returns for highly and less tangible companies.	21

List of Tables

1	Event list filter criteria	9
2	Summary of results.	18

1 Introduction

The influence financial analysts have on stock price movements has for long been a widely discussed topic. This has several reasons, but one of the most important ones is that according to the efficient market hypothesis, financial analysts' price targets should not affect stock prices, since all available information should already be incorporated in the price. To investigate whether or not analysts do have an impact, the effect of new price targets on stocks is analyzed using recent data from the Russell 3000 index. The index comprises most of the U.S.-traded stocks in terms of market capitalization and our sample spans from March 2011 to April 2018. We further refine the research question by investigating which characteristics make stocks more sensitive to analysts' price targets. In this thesis, we look at how volatility and tangibility impact the stock price changes caused by analysts' price targets. The motivation behind this is our hypothesis that price targets have a larger effect on more volatile and less tangible companies. Volatility and intangibility can be considered as measures of uncertainty. One factor that contributes to uncertainty is the quality and availability of price-relevant information. Therefore, highly volatile and intangible companies could be more strongly influenced by analysts' price targets. Our goal is to investigate if equity analysts influence stock prices, both from a theoretical and an empirical point of view. We formulate our research question:

Do financial analysts' price targets impact stock prices? Does volatility or tangibility lead to higher sensitivity to price target changes?

The results from our analysis indicate that stock prices are influenced by financial analysts' price targets. More optimistic price targets on average increase stock prices, and more negative price targets on average reduce stock prices. Less tangible and more volatile stocks react to a stronger extent than highly tangible and less volatile stocks. One of the most important limitations of these results is that the reason for a change in stock prices cannot be inferred from the data - it could have happened for many reasons other than the equity analysts' price targets.

This thesis is structured as follows: Section 2 presents theory and related literature on market efficiency, financial analysts, and stock characteristics. Section 3 describes our data, while section 4 explains our methodological approach and its limitations. In section 5 we present and discuss our empirical

findings. The final section concludes and suggests further research.

2 Theoretical Background and Literature

This chapter presents literature and theory about the efficient market hypothesis, financial analysts, volatility and tangibility, forming the theoretical basis for our empirical studies.

2.1 Efficient Market Hypothesis

The efficient market hypothesis suggests that it is not possible to systematically beat the market since all information should already be reflected in the stock price. This implies that financial analysts' price target should not have an impact on stock prices. However, this theory implies assumptions which are not always realistic. Explanations why markets are not always efficient can be found in behavioral finance and also in the transaction cost theory. If these market imperfections are applicable, the market efficiency hypothesis could be violated; analyst target could move security prices. A market is said to be efficient when the price of a stock fully reflects all available information, which means that it trades at fair value (Fama, 1970). This implies that it is not possible to systematically beat the market and earn abnormal returns, since there is an absence of under- and overvalued stocks. Patell and Wolfson (1984), and Edrington and Lee (1995) find that prices react very quickly once new information become public. After the change in price due to the new information, no further drift related to that information in stock price should materialize according to the efficient market hypothesis (EMH), (Bodie, Kane, & Marcus, 2014). The question is whether a stock price can fully reflect all available information. 'Fully' would be an unrealistic assumption since it would mean that all available information that exist in the universe is included in the stock price. However, no human and no computer have access to this, let alone the capacity to meaningfully process it. Therefore, this definition would imply that no market could ever be efficient (Sewell, 2011). The EMH also relies on the assumption that information is shared (to a certain degree, depending on the level of efficiency), and that stock prices are affected by current news rather than yesterday's trends. According to this, stock prices follow a random walk. Furthermore, the EMH assumes that investors are rational. Even if there was an irrational investor, their trades would be random and not systematically move stock prices. Finally, rational investors are assumed to eliminate noise created by irrational investors (Naseer & Tariq, 2015).

The EMH is often categorized into three versions: weak form, semi-strong form, and strong form. The difference is mainly how the term "all 'available' information" is defined. The weak-form hypothesis states that stock prices already reflect security market information, such as market trading data, past price history and trading volume (Bodie et al., 2014). The gathering of this information is associated with low costs, since access to most of the data, e.g. past stock prices, is free of charge. The weak form hypothesis implies that past returns cannot predict future excess returns since if the data signals information about future performance, all investors would exploit the signals which leads to a loss in value of the signals and an immediate price change (Bodie et al., 2014). A technical analysis of stock prices will according to the weak-form not result in abnormal returns (Naseer & Tariq, 2015). In addition to information about past prices, the semi-strong form states that all publicly available information, e.g. financial statements, quality of management, dividend-, earning- and acquisition announcements, political- and economic events, are incorporated in the stock price. According to the semi-strong form, abnormal returns are not possible through a fundamental analysis (Naseer & Tariq, 2015). The strong form of market efficiency states that, in addition to what is stated in the weak- and semi-strong form, stock prices reflect all possible information, including insider information. This implies that no public or private information can be used to predict future abnormal returns. In Fama's report from 1970, referred in Ang, Goetzmann, and Schaefer (2011), it is concluded that the empirical evidence up to that date gave support for the weak-form and the semistrong-form market efficiency. The strong form is unrealistic as there are legal structures available in most countries that prevent insider trading (Degutis & Novickyte, 2014).

The hypothesis of efficient markets has for long been a widely researched area amongst academics. Early researchers accepted this hypothesis, but later on, anomalies from the theory became more and more present in the literature (Brealey, Myers, & Allen, 2012). Researchers that tried to challenge the efficient market hypothesis found several consistent patterns: The January effect, which describes a pattern of higher returns in January compared to other months, and the Friday effect that describes higher returns on Fridays than on Mondays (Schwert, 2003).

The underlying assumptions of the EMH can conflict with behavioral finance. Empirical research has shown that investors and financial analysts are

not always rational. They are in fact subject to several different biases, which in turn lead to irrational decisions. Daniel and Titman (1999), argue that investors are biased due to overconfidence. Their research shows that this so-called momentum effect is more likely to be stronger when the analysis is based on more ambiguous information. Furthermore, they found that the momentum effect is stronger for growth stocks compared to value stocks. Shefrin and Statman (1985) find evidence for the tendency to sell winning stocks too early, and hold losers too long. The list of research that finds evidence for violations against EMH assumptions is long.

To conclude, many pieces of evidence cast doubt on market efficiency. Especially the criticism that it is not possible to include all information that exist, even if they are publicly available, is hard to dispute. On the one hand, the market anomalies described above argue against EMH. On the other hand, if investors can profitably trade on inefficiencies, these inefficiencies would vanish due to the market mechanisms. For example, if investors knew for certain that a stock was to raise the next day, they would trade on it immediately and the price of the security would go up until the point where no more excess return can be generated.

2.2 Financial Analysts

Collecting and analyzing information about a firm can be very costly for investors. They might lack the skill to perform a solid analysis, and it can be very time consuming to gather the required information. Financial analysts provide information to investors. More specifically, they give investors easier and quicker access to existing information, which can reduce the costs of monitoring a company and improve market transparency. However, not all companies are followed by financial analysts. For companies that are followed, reports might not be updated at all time, hence information on these companies is more costly and difficult to interpret.

The competition for information is tough amongst analysts, since uncovered information can give a competitive advantage. The incentives of financial analysts may differ due to how analysts are compensated, and who they work for. Analysts on the buy-side work for large institutional investment funds such as pension funds and mutual funds. The information produced is exclusively available to the particular fund and not to competing funds that can gain on the advice. Sell-side analysts usually provide information free of charge to

all of the brokerage firm's or investment bank's clients, rather than a specific client. This is usually gathered in a research report which contains information about the industry and the company, the analyst's beliefs whether the firm will succeed or fail, a target price of the stock for the next year(s), and finally a rating which gives a buy or sell recommendation. Since the information can give an investor lower research costs when deciding whether to buy or sell a stock, this can imply a higher trading frequency and therefore increased commissions to the brokerage firm or investment bank. The last category of analysts are those who are not on the sell- or buy-side. They are independent analysts, compensated by the company they are following, or by selling subscription-based reports. Their goal is to produce unbiased and objective ratings.

One source of information is financial accounting information, such as income statements, balance sheets and cash flow statements. Analysts also participate in public conference calls which offers opportunities to ask questions to the management, as well as visit the company to get more insight in their operations. This information can be classified as public information. The information is analyzed through a fundamental analysis, often in combination with a technical analysis. The aim is to uncover insights that are not yet known to the rest of the market (Bodie et al., 2014).

Grossman and Stiglitz (1980), referred in Bodie et al. (2014), question why one should expect prices to reflect all available information, since there is a possibility to find relevant information that the rest of the market has overlooked. Information can, as mentioned before, be costly to analyze but can also generate higher returns. Therefore, there is an incentive to gather and analyze information even though it contradicts the EMH. Empirical research shows that larger firms are followed by more analysts (Bhushan, 1989), which implies that larger firms' stock prices are priced more efficiently than smaller firms' stock prices, since potentially more information is covered. Research by Chan and Hameed (2006) shows that securities in emerging markets that are covered by more analysts incorporate greater market-wide information, and less firm-specific information. The reason for this can be due to the less transparency, and in turn, the higher costs to collect firm-specific information. Chan and Hameed's research was based on the observation that stocks that are followed by many analysts tend jointly move in the same direction, while others move more independently from one another. This implies that recommended price targets do not always need to reflect all available information and, in

turn, that the market is not efficient. In addition to which type of information analysts produce, it is more difficult to forecast a company's earnings when a company becomes more geographically diversified (Duru & Reeb, 2002). The same authors also find evidence that analysts' earnings forecasts become less accurate as the complexity of the analyses increases (Duru & Reeb, 2002). Lim (2001) found evidence for overoptimistic earnings forecasts amongst analysts, and that they fail to incorporate for example past earnings announcements and stock returns. Clement (1999) referred in Piotroski and Roulstone (2004), suggests that analysts' accuracy improved with industry specialization. To conclude, research shows that analysts' forecasts and analyses are most likely biased.

2.3 Stock Characteristics

In addition to our main research question, whether financial analysts impact stock prices, we are also interested in examining which characteristics of stocks are more sensitive to price target updates. There are endless variety of possible characteristics one can examine, and we have chosen to take a closer look at how volatility and tangibility impact the sensitivity of stocks to the analyst price updates. We chose tangibility and volatility since we saw a high chance that these factors influence how strongly stocks respond to price targets as both of them could be a sign of uncertainty in valuation. The degree of uncertainty can impact financial analysts' price targets. The question is then whether investors pay attention to the potential biases in the analysts' targets or not.

When we define the characteristics, we build on the same criteria as Baker and Wurgler (2006). Their research is mainly about how investors' sentiment affects stock prices. We are looking at how financial analysts affect stock prices through their price targets. The two characteristics that are analyzed and their definitions can be found below:

Volatility

The dispersion of stock returns is often measured by its volatility, which in turn can be described as the standard deviation or variance of returns. Higher volatility implies higher individual risk. One attribute that can lead to higher volatility is that the earnings are expected to materialize in the later future. The underlying intuition is that securities with high cash flows in the next five years but no cash flow afterwards are not affected as strongly by interest rate

changes as stocks that have their entire payout after 20 years. If this reason is prominent amongst the factors that lead to the high volatility, investors might put more emphasis on the expert opinion of analysts because it could be harder to estimate cash flows that occur so late in the future.

Tangibility

For investors and financial analysts, companies with mostly tangible assets are often easier to evaluate than companies whose assets are intangible due to the higher difficulty to evaluate a company's research and development (R&D), patents and goodwill. The higher the uncertainty in valuation of a stock, the riskier a stock tends to be. Research by Choi, Kwon and Lobo (2000) shows that intangible assets reported on the balance sheet are positively valued by financial markets. Their research is based on portfolio analyses where they use a control portfolio as a benchmark and compare the book-to-market value to test how the market values intangible assets. Baker and Wurglers (2006) criteria of tangibility are property, plant and equipment (PPE) over assets, and R&D over assets. Companies with high values for PPE over assets tend to be easier to evaluate compared to companies with high values for R&D over assets. In this paper, we used R&D over assets as a proxy for tangibility.

3 Data

In this chapter, we describe the data and how we apply the data to our research question. Several data sources were considered and we ended up with collecting data from Bloomberg.

3.1 Sample Selection

The Russell 3000 index was chosen to cover a broad range of the equity market. This index is broader than the Standard & Poor's 500, which only contains stocks with high market capitalization, and should therefore represent both, small and large companies. However, it only represents the US stock market, therefore only one part of the global equity market. The results from this thesis might vary if we would apply the same methodology to an Asian index.

3.2 Data Handling

We define an event as a change in the consensus price target by at least 3% in either direction. The consensus price targets are obtained from Bloomberg

and are calculated by taking an average of various analysts' price targets. The reason that not every new price target is assigned to an own event is that it would significantly complicate the data handling. For this reason and for computational reasons, we choose only those price targets that meaningfully change the consensus price target. Another important consideration is that we look at trading days and not calendar days. That means that in this thesis, we treat "180 days" as 180 trading days, a time period that spans over more than half a year. The reason for this is that we aimed to have standardized data sets that can be compared with one another.

In a next step, the data is split into two different groups: analyst price target upgrades and downgrades. Upgrades move the consensus price target up, and downgrades move the consensus price target down. This upgrade can happen irrespectively of what the current share price is. If a company trades at \$100, the previous price target was \$50 and is now \$70, this is an upgrade. The reason for this is that even though the analysts still are not optimistic on the company, they now perceive it as better than before, which is "good news" for the investors.

Finally, categories are defined: volatility, and R&D over total assets. With regards to volatility, we chose the 200-day volatility. There are tradeoffs to this: A shorter period for the volatility allows to include only very recent data. On the other hand, a longer volatility can give a more complete picture and is less susceptible to extreme events. If for example many export-oriented companies trade down on one day because of the introduction of a new tariff, a short volatility period could consider these stocks very volatile even though they are not that volatile on any other day.

Volatility is estimated using the sample standard deviation of 200 days of historical returns prior to the event window of the corresponding stocks. To compare the extremes of both categories, we calculate the 25th and the 75th percentile of both categories based on our event list:

Table 1: Event list filter criteria

	Volatility	Intangibility
25th Percentile	1.738%	0
75th Percentile	3.263%	7.11%

Notes: This table shows the criteria for the 25th and 75th percentile for volatility and intangibility, which is later applied on the event list to separate high- and less volatile and tangible companies respectively. A stocks' R&D over total assets represents the level of tangibility, and volatility is the 200-day volatility of returns. Our subgroup of highly tangible stocks include only companies that have no investments in R&D.

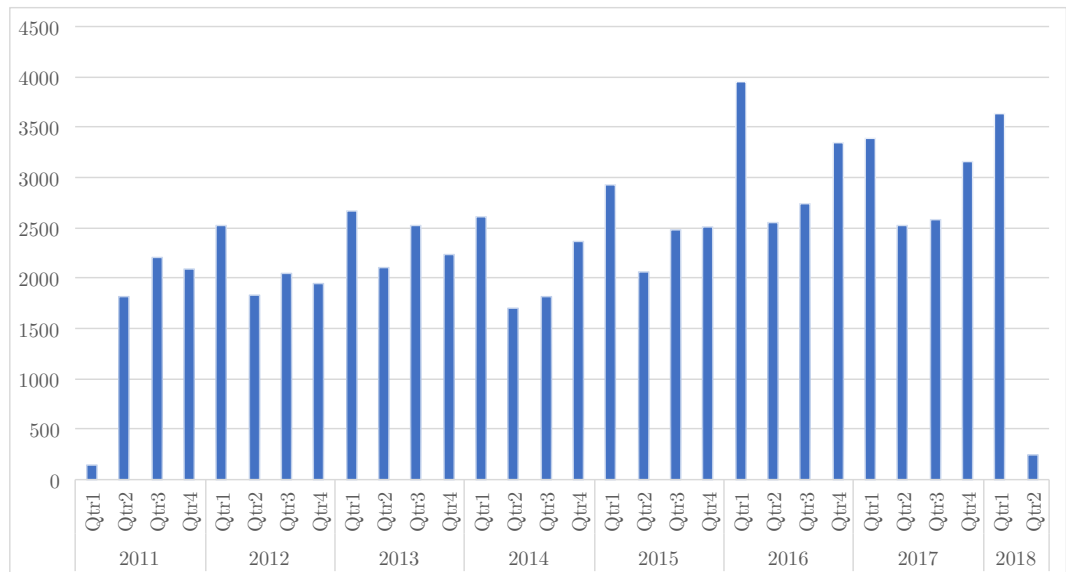
These values are then used to filter the event list to define the high and low volatility and tangibility groups. These steps give us various subsets of the total event list, which are all analyzed separately. In a next step, we remove missing data points and outliers from our event list. Outliers are defined as price changes by more than 50% on a single trading day.

3.3 Weaknesses of the Data

There are a few limitations to the explanatory power of our analysis that arise due to the characteristics of the data. First, we only look at the US equity market and therefore introduce a selection bias. This limitation was introduced due to practical reasons, but a more complete index could help to understand other equity markets better - and to compare, for example, developed and emerging markets.

Next, only daily historical data could be extracted from Bloomberg. A more granular approach could show at which point of time the investors react. For example, if we had a datapoint each minute, we could get a much clearer picture when exactly investors react to the price target. Finally, we only cover stocks going back to 2011. Therefore, we only see the market in relatively stable conditions. If we included a period with a crisis (e.g. 2000 or 2008), our results could also differ. We also analyze the distribution of the consensus price target updates that we covered during our dataset, it is shown in Figure 1. While the events analyzed are not entirely distributed equally across the time, all years are generally covered without any extreme biases towards a certain time period.

Figure 1: Distribution of events over the data period.

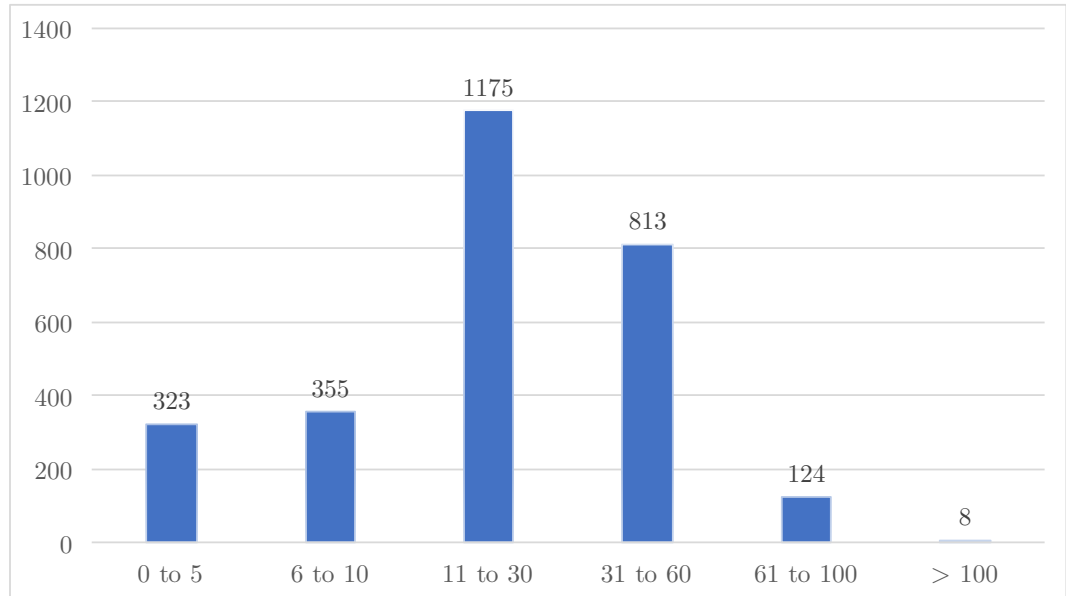


Notes: The figure shows the number of events, i.e. consensus price target changes $>3\%$, per quarter. While the events analyzed are not entirely distributed equally across time, all years are generally covered without any extreme biases towards a certain time period.

It happened a few times that some data points were missing from the dataset. The mitigation strategy for our dataset is to exclude these events from the event list. Since it did not occur very often, we do not expect a systematic bias as a consequence. However, it cannot be completely ruled out that these missing data points happen more often to small companies, as large companies are more likely to have more specialized reporting units that ensure that all the data is always complete and available.

Furthermore, we exclude a lot of events that don't move the consensus price target by more than 3% . This in turn could lead to a bias towards smaller companies: first of all, they might not get updates as often as large companies, and second, they are not covered by as many analysts so it could be easier to change the consensus price target. A distribution of how often companies produce "events" can be seen in Figure 2. A handful of companies produce more than 100 events, while the majority produces less than 60. Therefore, some companies are more prominent in this event study than others, potentially adding a bias.

Figure 2: Number of events per stock.



Notes: This figure shows how many companies produce how many events over the entire data period. We can see that only 8 companies produce more than 100 events over this period, and only 323 companies produce up to 5 events. Most of the companies are producing between 11 to 60 events.

While cutting the event list down to events that move the consensus price target by more than 3%, it still includes a high number of events in the time period. One issue connected with this high density is that while analyzing one particular event, another event could occur during the estimation period or even the event window. When considering all the events covered, in 67.96% of the cases there was such an intersection during the estimation period, and in 19.73% of the cases it even happened during the event window. This number is much lower for our event studies where we only look at a subset of events. For example if we only analyze highly volatile stocks that have recently gotten a consensus target price upgrade it reduces the event list from 70,688 events down to 8,233 events.

4 Methodology

This chapter explains our methodological approach. First, the event study methodology is explained. We also discuss limitations of our approach, which will be the basis for our discussion in section 6.

4.1 Event Study

To determine whether an analysts price target impacts stock prices, an event study approach is adopted based on the paper by MacKinlay (1997). The motivation for this is that even though it is more common to use an event study for larger firm announcements, we can consider analysts price target announcements as both overlooked information to the market, and as a main source of information for many investors which do not analyze new information themselves. Analysts price targets can to some degree include both information from large firm announcements and also daily macro economical and industrial news. We want to quantify our intuition that financial analysts do impact stock prices, which is also found in the literature.

Event Window

We define an event as a publication of a new price target. This price target needs to change the consensus price target by at least 3%. We then observe how this event impacts stock prices. The reason why the new consensus price target is compared to the previous one and not to the prevailing stock price is that it is easier to observe whether the analyst is more optimistic or pessimistic about the stock when the price target is released. For example, an analyst could have predicted that a stock price will fall significantly in the beginning. With a new price target, the analyst only predicts it to fall very slightly. This would be "good news" for the stock, but when comparing it to the stock price it would be regarded as negative, thus the comparison with the previous consensus price target. The minimum change requirement of the consensus stock price of 3% will give us less events than the original data. This event is assumed to be unknown to the market, since otherwise it should be incorporated in the price before the event takes place.

Further, we specify the event date, event window and estimation window. The event date is as mentioned the point in time where a new price target is published to the market. The event window can be defined as the period surrounding the event date where the affected firms are examined, and aims to capture the impact of the event through the calculations of abnormal returns (MacKinlay, 1997). Here, we see how the market responds before and after the event. Since we cannot see exactly the event time of the new price targets, e.g. if the new price target is published after closing time, we must choose a longer event window than the exact date of the event. According to the EMH there should be no drift in the stock price after the price target is published. Also,

there should be no reactions prior to the event, if the information is unknown to the market. In practice, one can imagine that there might be rumors that an analyst will publish a new target at a certain date, and that the target can be known to be either higher or lower than the previous price target. One other reason could be that other information has become known to some analysts before the market, and therefore their price target is based on that information.

In this paper, we examine the reactions five days prior, and five days after the event date, which results in an event window of 11 days. We expect that the market will adjust within these five days since data is readily available to investors and the exchange of information can happen very quickly. On the other hand, a shorter event window can be more suitable.

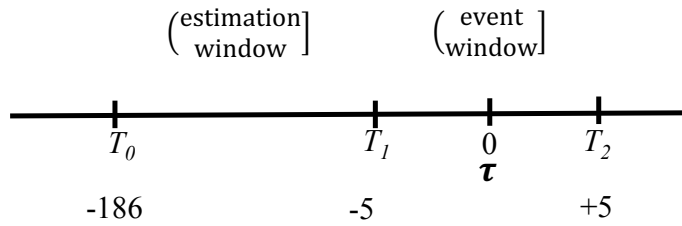
Estimation Window and Normal Returns

As a next step, we need to define the estimation window, which will be used to estimate the expected returns for the particular stock. The rationale behind this is to see what the returns are predicted to be in absence of new price targets, i.e. the normal returns. Looking at previous research within finance, there are several models that have been used to calculate normal returns. The Capital Asset Pricing Model (CAPM) is the core building block in models such as the factor model, e.g. the Fama-French five factor model, and other pricing models. The constant mean return model assumes the return to be constant over time. Since this method will most likely generate more biased results and is more suitable for shorter term studies, suggested by Kothari and Warner (2007), it would not have been appropriate in our study since our time frame would imply more variations in returns over time. For event studies, we have seen that in recent empirical research the market model is the most popular choice to estimate normal returns, e.g. Li and Lie (2006) and Dasilas and Leventis (2011). In the market model the relationship between the market return and the security return is linear and stable over time (MacKinlay, 1997).

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad (1)$$

Since the five-factor model requires more parameters, we choose to estimate normal returns through the market model with an estimation window that spans from 186 days to 6 days prior to the event date. Figure 3, based on MacKinlay (1997, p. 20), summarizes the timeline of our event study where τ is the event date, $T_1 - T_0$ is the length of the estimation window, and $T_2 - T_1$ is the event window length.

Figure 3: Event study timeline.

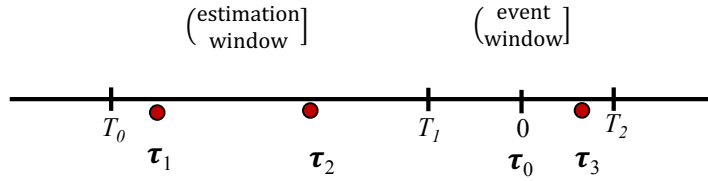


Notes: The figure shows the timeline of the event study, with an estimation window of 180 days, and event window of 11 days.

We use the ordinary least squares (OLS) method, suggested by MacKinlay (1997), to estimate the parameters in the market model (1). OLS gives us the parameter estimates that minimize the total sum of squares, i.e. the best fitted line to the data set. In the market model R_{it} are the returns on stock i at time t , R_{mt} are the returns on the market portfolio at time t , and ϵ_{it} is the zero mean disturbance term. The parameters a_j , b_i and the variance of the error term s_ϵ^2 are estimated with data from the estimation window.

Since we do not want the event itself to impact normal returns, it is ideal to set an estimation window that does not overlap the event window and does not include the event itself (MacKinlay, 1997). When looking at the data, we see that in some cases we have one or more events in our event window or estimation window due to the higher frequency of new price targets compared to other situations where there might be one or two events per year, e.g. dividend announcements. Since we are only looking at price targets that change the consensus price target by more than 3%, the probability of this is decreased. However, even though the definition of an event is changed, there will still be price target updates that are not classified as events in our estimation window and event window. One of the consequences of this is that our market model estimates for alpha and beta are noisier. Figure 4 illustrates a situation where we see additional events, τ_1 , τ_2 , and τ_3 , in addition to the specific event we are looking at, τ_0 . In other words, ideally, we want to exclude the additional events in the estimation window and event window.

Figure 4: Event study timeline with multiple events (τ_i).



Notes: In an event study, ideally, additional events should be excluded. This figure shows a timeline where additional events occur, which can impact the calculation of normal returns, and in turn abnormal returns.

To ease this potential problem or to discover how serious it is, we want to see how likely it is for another price target change other than the specific event we are looking at to happen in the event window or estimation window. This can affect normal returns and results for the specific event we are looking at. By looking at how often additional events occur in the same period, we can see which duration of our two event windows are most robust. For the event window, this problem has to occur systematically on the same days relative to the event we are analyzing, e.g. on day -2. Due to our large number of events, we might see that this is a minor problem since there is an average effect: if there is an additional event once during a 180-day period, it might not have a very drastic effect since there are still plenty of other days to smoothen out the effect. A quantitative analysis of this is given in section 3.3.

Abnormal Returns

Next, we calculate a firm's abnormal returns (2) and average abnormal returns (3) for every event by taking the difference between the actual return in the event window and the expected normal return calculated by the market model. The expected normal return is conditional on the information from the market model where X_t is the market return.

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_t) \tag{2}$$

$$\overline{AR}_\tau = \frac{1}{N} \sum_{i=1}^N AR_{i\tau} \tag{3}$$

After taking the average of the abnormal returns we retrieve the average abnormal return \overline{AR} (3). To arrive at the cumulative average abnormal return (4), we add up the average abnormal returns over the 11-day event window. According to the EMH there should be no drift, but if we see a drift due to

the price target announcement the \overline{CAR} will be affected.

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau \quad (4)$$

Barber and Lyon (1997) argue that instead of calculating \overline{CAR} , one should calculate abnormal returns such as the buy-and-hold return on a reference portfolio. According to their paper, this method gives less biased abnormal returns and is more consistent with actual investor behavior. In this approach, one compares the returns of a buy-and-hold sample firm and the buy-and-hold returns of a control firm (Barber & Lyon, 1997). However, due to computational limitations and the large data set we chose to focus on the \overline{CAR} .

Statistical Significance and Hypotheses

To check for statistical significance in our results, we use a two-sided (since abnormal returns can be both positive and negative) test statistics of the null hypothesis, i.e. abnormal returns are zero. The null hypothesis is tested against the alternative hypothesis that abnormal returns are different from zero.

$$H_0 : \overline{CAR} = 0$$

$$H_1 : \overline{CAR} \neq 0$$

Several other test statistics have been suggested in the literature, but in this thesis, we choose to follow MacKinlay's (1997) approach. We check if the calculated abnormal returns are statistically significantly different from zero at the 99% (***) , 95% (**) and 90% (*) confidence level. From the market model, we estimate the variance of the error term σ_ϵ^2 . This is then used to calculate the variance of the abnormal returns (5) and the variance of the \overline{CAR} (6).

$$var \overline{AR}_\tau = \frac{1}{N^2} \sum_{i=1}^N \sigma_{\epsilon_i}^2 \quad (5)$$

$$var(\overline{CAR}(\tau_1, \tau_2)) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR}_\tau) \quad (6)$$

Further, we use equation (4) and (6) to calculate the test statistic (7), suggested by MacKinlay (1997).

$$t = \frac{\overline{CAR}(\tau_1, \tau_2)}{\sqrt{var(\overline{CAR}(\tau_1, \tau_2))}} \sim \mathcal{N}(0, 1) \quad (7)$$

4.2 Limitations of the Methodology

Due to our large dataset of events, we face the issue of not being able to filter out other events, e.g. earnings announcements, which can have an impact on the stock price and the price target itself. It is difficult to see if investors are reacting to the price target or the news itself. As mentioned, analysts base their price targets on company specific and industrial news. If a company announces that they will reduce their dividends, or if the oil price is decreasing significantly one day, the price target will most likely reflect that as it happens. As a consequence to this, some of our stock returns might not result from analyst target changes but are merely a reaction to macroeconomic or company events.

An issue in connection with event studies is that abnormal returns need to be calculated. To be able to define "abnormal returns", one needs expected returns, which come from a financial model like the market model in our case. It could always be the case that returns are in reality not "abnormal", but the model simply cannot capture the returns as desired. This problem is also known as the *joint hypothesis problem* (Fama, 1991). MacKinlay (1997) suggests comparing the R^2 of the market model and the constant mean return model to find out if one of them fits the data better.

5 Empirical Results and Discussion

In this chapter, we discuss our empirical findings. We start by discussing our findings on whether or not financial analysts influence stock prices or not, and to which degree. We discuss if the effect of an upgrade- or downgrade differ. We then present our findings on stock characteristics. We look at the impact of downgrades and upgrades on highly volatile and less volatile companies, and on highly tangible and less tangible companies. Furthermore, robustness and significance tests are applied to our results followed by a conclusion in section 6.

Due to our large number of observations we end up with significant results at 99% significance level for almost all of our hypotheses. From formula (5), where we calculate the variance of the abnormal return, we will always get a small number due to our high number of observations. This in turn will lead to our results being significant, see table 2.

Table 2: Summary of results.

	N	-5 to -2	-1	0	1	2 to 5	CAAR	t-statistics
Panel A - Whole event list								
All stocks	70.036	-0.09%	0.01%	0.15%	-0.22%	-0.89%	-1.04%	-7.18 ***
Upgrades - All stocks	40.683	0.66%	0.82%	1.78%	0.09%	-1.17%	2.18%	18.03 ***
Downgrades - All stocks	29.353	-1.13%	-1.11%	-2.12%	-0.65%	-0.50%	-5.51%	-18.08 ***
Panel B - Volatility								
Upgrades - High Volatility	8.233	1.21%	1.06%	2.03%	0.07%	-1.48%	2.90%	78.66 ***
Upgrades - Low Volatility	11.360	0.29%	0.61%	1.30%	0.02%	-0.90%	1.32%	2.37 **
Downgrades - High Volatility	8.277	-2.11%	-1.15%	-2.33%	-0.71%	-0.68%	-6.99%	-6.53 ***
Downgrades - Low Volatility	5.187	-0.56%	-1.15%	-2.01%	-0.52%	-0.53%	-4.79%	-85.50 ***
Panel C - Tangibility								
Upgrades - Low Tangibility	18.172	0.74%	0.69%	2.34%	0.26%	-1.42%	2.61%	20.85 ***
Upgrades - High Tangibility	15.992	0.66%	0.95%	1.69%	0.05%	-1.15%	2.19%	7.46 ***
Downgrades - Low Tangibility	12.332	-1.07%	-1.07%	-3.19%	-1.14%	-0.62%	-7.08%	-46.24 ***
Downgrades - High Tangibility	13.180	-1.28%	-1.23%	-1.99%	-0.58%	-0.53%	-5.60%	-8.33 ***

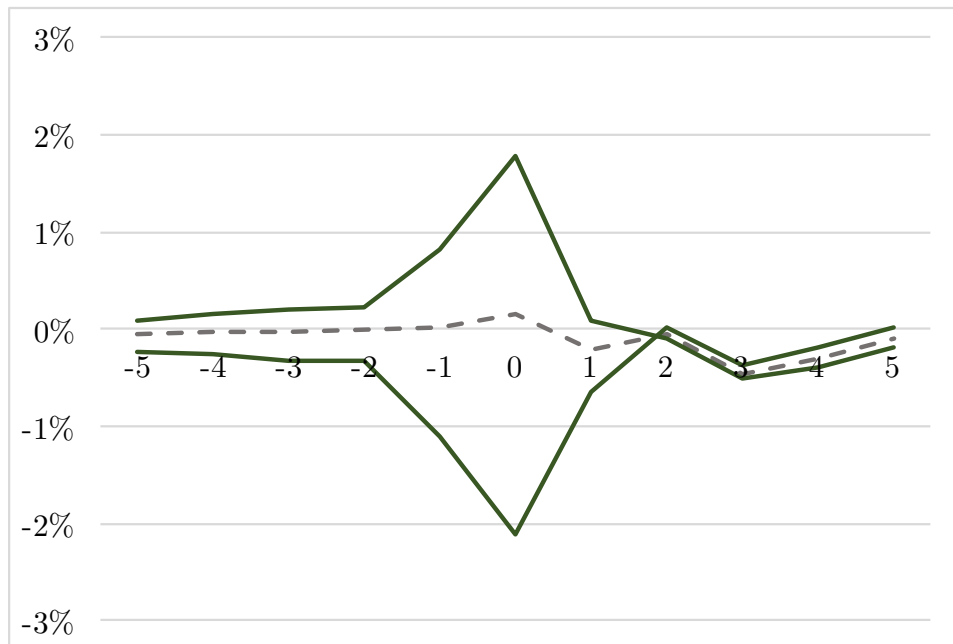
Notes: This table summarizes the results and statistical output. N is the number of events for every analysis. Furthermore, the \overline{CAR} is the sum of abnormal returns from five days prior and after the event day. The t-statistics shows that all results other than "Upgrades - Low Volatility" are significant at a 99% level. Panel A summarizes the results for the whole event list, i.e. no application of filters. Panel B and panel C summarize the results for volatility and tangibility. As expected, we see negative \overline{CAR} for downgrades, and positive \overline{CAR} for upgrades.

5.1 Do Analysts' Price Targets Influence Stock Prices?

In our event list, we had 70,036 consensus price target updates -40,686 were higher than the previous price target, 29,353 were lower than the previous price target. To answer the first part of our research question we did not discard any events. The average abnormal returns were relatively stable over the first days (-5 to -1). On day 0, the average abnormal return increases to 0.15% and were negative the following days. As expected, we observe quite stable abnormal returns, without any extreme peaks during the event date. This could be upgrades and downgrades canceling each other out

When an analyst releases a price target that makes the consensus price go up by 3% or more, the price goes up by 1.78% on average on this day, and 2.18% on average over the 11-day period. One result that was not expected is that the price even reacts one day before the price target was released - although to a much lower extend (0.82%). A consensus price downgrade has a much stronger effect on the stock prices than an upgrade: An upgrade leads to a \overline{CAR} of 2.18% over the 11-day observation period, a downgrade to a \overline{CAR} of -5.51%. The effect is also stronger on the very day the event happens with -2.12%.

Figure 5: Average abnormal returns for the whole event list.

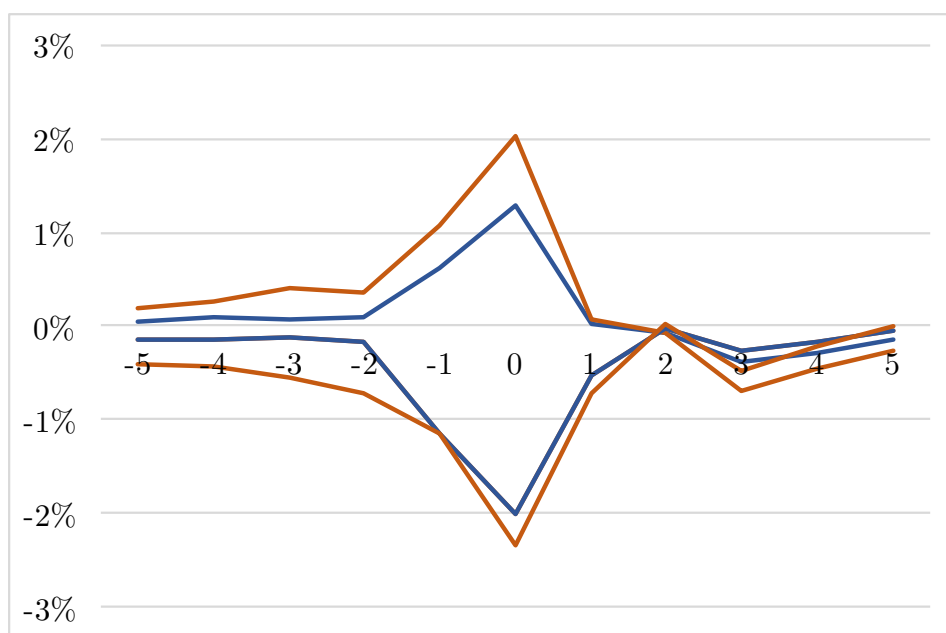


Notes: This figure shows the average abnormal return (\overline{AR}) for the whole event list, and with only upgrades and downgrades. The dashed line shows the \overline{AR} for the whole event list. The positive green line represents \overline{AR} for financial analysts upgrades, and the negative green line represents \overline{AR} for financial analysts downgrades.

5.2 The Impact of Volatility

In our data, we can observe that volatile stocks respond to a greater extent to price target updates than less volatile stocks. A positive price target update leads to a cumulative average abnormal return of 2.90% on highly volatile stocks compared to 1.32% on less volatile stocks. When looking at downgrades, we can observe a \overline{CAR} of -6.99% for stocks with higher volatility compared to a loss of 4.79% for stocks with lower volatility.

Figure 6: Average abnormal returns for highly and less volatile companies.



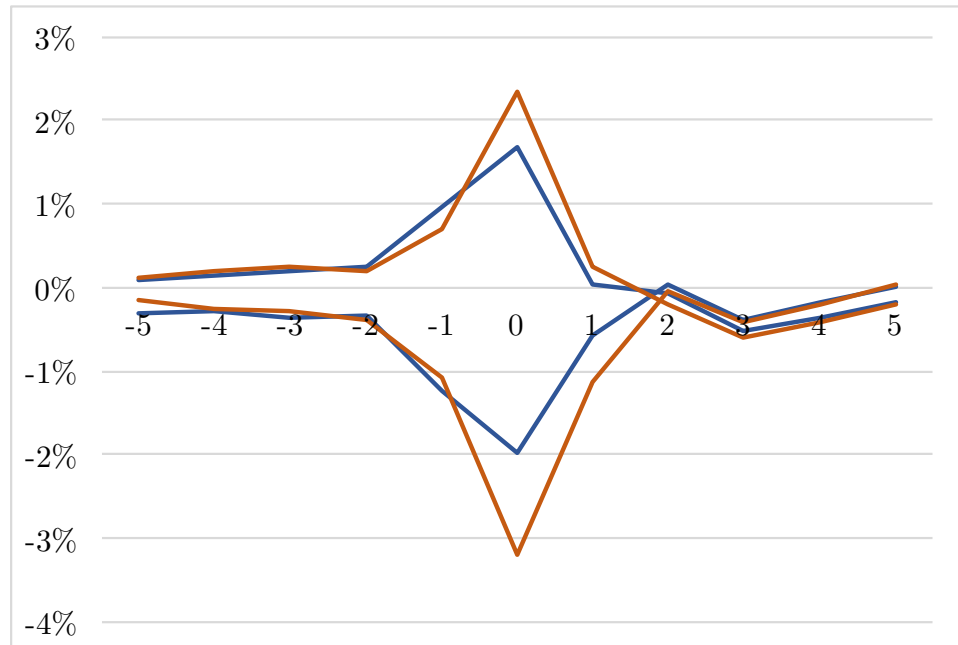
Notes: This figure shows the average abnormal returns for highly and low volatile stocks. The orange line represents highly volatile companies during upgrades (positive \overline{AR}) and downgrades (negative \overline{AR}), and the blue line represents less volatile companies during upgrades (positive) and downgrades (negative). The figure shows that the returns for highly volatile stocks are higher during upgrades and lower during downgrades compared to less volatile stocks. We see that the difference is larger during upgrades.

5.3 The Impact of Tangibility

A similar effect as for volatility can also be observed for tangibility. In this case, we use R&D over total assets as a proxy for tangibility. Stocks with a high R&D ratio respond more strongly to analyst price updates in both directions. When there is a positive consensus price movement, stocks with high R&D ratio react on average with an abnormal price movement of 2.34% on the day of the announcement, and with -3.19% for negative consensus price target changes. The \overline{CAR} over the 11-day event window is 2.61% and -7.08% respectively. For stocks with lower proportional investments in R&D, the effect

is not as strong: the \overline{AR} on day 0 is 1.69% for consensus price upgrades and -1.99% for downgrades on average. The \overline{CAR} amounts to 2.19% and -5.60% for these events.

Figure 7: Average abnormal returns for highly and less tangible companies.



Notes: This figure shows the average abnormal returns for highly and less tangible stocks. The orange line represents less tangible companies during upgrades (positive \overline{AR}) and downgrades (negative \overline{AR}), and the blue line represents more tangible companies during upgrades (positive) and downgrades (negative). The figure shows that the returns for less tangible stocks are higher during upgrades and lower during downgrades compared to more tangible stocks.

5.4 Comparing the Results and Additional Remarks

The first observation is that there are more consensus price target upgrades than consensus price target downgrades. For this, multiple explanations are possible, amongst them:

- The time span we observe (March 2011 - April 2018) does not include any major financial crises and stock prices went up on average. Even if all that analyst did was following trends, they would end up with more positive than negative targets.
- Analysts that work for large banks or asset managers might have an incentive to convince investors to buy stocks to increase fees incurred.

A trend that can be observed across all characteristics is that negative consensus price target updates lead to abnormal price movements of a higher

magnitude than the positive counterparts. In the data we observe, the volatility and tangibility also had an impact on the degree of the price movements. Tangibility had the strongest influence when it comes to downgrades: R&D-focused companies react the strongest to analysts' downgrades.

One result that is not intuitive on first sight is that stocks respond already one day before the event - albeit to a lower extent. Amongst others, two possible reasons could add explanatory power:

- Some investors are aware of the consensus price target update before others, e.g. because of insider information.
- Potentially, publicly known price relevant news could have been released one day before the consensus price target update. Some informed investors take action right away, but others need to wait until analysts and the financial media cover it sufficiently. This however would contradict the efficient market hypothesis, according to which the price should be adjusted almost immediately.

6 Conclusion and Further Research

Our paper provides meaningful insight on how investors react to price target updates. The three most important results are:

1. When a new price target is released, on average stock prices move as well. When the consensus price target goes up, stocks go up and vice versa.
2. Downgrades lead to a stronger price reaction than upgrades.
3. Both characteristics, volatility and tangibility, influence how strongly a stock responds to consensus analyst price target updates. Stocks with low volatility and high tangibility respond to a lower degree than their counterparts. Highly intangible stocks respond the strongest to a new negative consensus target.

For the first result, one explanation is that investors consider the opinion of analysts and invest accordingly. For the second result, we could refer to the research of loss aversion. Kahneman, Tversky, and Thaler (1991) describe loss aversion as *"The disutility of giving up an object is greater than the utility associated with acquiring it."*, meaning that for investors, it is worse to lose \$100 than to gain \$100. For the third result, various explanations are possible:

One possible explanation is that volatile stocks fluctuate more in general. In responding more strongly to the analysts, they simply follow a pattern that they follow in general. Uncertain returns in the future for intangible companies could lead investors to put more emphasis on analysts' opinions, since it is harder to evaluate these companies.

As mentioned before, one result that can be observed across all stocks and analyzed characteristics is that negative price target updates have a stronger effect on stocks than positive ones. For example, across all stocks, if there is a negative consensus analyst price target change, the stocks react on average with returns of -2.12% on the day of the event, and with a \overline{CAR} of -5.51% over the 11-day period. Positive changes only lead to a reaction of 1.78% and a \overline{CAR} of 2.18%. To put these results into context it is important to remember that only consensus price target changes of more than 3% enter the event list. If all events were considered, the price movements would likely be less pronounced. And since the consensus price target changes by more than 3%, investors seem to discount the opinion of the analysts on average if the upgrade is positive - the stock price reaction is lower than the change in the consensus price target. However, if the new consensus price target is negative, it leads to a \overline{CAR} smaller than 3%.

What can also be observed across all tests is that the stock prices already react the day before the event occurs - although to a smaller extent. There are multiple explanations for this, for example insider trading. Another explanation could be that the price movement on day $t = -1$ is caused by a macroeconomic or company event. The day after this, at $t = 0$, equity analysts update their price targets. Some investors may react right away, but others might wait until the experts update their opinions on the stock and only trade then, after the new price target is out. Other than this, there are also some minor adjustments on the day after the price target update ($t = +1$). On all the other days, there is little movement in the stock prices.

Summing up the results, we can observe excess returns following consensus price target changes. One conclusion for this could be that the semi-strong form of the efficient market hypothesis is violated: since all information are already incorporated in the price, we would not expect statistically significant abnormal returns. However, the fact that we observe them cannot disprove the EMH, as there could always be a more precise model that explains the abnormal returns. Since we can never be sure that we have found the perfect

model, we cannot prove that markets are inefficient this way. What remains are additional clues that render absolute market efficiency less likely.

The results of this thesis do not cover the topic completely, there are many areas where further research could yield valuable insights. For example, another index could be used to compare the results of this study to another market. Furthermore, other pricing models than the market model could be utilized, for example one of Fama-French's factor models or the constant mean return model. Next, additional test statistics could be employed to evaluate the significance of the results. An especially valuable insight could be to analyze the stock returns on a more detailed timeline, ideally with stock price data every minute - this could then be used in combination with corporate data. This way, when a company releases new quarterly results, the effects of those news could be clearly separated from the effect of the subsequent analyst' reaction.

References

- Ang, A., Goetzmann, W. N., & Schaefer, S. M. (2011). Review of the Efficient Market Theory and Evidence.
- Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, *61*(4), 1645-1680.
- Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of financial economics*, *43*(3), 341-372.
- Bodie, Z., Kane, A., & Marcus, A. J. (2014). *Investments, 10e Global Edition*. McGraw-Hill Education.
- Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics*, *11*(2), 255-274.
- Brealey, R. A., Myers, S. C., Allen, F., & Mohanty, P. (2012). *Principles of corporate finance*. Tata McGraw-Hill Education.
- Chan, K., & Hameed, A. (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics*, *80*(1), 115-147.
- Choi, W. W., Kwon, S. S., & Lobo, G. J. (2000). Market valuation of intangible assets. *Journal of Business Research*, *49*(1), 35-45.
- Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?. *Journal of Accounting and Economics*, *27*(3), 285-303.
- Daniel, K., & Titman, S. (1999). Market efficiency in an irrational world. *Financial Analysts Journal*, *55*(6), 28-40.
- Dasilas, A., & Leventis, S. (2011). Stock market reaction to dividend announcements: Evidence from the Greek stock market. *International Review of Economics & Finance*, *20*(2), 302-311.
- Degutis, A., & Novickyte, L. (2014). The efficient market hypothesis: a critical review of literature and methodology. *Ekonomika*, *93*(2), 7.
- Duru, A., & Reeb, D. M. (2002). International diversification and analysts' forecast accuracy and bias. *The Accounting Review*, *77*(2), 415-433.
- Ederington, L. H., & Lee, J. H. (1995). The short-run dynamics of the price adjustment to new information. *Journal of Financial and Quantitative Analysis*, *30*(1), 117-134.
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417.
- Fama, E. F. (1991). Efficient capital markets: II. *The journal of finance*, *46*(5), 1575-1617.

- Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American economic review*, 70(3), 393-408.
- Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic perspectives*, 5(1), 193-206.
- Kothari, S. P., & Warner, J. (2007). Econometrics of event studies. *Handbook of empirical corporate finance*, 1, 3-36.
- Li, W., & Lie, E. (2006). Dividend changes and catering incentives. *Journal of financial economics*, 80(2), 293-308.
- Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance*, 56(1), 369-385.
- MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, 35(1), 13-39.
- Naseer, M., & Bin Tariq, Y. (2015). The efficient market hypothesis: A critical review of the literature. *IUP Journal of Financial Risk Management*, 12(4), 48.
- Patell, J. M., & Wolfson, M. A. (1984). The intraday speed of adjustment of stock prices to earnings and dividend announcements. *Journal of Financial Economics*, 13(2), 223-252.
- Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review*, 79(4), 1119-1151.
- Sewell, M. (2011). History of the efficient market hypothesis. *RN*, 11(04), 04.
- Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance*, 1, 939-974.
- Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, 40(3), 777-790.