Non-GAAP earnings metrics and its effect on sell-side analysts' earnings forecasts

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Abstract: This thesis looks at the relation between non-GAAP earnings metrics and several analyst attributes. These analyst attributes are analyst following, analysts' earnings forecast accuracy and dispersion. Furthermore, I make a distinction between the informative and misleading motive for disclosing non-GAAP earnings metrics. I find that analyst following is higher for firms that disclose non-GAAP earnings metrics, but accuracy of the analysts' earnings forecasts is lower. When zooming in on the incentive, I find that analyst following is lower for firms that disclose informative non-GAAP earnings metrics. Based on these findings, it seems that analysts are not able to fully incorporate the motive of firms for disclosing non-GAAP earnings metrics.

Keywords: Non-GAAP earnings metrics; Sell-side analysts; Analyst following; Analysts' earnings forecast accuracy; Analysts' earnings forecast dispersion

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1. Introduction

The focus of this thesis is on the effects of non-generally accepted accounting principles (non-GAAP) earnings metrics on financial analysts' earnings forecasts. For this, I focus on firms in the United States of America (US). Therefore, the GAAP that is discussed is US GAAP. Non-GAAP earnings metrics, now being used more than ever before (Coleman & Usvyatsky, 2015), are a useful tool for managers to provide a better insight in their company to the outside investors and other users of financial statements. In 2015, over 80% of the companies in the S&P 500 disclosed some form of non-GAAP earnings (Coleman & Usvyatsky, 2015). Since these metrics are used more often, it is important to know the effect on financial analysts, since they are important information intermediaries in capital markets and provide information and stock recommendations of several firms (Lys & Sohn, 1990; Francis & Soffer, 1997; Elgers et al., 2001; Frankel et al., 2006). I therefore state my research question as:

> *Does the disclosure of non-GAAP earnings metrics by firms influence financial analysts' earnings forecasts?*

This question is quite general. To find out whether analysts are influenced, I zoom in on three characteristics, namely analyst following, the accuracy of the forecasts of earnings that analysts make, and dispersion among the forecasts of these analysts. Prior research shows two motives for disclosing non-GAAP earning metrics, these motives being informative and misleading (Lougee & Marquardt, 2004; Bowen et al., 2005; Doyle et al., 2013; Isidro & Marques, 2015; Choi & Young, 2015). Therefore, I also make a distinction between these motives for disclosing the non-GAAP earnings metrics.

Getting an answer to this question is important. Since some firms use non-GAAP earnings metrics to mislead investors, it is unclear what the effects will be on financial analysts. Firms that have an incentive to mislead investors, would benefit if they mislead analysts, since investors rely on information provided by these analysts. Frederickson & Miller (2004), Elliott (2006) and Allee et al. (2007) show that non-GAAP earnings metrics influence less-sophisticated investors, but not more-sophisticated investors like analysts. However, Andersson & Hellman (2007) do find that analysts are influenced by the use of non-GAAP earnings metrics. In this thesis, I go further than these studies by looking at the motive for disclosing non-GAAP earnings metrics. This way, I try to find whether analysts are influenced by the use of non-GAAP earnings metrics of firms.

For this thesis, I focus on firms in the US, since US GAAP is considered a high quality standard (Guan et al., 2006). In the early 2000's, there have been several regulations issued by the Securities and Exchange Commission (SEC) on both non-GAAP earnings metrics and financial analysts. The SEC issued Regulation G in 2003, since it was concerned that non-GAAP earnings were used to mislead investors and therefore lowering the quality of the financial reporting (Levitt, 1998). This regulation was a set of rules on the use of non-GAAP earnings metrics. It required firms to make a reconciliation of the disclosed non-GAAP financial measure to the most directly comparable GAAP financial measure. Regulation G was first enforced against SafeNet, where non-GAAP earnings were misused to meet earnings targets (Securities and Exchange Commission, 2009).

Another important regulation that was issued by the SEC is Regulation Fair Disclosure (Reg FD). Before this regulation, firms could privately disclose information to analysts. Since the SEC wants that all material information concerns all investors, it should be disclosed publicly and not only to analysts (Securities and Exchange Commission, 2000). The regulation resulted in less analysts following a firm and a higher dispersion among analysts' earnings forecasts (Irani & Karamanou, 2003).

Since these regulations had an effect on the variables I use, I look at a period that is several years after these regulations. The period I look at are the years 2010 till 2016. With data from this period, I look what the effects of non-GAAP earnings metrics are on analyst following, analysts' earnings forecast accuracy and dispersion. I control for several variables that are related to these dependent variables, based on prior research.

I use OLS regressions to test my hypotheses and find that the disclosure of non-GAAP earnings metrics by firms leads to higher analyst following, which is conform expectations. I also find that non-GAAP earnings metrics results in lower analysts' earnings forecast accuracy. This is not what I expected, but shows that non-GAAP earnings metrics influence analysts. No significant relation between non-GAAP earnings metrics and analysts' earnings forecast dispersion is found. I then look whether making a difference between informative and misleading non-GAAP earnings metrics can give me more insight in the aforementioned effects on analysts attributes. I find that analyst following is lower for informative non-GAAP earnings metrics. I do not find a significant relation between the incentive of non-GAAP earnings metrics and analysts' earnings forecast accuracy. Also no significant relation between the incentive of non-GAAP earnings metrics and dispersion among analysts' earnings forecasts is found. These findings are not as expected, but can be seen as a signal that analysts find it hard to see through the real incentive for firms to disclose non-GAAP earnings metrics.

This thesis contributes to the existing literature in that it is, as far as I know, the first study that looks at the effects of non-GAAP earnings metrics on analyst attributes, while making a distinction between the two motives for disclosing non-GAAP earnings metrics. My findings show that analysts have difficulty in identifying the underlying motive for disclosing non-GAAP earnings metrics. This is important information for standard setters and firms, but also for investors using the analyst forecasts.

This thesis is divided in several chapters. Chapter 2 presents the theoretical background of analysts and non-GAAP earnings, and several key concepts are explained. Chapter 3 provides a summary of important prior research. Chapter 3 leads up to the hypotheses, which are developed in chapter 4. Chapter 5 shows the research design that is used and how the data is collected. The results are presented in chapter 6. Chapter 7 draws the conclusions, acknowledges limitations and provides possibilities for further research.

2. Background

This section focuses on several theories and concepts to better understand the underlying subject. The concepts and theories in this thesis can be divided into two categories. The first being the non-GAAP performance metrics, and the second being financial analysts' behavior.

2.1 Non-GAAP earnings metrics

When the stock market crashed in 1929, the U.S. government looked for ways to regulate the accounting practices that firms used. After the approval of two major Securities Acts in 1934, which were issued to restore the confidence in the stock market, the Securities and Exchange Commission (SEC) was created. The SEC was given the authority to set standards on accounting practices. The term Generally Accepted Accounting Principles (GAAP) was first introduced in 1936 in 'Examinations of Financial Statements', which was published by the American Institute of Accountants (AIA) (Zeff, 2005).

In 1939, the AIA created the Committee on Accounting Procedure (CAP), which had the task of establishing accounting standards. The CAP was replaced by the Accounting Principles Board (APB) in 1959, which on its turn was replaced by the Financial Accounting Standards Board (FASB) in 1973. The decisions made by APB and the FASB form the GAAP as we know it today. They form a standard framework of guidelines on how the financial statements should be prepared.

Besides these mandatory financial information that companies have to disclose, many companies also disclose extra or modified information to better reflect the underlying performance of the company. These alternate measures are called non-GAAP or 'pro forma' performance measures. Disclosing non-GAAP earnings next to the GAAP earnings has become very popular among companies. Coleman & Usvyatsky (2015) saw that 449 (88%) companies of the S&P 500 also disclose non-GAAP earnings next to GAAP earnings in 2015. Isidro & Marques (2015) found similar results in Europe, where 79.5% of large European firms report non-GAAP earnings.

Coleman & Usvyatsky (2015) saw that of the 449 companies of the S&P 500 that disclosed non-GAAP earnings, 426 used more than one non-GAAP adjustment. Some of these companies used up to 33 different adjustments. The most common difference between GAAP and non-GAAP financial measures are the exclusion of unique and unusual items. These items are not a good representation of underlying trends and are often excluded from the non-GAAP numbers. The differences do not stop there. Other common non-GAAP measures can be found in earnings before interest, tax, depreciation and amortization (EBITDA), adjusted EBITDA, adjusted earnings per share (EPS), but also in net debt (PWC, 2014).

An often used measure of financial performance is economic value added (EVA). EVA is the surplus of profits that are generated above the invested amount. So a higher EVA is a sign of a better company. Non-GAAP earnings measures often calculate a different profit due to exclusions or other alterations. There has been debate on what adjustments can really add value to earnings information. A good example of this is the stock-based compensation expense. Stock-based compensation expense is an operating expense and is the value of the stock that is given to employees as a compensation. Some companies exclude this cost when they calculate their non-GAAP earnings. These companies see this expense as a "non-cash" expense, but since many companies buy back the stock to prevent stock dilution, it becomes a cash expense. According to Barth et al. (2012), the main reason for managers to exclude this cost from non-GAAP earnings is to increase earnings, smooth earnings, and meet earnings benchmarks. They also found that analysts exclude the expense from their forecasts when it makes their forecast a better prediction of the future. But as Warren Buffett states in his annual letter to the shareholders of his company, "The very name says it all: 'compensation'. If compensation isn't an expense, what is it? And, if real and recurring expenses don't belong in the calculation of earnings, where in the world do they belong?" (Buffett, 2015).

With all these different ways of disclosing non-GAAP earnings, the question that arises is whether these disclosures are even relevant to investors. Brown & Sivakumar (2003) compared the value relevance of two operating income measures, non-GAAP earnings reported by managers and operating earnings derived from the GAAP earnings. Value relevance can be defined as how well disclosed information on the financial statements can capture and summarize the firm's value. Brown & Sivakumar (2003) find that the operating earnings reported by managers and analysts had more value relevance than the operating earnings that could be obtained from GAAP earnings by sophisticated users.

Following the increase in the use of non-GAAP and the fear that investors may be misled, the SEC has issued some regulations to minimize misuse. The biggest and most important regulation is Regulation G, which came in effect on March 28, 2003. At the end of 2002, the SEC proposed Regulation G to prevent investors and others being misled by non-GAAP performance measures. Regulation G requires public companies to include in any non-GAAP financial measure that is disclosed, the GAAP financial measure that is most directly comparable (Securities and Exchange Commission, 2003). Regulation G was successful in pushing back the opportunistic use of non-GAAP disclosures. The amount of disclosures, the magnitude, and the probability of firms disclosing earnings that meet or beat earnings forecasts, all saw a decline (Heflin & Hsu, 2008).

It is also important to note that a company is completely free in choosing their non-GAAP measures and how to calculate such metrics. Reporting a measure in one year, does not necessarily mean that the company will report the same measure in the following year. Because a company can calculate their own metrics, non-GAAP earnings might not be comparable to that of other companies. It might also not be comparable to a company's prior statement due to the fact that the same metrics do not have to be applied every year.

2.2 Financial analysts

When we are talking about financial analysts, there are two main types of analysts. The first are the "sell-side" analysts, which are analysts that provide information and reports in which they give their opinion about a company. A sell-side analyst can follow multiple companies which are often in the same industry. A sell-side analyst does research into a company and gathers data. Based on this data, he makes forecasts of financial information, set a stock price target and will give a recommendation about what to do with the stock of the company. The second type of analysts are the "buy-side" analysts. These are analysts that work for investment firms. Their focus is on the characteristics and risks of securities. Based on these characteristics and risks, they identify the suitability of a stock for an investment portfolio. Since this research is on analysts' forecasts, I will focus on sell-side analysts in this thesis.

Sell-side analysts work for brokerage houses for which they do research and provide stock recommendations. In order to keep his job, an analyst has to be accurate. A high accuracy leads to promotions and "All-Star"[1] rankings and awards, while low accuracy can lead to job loss. A sell-side analyst has many sources to gather their information. One important source is the

[1] An analyst becomes an All-Star when he is part of the annual ranking 'Best on the Street' by the Wall Street Journal in the United States.

management of a company. The management can provide the analyst with a better understanding of the business.

However, managers are better off when long-term forecasts are optimistic and short-term forecasts are pessimistic. An important theory concerning these metrics is the so-called expectation game. In the expectation game, companies are judged by their ability to meet or exceed expectations. Expectations are mostly set by analysts, who issue earnings forecasts of the companies during the year. But expectations can be managed. This is also done with analysts' forecasts. In the forecasts of analysts, a so-called walkdown can be observed (Matsumoto, 2002; Bartov et al., 2002; Richardson et al, 2004; Bradshaw et al., 2016). In the long run, analyst provide optimistic earnings forecasts and 'walkdown' to pessimistic earnings forecasts in the short run. Analysts tend to perform this walkdown to favor management to obtain better access to management information (Ke & Yu, 2006). The walkdown favors management of companies for that it provides a positive image in the long run and a more beatable target in the short run. The beating of analyst forecasts is favorable for a company's share price. Several studies found that companies that meet or beat analyst forecast, see a positive increase in share price (Kasznik & McNichols, 2002; Bartov et al., 2002).

An analyst walks down because a better relationship with management results in better information from the company (Ke & Yu, 2006). To prevent this, the SEC passed Reg FD in October 2000 in order to reduce the selective disclosure by firms and make information more publicly available. It is no longer allowed for firms to disclose material information only to analysts. Material information that is disclosed to analysts, also has to be made publicly available. The situation before Reg FD was very beneficial to analysts. In exchange for favorable forecasts, analysts could get their hands on information that was not publicly available. Because this information was not publicly available, analysts could make more accurate forecasts and in turn gain more brokerage business (Ke & Yu, 2006). Irani & Karamanou (2003) find evidence that analyst following decreased after the implementation of Reg FD. They conclude that this was consistent with the argument that Reg FD decreases the quality and quantity of companies' disclosures. This argument states that companies may become less forthcoming in providing information because they are afraid of litigation problems. Companies might also be afraid to publicly reveal information for competitive reasons (Bailey et al., 2003).

Another important theory is the agency theory. In this theory, there is a relationship between an agent and a principal. Because the principal and the agent might have different goals or desires, or have different attitudes towards risk, problems may arise. We can observe several relationships here. The first one is the relationship between the management of a company and the shareholders of a company. In this relationship, the shareholders are the principal and the management is the agent. The management is put in place by the shareholders to manage the company. A problem arises when managers have different goals than the shareholders. An analyst can help solve this problem by aligning the interest of the management with that of the shareholders. Since managers' compensation often exists of stock options, management has a motivation to care about the company's stock price (Hall & Liebman, 1998). Kasznik & McNichols (2002) find that share price increases when a company meets or beats analyst forecasts. Taking this into account, the forecasts made by analysts are important to reduce the differences in incentives between management and shareholders. When a manager fails to reach these targets, he risks foregoing a bonus or even lose his job.

A second relationship is observed between the analysts and investors. In this relationship, the investors are the principal and the analysts are the agents. Analyst provide information for investors to use. Investors want analysts to provide them with the best information available, so they can make the most informed decisions. At first glance, the incentives appear to be aligned between the two parties. Analysts get paid for the better information they provide and the more accurate their forecasts are. However, as earlier stated, analysts have incentives to issue biased forecasts to please the management of a company. Pleasing the management of a company results in receiving better information of a company (Ke & Yu, 2006).

Also the efficient market hypothesis (EMH) is important to this thesis. This theory was developed by Eugene Fama in 1970 and states that is not possible to outperform the market because stock prices always reflect all relevant information. Because of this, it is not possible to buy undervalued stock, since the market should know the stock is undervalued, causing the price to increase. Market efficiency argues that everyone has access to the same information, and thus that no one has an advantage. According to the EMH, it is only possible to make higher profits in trading stocks by purchasing stock that are accompanied by more risks.

However, markets are not fully efficient. Although regulation FD was put in place to make disclosed information available to everyone, investors can still outperform the market just based on skill and knowledge, or just luck.

When a company misses or beats a forecast, this does not refer to the forecast of a single analyst. The forecast that is referenced at, is the consensus forecast. The consensus forecast is a forecast that is made on the combined estimates of several analysts following a company. Since the consensus is a combination of the most recent estimates, the consensus changes when an analyst that is part of the consensus changes his forecast.

Analyst forecasts have several metrics. Accuracy and dispersion among individual analysts are good examples. Another metric that is researched concerning analysts' earnings forecasts is forecast revisions. An analyst can revise his forecast when he believes it is no longer accurate. For this thesis, I look at the effects of non-GAAP earnings metrics on analyst following, analyst forecast accuracy and dispersion among analysts. I choose to test the effects of non-GAAP earnings metrics on these analyst attributes because prior literature shows that they are influenced by voluntary disclosures (Lang & Lundholm, 1996; Healy et al., 1999; Hope, 2003; Lakhal, 2009; Dhaliwal et al., 2012; Hamrouni et al., 2017). I do not test for an effect of non-GAAP earnings metrics on forecast revisions, since Lang & Lundholm (1996) find no significant relation between forecast revisions and information published by the firm.

Analyst following is basically the number of analyst that follow a company and provide information about them to investors. The amount of analyst that follow a company is dependent on several factors. Examples of these factors are the ownership structure, the size of the company, and whether returns are irregular (Bhushan, 1989).

Analysts' earnings forecast accuracy can be determined by comparing the forecasted earnings with the actual earnings. The closer the analyst was with his forecasts to the actual earnings, the more accurate his forecasts were. The accuracy of a forecast can only be determined after the actual earnings are released.

Dispersion among analysts' earnings forecasts can be seen as the level of uncertainty among analysts (Barron et al., 1998). When a firm has a high analyst following, and all of these analysts provide different forecasts that are far from the consensus forecast, we speak of high analysts' earnings forecast dispersion. When these analysts provide forecasts close to the consensus, there is low dispersion among analysts.

2.3 Summary

This chapter provides an overview of all underlying theories and background information of both non-GAAP earnings and financial analysts. Non-GAAP earnings disclosures have increased in prior years and is at an all-time high (Coleman & Usvyatsky, 2015). Non-GAAP earnings are different from GAAP earnings, because they exclude unique and unusual items to better reflect the underlying performance of a company. There are many different non-GAAP earnings metrics that firms disclose. Common non-GAAP earnings metrics can be found in the EBITDA, adjusted EPS and net debt (PWC, 2014). Companies are free to choose whichever non-GAAP earnings metrics they want, and can switch between them every year. To prevent firms from misusing the disclosing of non-GAAP earnings, the SEC has issued Regulation G. Regulation G requires firms to make a reconciliation of the disclosed non-GAAP financial measure to the most directly comparable GAAP financial measure. Regulation G resulted in a decrease in the amount of firms disclosing non-GAAP earnings, and the firms that still disclosed them were less likely to meet or beat analyst earnings forecasts (Heflin & Hsu, 2008).

Managers of a company are better off with optimistic forecasts in the long run and pessimistic forecasts in the short run. Pessimistic forecasts are easier to beat, which is beneficial for the stock price. In the forecasts of analysts, a walkdown is observed (Matsumoto, 2002; Bartov et al., 2002; Richardson et al., 2004; Bradshaw et al., 2016). Analysts have incentives to provide accurate forecasts, because of promotions and awards. However, they also have an incentive to please management for more and better information about the company (Ke & Yu, 2006). In an attempt to make this information more publicly available and reduce this walkdown effect, the SEC passed Reg FD. Reg FD reduced the private information flow to analysts, which resulted in less analyst following a firm (Irani & Karamanou, 2003).

3. Literature review

Two streams of prior literature are relevant to this thesis. The first being research done on non-GAAP earnings metrics and the second being research done on analysts. Because lately, non-GAAP earnings metrics are a much more observed phenomenon, there is a lot of recent research to find on this subject. Also financial analysts are a subject that is often researched. Although there is research done on the effects of voluntary disclosures on analysts, there is less research done on the relation between non-GAAP earnings metrics and analysts. This chapter will focus on the relevant literature of both streams. First, non-GAAP earnings metrics are discussed, followed by analysts. The chapter ends with a discussion of literature on the relation between the non-GAAP earnings metrics and analysts. A summary table with an overview of all papers is included in appendix 2.

3.1 Non-GAAP earnings metrics

Non-GAAP earnings metrics are nothing new. As earlier mentioned, the SEC issued several warnings and regulations to keep the use of non-GAAP earnings metrics in check already back in the early 2000's. One of the first questions that arises when talking about non-GAAP earnings metrics is why companies use them. According to prior literature on non-GAAP earnings metrics, there are two main reasons. The first reason is to give more and better information to investors and other users of the financial statements. The second reason is to mislead investors and putting the company in a better light. Arguments for non-GAAP earnings metrics being informative are the value relevance compared to normal GAAP earnings. As earlier mentioned, the value relevance of information is how good it captures and summarizes the firm's value. Non-GAAP earnings provide better information since transitory items are excluded. The exclusion of these transitory items gives a better view of a company's core performance and so, a better prediction of future performance. The other side of the coin is the misleading incentive of managers to report non-GAAP earnings metrics. When managers fail to meet analyst forecasts, they tend to opportunistically define non-GAAP earnings metrics in order to meet these analyst forecasts (Choi & Young, 2015).

Strategically disclosing earnings is done in many ways. For instance, Schrand & Walther (2000) look what benchmark managers use to compare their current earnings with. They argue that managers choose a strategic benchmark to curry their earnings announcement with a favorable light. They mainly focus on firms with disclosures of earnings from a prior period that had a nonrecurring gain or loss on sale of property, plant, and equipment (PPE), and use a sample of 130 observations over the years from 1988 through 1994. They find that managers strategically lower the earnings from the prior period by reporting the different components of these earnings separately in the case of a gain on sale of PPE. This way managers can present a more favorable change than when comparing the total earnings with that of a prior period. The opposite was also observed, when earnings from prior period are low due to a nonrecurring loss on a sale of PPE, earnings are not reported separately. This way, a high increase in earnings compared to the prior period is reported.

The findings of Schrand & Walther (2000) are a good example of how non-GAAP earnings metrics can be used strategically to put the firm in a more favorable light. Using a sample of 98.467 firm-quarter observations, Bradshaw & Sloan (2002) do not only see an increase in the use of non-GAAP earnings metrics in the period from 1986 till 1997, but also see an increase in the difference between the GAAP and non-GAAP earnings. More and more firms exclude expenses from reported earnings and class them as non-recurring. Bradshaw and Sloan (2002) mention that the use of non-GAAP earnings is driven by the reporting strategies of management. They give two possible incentives for management and analysts for the use of non-GAAP earnings metrics, namely the strategic incentive and the informative incentive. However, Bradshaw and Sloan (2002) were unable to find conclusive evidence on these possible explanations for the use of non-GAAP earnings metrics.

Lougee & Marquardt (2004) do find conclusive evidence on the use of non-GAAP earnings metrics. They perform research on the characteristics of firms that report non-GAAP earnings, whether investors respond different on these different characteristics, and whether their response to non-GAAP earnings is consistent with the market efficiency. They look at 249 press releases in the period between 1997 and 1999, to determine whether firms report non-GAAP earnings. By matching each firm that reports non-GAAP earnings with a firm that does not within the same industry, they find that firms that report non-GAAP earnings have smaller earnings response coefficients (ERCs), smaller adjusted R^2s (RSQs), greater sales growth, and more earnings variability. This means that firms that report GAAP earnings that are less informative, are more likely to report non-GAAP earnings. Another factor that increases the likelihood of disclosing non-GAAP earnings is a negative earnings surprise.

Lougee & Marquardt (2004) also find that when GAAP earnings are less informative or GAAP earnings show a positive earnings surprise, non-GAAP earnings are more relevant and provide more information. This is not observed when GAAP earnings are informative by themselves or have a negative earnings surprise, meaning that non-GAAP earnings are used to mislead investors. They argue, that dependent on the context, non-GAAP earnings can be either misleading or informative.

Bowen et al. (2005) also look at the use of non-GAAP earnings, mainly in quarterly earnings press releases. They focus on the emphasis placed on non-GAAP and GAAP earnings by managers, and looked if emphasizing non-GAAP earnings influences the market. They make a distinction between the relative emphasis and the level of emphasis placed on GAAP and non-GAAP earnings metrics. The relative emphasis is the emphasis placed on either GAAP or non-GAAP relative to the other. The level of emphasis is measured by where the GAAP and non-GAAP are first mentioned in the press release. Their findings are in line with that of Lougee & Marquardt (2004). By using a sample of 1.188 press releases between the second quarter of 2001 and the third quarter of 2003, they find that firms with prior losses tend to place higher relative emphasis on non-GAAP earnings. However, the level of emphasis appears not to be higher. Bowen et al. (2005) also find that firms place greater emphasis on the earnings metric that shows the better performance. Non-GAAP earnings have a higher level of emphasis and more relative emphasis when these non-GAAP earnings show a profit, where GAAP earnings present a loss. Emphasis on non-GAAP earnings was also more likely when firms have a greater media coverage. In 2002, the emphasis moved more to GAAP earnings. This finding was linked to the cautions uttered by the SEC on the use of non-GAAP earnings. The market reaction of a non-GAAP earnings surprise was stronger when more emphasis was placed on the surprise. A similar, but somewhat weaker, effect was measured for GAAP earnings. Overall, Bowen et al. (2005) conclude that the use of emphasis in press releases is not random and is used by managers to influence investors.

As earlier mentioned, the SEC tried to decrease the misleading use of non-GAAP earnings metrics by issuing regulations. Marques (2006) looks at the effects of these SEC interventions in the early 2000's. These interventions were a cautionary warning in December of 2001 and the issue of Regulation G in January 2003. Marques (2006) uses the quarterly press releases of all firms in the S&P 500 in quarters before the cautionary warning, between the cautionary warning and regulation G, and after Regulation G. This brings her sample to 4.234 press releases from 2001 through 2003. She finds that the disclosure of non-GAAP earnings saw a decrease after regulation G. When only looking at non-GAAP financial measures other than earnings, the decline already started after the cautionary warning in December of 2001. Value relevance of the non-GAAP earnings was higher after Regulation G. Investors were more positive of the non-GAAP earnings after regulations. Marques (2006) also looks at the market reaction to different exclusions in each of the three periods. She compares the exclusions made by analysts and the adjustments made by the firms, and finds that the analysts' exclusions, as in the Institutional Brokers' Estimate System (I/B/E/S) database, is seen as a good method for exclusions. The reaction of the market to the incremental adjustments done by the firms is very low. The overall conclusion of Marques (2006) is that after the implementation of Regulation G, a decrease in the use of non-GAAP is observed, but that the market reacts more positively to the non-GAAP earnings measures after the implementation. This conclusion is consistent with that of Heflin & Hsu (2008), who also find that the differences between GAAP and non-GAAP earnings decreased and that firms have a smaller chance of meeting or beating forecasts.

Kolev et al. (2008) look at the effects of the SEC interventions as well. Their focus is on the quality of the exclusions made in the non-GAAP reporting. They measure the quality of exclusions by looking how transitory an exclusion is. The more transitory the exclusion, the higher its quality. By looking at the future earnings realization in the four following quarters, they can determine how transitory an exclusion is. To find what the effect of the SEC interventions is on the quality of the non-GAAP earnings, they use three different analyses. First, they look whether the average quality of the exclusions increased after implementation of the interventions. Second, they make a subsample of firms that stopped reporting non-GAAP earnings after the interventions, but reported non-GAAP earnings before the interventions. On this subsample, they test whether there was a difference in the quality increase compared to the other firms. Third, they divide the exclusions into two groups, being special items and other exclusions, and looked at the difference in quality of each group before and after the interventions. By using a sample of 104.954 firm-quarters between 1998 and 2004, they find a significant increase in quality from before and after the SEC interventions. For their second test, they use a subsample of 28 firms. With this subsample, they find that the quality of non-GAAP exclusions for firms that stopped reporting non-GAAP earnings is significantly lower in the period before the interventions than firms that kept reporting non-GAAP earnings. Their last analysis saw a decrease in the special items, but a significant quality increase for other exclusions. The conclusion they draw is that the interventions of the SEC are effective in that it improves the quality of the non-GAAP exclusions. However, the decrease in the quality of special items could mean a shift from recurring costs into special items.

Doyle et al. (2013) research if the defining of non-GAAP earnings is another tool used by management to meet or exceed analyst forecasts. They identify three tools that are already being used by management, being accrual manipulation, expectations management and real activities manipulation. To test if defining non-GAAP earnings is another tool, they look at three aspects. They look whether non-GAAP exclusions are used to meet or beat analyst forecasts, whether these non-GAAP exclusions are a substitute for the other three tools mentioned, and what the effect is of the use of non-GAAP earnings on the market. Because non-GAAP earnings can be derived from GAAP earnings by excluding several items, Doyle et al. (2013) separate these exclusions into expected and unexpected exclusions to test their hypotheses. Their sample consists of 237.617 firm-quarter observations from 1998 through 2009, with which they find that firms that use non-GAAP earnings have a higher likelihood to meet or beat the analyst forecasts, when these non-GAAP earnings are higher than the GAAP earnings. This likelihood is even higher for firms that exclude unexpected items. Other findings are that the use of non-GAAP is a substitute for other tools to beat benchmarks, and that firms which use non-GAAP earnings have lower ERC's. These findings can be interpreted as that managers use non-GAAP earnings opportunistically. The market is only partially efficient at identifying the firms that use non-GAAP earnings opportunistically.

Isidro & Marques (2015) recognize the strategic use of non-GAAP earnings metrics and want to know what the effects of different factors like institutional and economic conditions are on the use of this form of non-GAAP earnings metrics. They choose European firms, since there have not been interventions like the interventions of the SEC in the early 2000's. This means that European firms have more freedom in reporting non-GAAP earnings. By using a sample of 500 largest European firms in the period between 2003 and 2007, with a total of 1.301 firm-year observations of 316 firms, they find evidence that suggests that firms use non-GAAP earnings metrics strategically. 72% of the times non-GAAP earnings metrics are used, they exceed GAAP earnings and in 93% of these cases, more emphasis is placed on the non-GAAP metrics. Another finding is that firms tend to meet or beat benchmarks with non-GAAP earnings, where they do not with their GAAP earnings. This is even more the case for countries with a proper legal structure, open communication rules and strong investor protection. Isidro & Marques (2015) see this as an indication of higher pressure to perform well and meet or beat their targets, and without opportunities to manipulate GAAP earnings, firms tend to do this by using non-GAAP earnings metrics.

Since prior literature shows that non-GAAP earnings can be either misleading or informative, it is important to know how to identify these incentives. Choi & Young (2015) try to separate the informative and misleading incentives by looking at the association between non-GAAP earnings disclosures and transitory items in GAAP earnings. They argue that if GAAP earnings have more transitory items, they are less informative. Thus, management has more incentives to remove the transitory items in the non-GAAP earnings. To separate the incentives, Choi & Young (2015) test two hypothesis. They first test if the relation between non-GAAP EPS and transitory items varies with the sign of the GAAP earnings surprise. An earnings surprise is when a firm's actual earnings differ from the by analysts' expected earnings. Second, they test if the magnitude of the GAAP earnings surprise has an influence. Their sample consists of large UK firms between 1993 and 2001, resulting in a total of 3.914 firm-year observations. With this sample, they find evidence that there is a significant asymmetric relation between disclosure propensity and transitory items in GAAP earnings. When GAAP earnings are higher than expectations, the relation between non-GAAP disclosure and transitory items is positive. When GAAP earnings are lower than expectations, this relation is less positive. The results indicate that in case of GAAP exceeding expectations, non-GAAP reporting tends to be informative and when GAAP falls short of expectations, non-GAAP reporting tends to be misleading.

3.2 Financial analysts

Financial analysts provide information and stock recommendations of several companies. Prior research shows us that they are important information intermediaries in capital markets. Francis & Soffer (1997) investigate what the effect is of two analyst forecasts characteristics on stock prices. These characteristics are stock recommendations and earnings forecast revisions. By looking at market reactions to 576 analyst reports, they find a positive association between stock prices and recommendations and revisions in forecasts made by analysts. This finding is consistent with that of other research (Lys & Sohn, 1990; Elgers et al., 2001; Frankel et al., 2006). Based on the conclusions of these studies, the work of analysts is relevant and used by investors to make decisions on the stock market.

As earlier mentioned, I look at three analyst attributes, being analyst following, analysts' earnings forecast accuracy and dispersion among analysts. Prior research shows that several factors have an effect on these attributes. The three attributes are treated separately.

3.2.1 Analyst following

Analyst following differs per firm and is basically the amount of analysts that follow the firm. Analyst following is often used as a proxy for competition between analysts (Lys & Soo, 1995). Because analyst following is influenced by a firm's disclosure practices (Lang & Lundholm, 1996; Healy et al., 1999; Chen et al., 2011; Hamrouni et al., 2017), it is important to know what other factors influence analyst following. Bhushan (1989) interprets the amount of analysts following a firm as a result of the supply and demand of analyst services for that company. To see which factors influence this supply and demand, he looks at several company characteristics. These characteristics are ownership structure, size, return variability, number of lines of business, and the correlation between the company's return and the market's return. He uses a sample of 1.409 firms with data from 1985, and finds that the ownership structure, size, return variability and the correlation between the company's return and the market's return are positively related to analyst following. When a company has more lines of business, a significant decrease in analyst following is observed.

Barth et al. (2001) study the effect of intangible assets on analyst following. Since intangible assets are not always fully taken in account in the firm's financial statements. Analyst thus have more opportunities to provide recommendations. Therefore, Barth et al. (2001) expect that analyst following is higher for firms with more intangible assets and tests this with a sample of 10.631 firm-year observations from 1983 through 1994. Their findings are consistent with their expectations. Analyst following is significantly higher for firms with more intangible assets, like research and development and advertisements. Besides this, they also find that analyst following is higher for firms where less effort is needed to follow the firm. There are also other factors that have a positive relation with analyst following. These are firm size, growth, trading volume of the firm's shares, and the use of public debt and equity markets. A negative relation is observed between analyst following and the size of the brokerage houses the analysts.

A way of disclosing the information about these intangible assets is through voluntary disclosures. The relation between analyst following and voluntary disclosures is studied by several researchers. So did Lang & Lundholm (1996) investigate whether analyst following has any relation to the disclosure policies of firms. To measure the informativeness of firms' disclosures, they used ratings of the First American Financial Corporation (FAF) which contains evaluations by analysts on the informativeness of a firm's disclosures by looking at three aspects: annual published information, quarterly and other published information, and investor relations. They collect data from 1985-1989, resulting in a sample of 2.272 firm-year observations. From this data, they draw the conclusion that firms with more informative disclosures, as measured by the FAF ratings, have a higher analyst following. They argue that the increase in analyst following could be due to the increased demand as a result of more disclosures or because of lower costs for analysts. Also studies of Healy et al. (1999), Lakhal (2009) and Hamrouni et al. (2017) find that analyst following increases with more voluntary disclosure policies of the firm.

3.2.2 Analysts' earnings forecast accuracy

One of the first papers about accuracy of analysts' earnings forecasts is that of O'Brien (1988). She compares several ways of determining a consensus of analyst forecasts. Among these are the mean of the available forecasts, the median of the available forecasts, and the most recent forecast. For this, she uses a sample of 508 firms and a total of 3.556 firm-year observations from 1975 through 1981. In her research, she finds that the most recent forecast is more accurate than both the mean and the median of the available forecasts. This means that the forecast with the shortest forecast age, is generally the most accurate forecast. The forecast age of a forecast is the period between the time the forecast is issued and the time of the earnings announcement.

After the study of O'Brien (1988), more research is done on analyst forecast accuracy. So did Lys & Soo (1995) investigate whether competition between financial analysts is beneficial for the accuracy of forecasts. To measure competition, they use the amount of analyst following a firm as a proxy. By using a sample of 378 observations, they find that more competition, thus a higher analyst following, leads to a higher forecast accuracy.

Clement (1999) studies what causes differences in analysts' earnings forecast accuracy by looking at different analysts' characteristics. The first characteristic he looks at is the experience of the analyst, for which he uses two different kinds of experience, being overall experience and firm-specific experience. The second characteristic is portfolio complexity, which is measured by using two different proxies, being the number of firms and the number of industries followed. He assumes that it is more difficult to follow more firms and industries, making the portfolio more complex. The third characteristic is the amount of resources. The assumption he uses is that analysts that work for large brokers have more available resources.

Thus, the amount of resources is measured by the size of the broker the analyst works for. Clement (1999) uses a dataset with a considerable size, namely over one million forecasts for over 9.500 companies by almost 6.500 analysts in the period from 1983 till 1994. With this dataset, he finds that earnings forecast accuracy increases with the amount of experience. Also the amount of resources increases accuracy. Portfolio complexity on the other hand, decreases accuracy. These findings are consistent with his expectations.

Jacob et al. (1999) also studies several analysts' characteristics which may have an effect on analysts' earnings forecast accuracy. The characteristics that Jacob et al. (1999) look at are analyst aptitude, learning-by-doing, and brokerage house characteristics. For this, they use a sample of 750.633 forecasts of 3.515 analysts for 4.357 firms in the period from 1981 through 1992. Consistent with Clement (1999), they find that brokerage size and industry specialization have a positive effect on analyst' forecast accuracy. However, Jacob et al. (1999) find that experience does not have an effect on earnings forecast accuracy. Jacob et al. (1999) explains this difference by stating that Clement (1999) does not control for analysts' aptitude and that his results are more consistent with a random effect. Jacob et al. (1999) also find that if an analyst brings out a forecast more frequently, the forecast accuracy is higher.

Following the fact that the Wall Street Journal uses past earnings forecast accuracy as a tool to rate analysts, Brown (2001) compares using past earnings forecast accuracy with that of a model that measures accuracy by different characteristics of analysts, like Clement (1999). The model of Clement (1999) uses five different characteristics. As earlier mentioned, these characteristics are two proxies for experience, overall experience and firm-specific experience, two proxies for complexity, number of firms and number of industries, and one proxy for resources, being the size of the brokerage house. With a sample of 123.670 observations from 1986 through 1998, Brown (2001) finds that the model with analysts' characteristics, as used by Clement (1999), does not outperform the model that is solely based on past accuracy, meaning that it is more cost-efficient to use a model based on solely past accuracy.

Brown & Mohd (2003) look at the predictive value of analyst characteristics. To do this, they compare a model based on analyst characteristics with a model that is based on forecast age alone. The model they use is compiled of six different characteristics, being forecast age, analyst experience, number of industries followed, number of firms followed, brokerage size, and forecast frequency, consistent with the aforementioned papers of O'Brien (1988), Clement (1999) and Jacob et al. (1999). To measure the predictive value, they use a weighted consensus that puts more weight on which forecasts are expected to be more accurate. Their sample consists of 172.837 observations from 1987 through 1999. Results show that both models show similar results, and that the use of the analyst characteristics does not outperform the model only based on forecast age. This result is similar to that of Brown (2001), which also showed that a model based on analyst characteristics is not better in determining accuracy than a model that is only based on forecast age.

The earlier mentioned study by Lang & Lundholm (1996) also looks at the effect of disclosure policies on forecast accuracy. Since more informative disclosures provide analyst with more information about the future performance of the firm, they expect a positive relation. Again, they use FAF ratings to measure the informativeness of a firm's disclosures. With their sample of 2.272 firm-year observations from 1985 till 1989, they find that their results are as expected. Analyst forecast accuracy increases with more informative disclosures.

Also Hope (2003) looks at the relation between disclosures and analyst forecasts. He investigates whether the amount of disclosures in the annual report have an effect on the earnings forecasts of financial analysts. For this, he uses data from 22 countries, which results in a total sample of 1.309 observations of 890 firms in the years 2001 through 2003. By using this sample, he shows that a higher level of disclosure in the annual report results in a higher forecast accuracy, which suggests that these disclosures are informative for financial analysts.

3.2.3 Analysts' earnings forecast dispersion

The earlier mentioned study by Lang & Lundholm (1996) also looks at the effect of disclosure policies on dispersion among analysts. They do not know what to expect, since they identify two factors that may affect dispersion among analyst. If analysts all use the same model to build their forecasts, forecasts differ based on their private information. Therefore, if a firm provides more public information, less weight is placed on the private information, resulting in a lower dispersion among analysts. On the other hand, if all analysts have the same public and private information, but place different weights on these information, dispersion among analyst might increase with more firm disclosures. Lang & Lundholm (1996) find that more informative disclosures lead to more consensus, and thus a lower dispersion, among analysts.

Barron et al. (1998) design a model to observe the effect of two streams of information on predictability of future earnings. These two streams are public information and private information. From this model, they conclude that dispersion among analysts is the result of errors in private information. Errors in public information have no effect on dispersion. This means that when analyst rely more on public information, dispersion among analysts is lower. This is consistent with the findings of Lang & Lundholm (1996), since more public information leads to lower dispersion among analysts and less weight is placed on the private information.

3.2.4 Reg FD

The most ideal situation for an analyst is that he has information of a company that is not available for everyone. This way, he has an advantage over others, since he is able to make better forecasts of a firm. When investors can collect the same information themselves without much effort or costs, the role of analysts becomes really small, if not superfluous. An important source for information is the management of a company. But, as analysts also do not work for free, information comes with a cost. What does the management want in return for sharing private information with analysts? An important observation that is found by several studies in answering this question is that financial analysts issue biased earnings forecasts to please firm management (Richardson et al., 2004; Ke & Yu, 2006).

Ke & Yu (2006) look for the reason why analyst issue these biased earnings forecasts. They do this by looking at the earnings forecast accuracy and the job security of the analysts. They consider four different patterns of biases that analysts use in their earnings forecasts. These four patterns are: being optimistic on the long term and pessimistic on the short-term, optimistic in the long- and the short term, pessimistic in the long term and optimistic in the short term, and being pessimistic in the long- and short term. With their sample of 228.903 firm-analyst-year observations between 1983 through 2000, they find that analysts that issue optimistic earnings forecasts in the long term but issue pessimistic earnings forecasts in the short term, have more accurate earnings forecasts and have a smaller chance of getting fired by their employers. They also find that that these analysts have more experience, work for larger brokerage firms, and are more often an All-Star.

Ke & Yu (2006) researched this effect in the years prior to Reg FD. As earlier mentioned, Reg FD was called into life to reduce the selective disclosures by firms and make information more publicly available. Since my research takes place after Reg FD, it is important to know if Reg FD changed the communications between analysts and management.

Shortly after implementation, Irani & Karamanou (2003) find that analyst following had decreased and dispersion among analysts has increased as a result of the implementation of Reg FD. A few years later, Bagnoli et al. (2008) look at the effect of Reg FD on the competitiveness of All-Star analysts. The All-Americans, a list of top analysts published annually by the magazine Insitutional Investor, saw a significant increase in the turnover after the implementation of Reg FD. This effect was only observed in the first two years after implementation of Reg FD. After these two years, the level returned to the original level.

Although private disclosing of material information between analysts and management is no longer allowed after the implementation of Reg FD, analyst still communicate with management. Brown et al. (2015) survey in total 365 analysts and had 18 follow-up interviews with analysts to find out what inputs analysts use and what incentives they face. Their most important finding is that in analysts' earnings forecasts, the most useful input is the private communication with management. It is even more useful than their own research and recent earnings performance. Another finding is that the credibility of an analyst increases when he issues earnings forecasts and stock recommendations that are well below the consensus. The conclusion that can be drawn is that despite the restrictions of Reg FD, private information obtained from management is still used by analysts. This does not have to be a violation of Reg FD, since managers are allowed to disclose immaterial information to analysts. This immaterial information "helps the analyst complete a 'mosaic' of information that, taken together, is material" (Securities and Exchange Commission, 2000).

As earlier mentioned, Clement (1999) and Jacob et al. (1999) look at several analyst characteristics that are related to analyst forecast accuracy. Keskek et al. (2017) look at the effect of several disclosures and regulations issued by the SEC on different analyst characteristics. The most important regulations they look at are Reg FD, SOX and the Global Settlement Act, all enforced in the early 2000's. Based on prior research, they identify several analyst characteristics which have an effect on analyst forecast accuracy. These characteristics being "experience, effort, brokerage house size, All-Star status, prior forecast accuracy, the number of industries and firms followed, days since the last forecast, forecast horizon and upward and downward forecast boldness". They use a sample of 150.438 observations from 1995 through 2010. By comparing the data before the regulations in the period from 1995 till 2000 and after the regulations from 2004 till 2010, they find several changes in the importance of analyst characteristics. So do experience, effort, brokerage house size, All-Star status, and the number of industries and firms followed all show a significant decrease in importance.

Their results even show that experience and All-Star status have no effect on analyst forecast accuracy after the implementation of the before called regulations. On the other hand, there is only one characteristic that shows a significant increase in importance, which is prior year accuracy. Their results suggest that analyst with more experience and All-Star status were more accurate in their forecasts due to their access to private information.

3.3 Analysts and non-GAAP earnings metrics

As already mentioned before, there is a lot of research on the effects of voluntary disclosures on analyst following, analyst forecast accuracy and dispersion among analysts. Lang & Lundholm (1996) find that analyst following is higher, analyst's earnings forecasts are more accurate and dispersion among analysts is lower for firms that have more informative disclosures. Hope (2003) looks at the amount of disclosures in the annual report and finds that more disclosures lead to a higher analyst forecast accuracy. Following the studies by Lang & Lundholm (1996) and Hope (2003), Lakhal (2009) performs a similar study by looking at the effects of voluntary disclosures on financial analysts, by looking at analyst coverage, forecast error and dispersion among analysts. By using a sample of 154 firms in the years 1998 through 2001, she finds that financial analysts are more likely to follow firms with more extensive earnings disclosures. Her results also show that more extensive earnings disclosures also increases forecast accuracy and lowers dispersion among analysts. Not only voluntary financial disclosures have an effect on analyst accuracy. Dhaliwal et al. (2012) show that also non-financial disclosures lead to higher forecast accuracy. Also Hamrouni et al. (2017) find a significant positive relation between analyst following and the extent of voluntary disclosures, a finding that is consistent with that of Lang & Lundholm (1996) and Lakhal (2009).

Since non-GAAP earnings metrics are also a form of voluntary disclosures, the question that arises is if these metrics also have an effect on analyst following, analysts' earnings forecast accuracy and dispersion among analysts. Besides, prior research has shown that non-GAAP performance metrics can be used to mislead investors (Lougee & Marquardt, 2004; Bowen et al., 2005; Doyle et al., 2013; Isidro & Marques, 2015; Choi & Young, 2015). It is therefore important to know whether analysts can be 'tricked' by these metrics or can use them as more information about the company.

Frederickson & Miller (2004) set up an experiment to test whether analysts (more-sophisticated investors) and nonprofessional (less-sophisticated) investors are affected by a company's use of non-GAAP earnings disclosures. To test this, they use M.B.A. students as a proxy for less-sophisticated investors. A total of 24 M.B.A.s and 18 analysts participate in this experiment. Participants had to make several judgments about a non-existing company. Part of the participants received only GAAP earnings disclosures, while the others received both pro forma and GAAP earnings disclosures. From their results it appears that analysts' judgments did not differ in both conditions, but the judgment of nonprofessional investors did. Non-professional investors perceive the case with pro forma earnings disclosure to be more positive than the one with only the GAAP earnings disclosure.

Elliott (2006) also performs an experiment on the effects of pro forma earnings disclosures on investors and analysts. Consistent with Frederickson & Miller, she uses M.B.A.s as a proxy for less-sophisticated investors. Her sample consists of 89 M.B.A.s and 55 analysts. She finds that not the pro forma earnings itself, but the emphasis placed on them by management is the biggest influence on investors' judgments. However, this result is mitigated when there is a reconciliation. She also finds that the presence of a reconciliation makes analysts rely more on the pro forma disclosure.

As a result of the experiments performed by Frederickson & Miller (2004) and Elliott (2006), Allee et al. (2007) performs an archival study investigating the same relation, namely how pro forma disclosures influence investors and analysts, while looking at their level of sophistication. With 4.928 announcements in the period from 1998 through 2003, they find that less-sophisticated investors rely more on pro forma earnings than more-sophisticated investors. They also find that the location of the non-GAAP earnings in the presentation of the earnings has more effect on less-sophisticated investors. These results are consistent with the experimental results found by Frederickson & Miller (2004) and Elliott (2006).

However, Andersson & Hellman (2007) find different results. They also perform an experiment on the relation between non-GAAP reporting and analyst forecasts, but find that analysts predict a significant higher EPS when non-GAAP earnings are disclosed. 36 analysts were provided with either a GAAP earnings release or a non-GAAP earnings release of a fictitious Swedish firm. The experiment differs from that of Frederickson & Miller (2004) and Elliott (2006) in that there was a significant profit in the non-GAAP earnings and a significant loss in the GAAP earnings. This is not the case in the experiments of Frederickson & Miller (2004) and Elliott (2006). With this setting, Andersson & Hellman (2007) find that the predicted EPS in the case of non-GAAP earnings was significantly higher than when only GAAP earnings were disclosed.

The conclusion that can be drawn from these studies is that non-GAAP earning metrics tend to affect less-sophisticated investors when managers put more emphasis on them. Although non-GAAP earning metrics can be used to mislead less sophisticated investors, it is important to note that this is not always the case. As earlier mentioned, non-GAAP earnings can also be used to better understand the GAAP earnings. It is not always possible to get a clear image from the GAAP earnings, so management decides to provide additional information. It is unclear what the effect on more-sophisticated investors like analysts is, since the aforementioned studies find different results.

3.4 Summary

The most important findings from the prior literature are that non-GAAP earnings can be used to either inform or mislead investors (Bradshaw & Sloan, 2002; Lougee & Marquardt, 2004; Choi & Young, 2015). Lougee & Marquardt (2004) find that firms are more likely to use non-GAAP earnings metrics when GAAP earnings are less informative. Bowen et al. (2005) find that firms put more emphasis on the non-GAAP earnings metric when GAAP earnings show a worse performance. This was also observed by the SEC, which was able to push back the use of non-GAAP earnings metrics and the difference between the non-GAAP earnings metric and the GAAP earnings metric after the issuance of regulation G (Marques, 2006; Heflin & Hsu, 2008; Kolev et al., 2008). Doyle et al. (2013) find that firms still use non-GAAP earnings, and that non-GAAP earnings metrics are used to meet or beat analyst forecasts. Because it is hard to find out whether the non-GAAP earnings metrics are used to mislead or inform investors, Choi & Young (2015) try to separate these incentives. They find that if GAAP earnings are higher than expected, non-GAAP earnings tend to be informative, whereas if GAAP earnings are lower than expected, non-GAAP earnings tend to be misleading.

Analyst following, analysts' earnings forecast accuracy and analysts' earnings forecast dispersion are influenced by several factors. So does the number of analyst following a firm depend on factors like the size of the firm, how many lines of business the firm operates in and ownership structure (Bhushan, 1989; Barth et al., 2001). Analysts' earnings forecast accuracy is influenced by the analyst experience of the firm, the amount of resources the analyst has, and the complexity of his portfolio (Clement, 1999; Jacob et al., 1999). However, Brown

(2001) shows that using these characteristics to determine analyst forecast accuracy are as good as just using past forecast accuracy. Keskek et al. (2017) find that these characteristics are no longer important after the implementation of Reg FD, and that only prior year accuracy has a significant importance. Dispersion among analysts is reduced by more public information (Lang & Lundholm, 1996; Barron et al., 1998).

Another factor that influences analyst following, analysts' earnings forecast accuracy and analysts' earnings forecast dispersion are voluntary disclosures (Lang & Lundholm, 1996; Hope, 2003; Lakhal, 2009; Dhaliwal et al., 2012; Hamrouni et al., 2017). On the effect of disclosing non-GAAP earnings on analysts, not much research is done. Prior research even shows contradicting findings. Frederickson & Miller (2004), Elliott (2006) and Allee et al. (2007) show that non-GAAP earnings influence less-sophisticated investors, but not more-sophisticated investors like analysts. Andersson & Hellman (2007) do find that analyst are influenced by the use of non-GAAP earnings metrics.

4. Hypotheses

Whether analysts are influenced by the non-GAAP earnings metrics in their earnings' forecasts is unclear. Frederikson & Miller (2004), Elliot (2006) and Allee et al. (2007) show that analysts are not influenced by the strategic use of non-GAAP earnings metrics. Contrary to these findings, Andersson & Hellman (2007) do find that analyst are influenced by the use of non-GAAP earnings metrics. Since these studies are mostly experiments and do not involve real firms, they do not look at analyst following, analysts' earnings forecast accuracy and dispersion among analysts' earnings forecasts. Therefore, I base my research on that of voluntary disclosures, since non-GAAP earnings metrics are voluntarily disclosed by firms.

Lang & Lundholm (1996) find that more informative disclosures lead to higher analyst following. Also Healy et al. (1999), Lakhal (2009) and Hamrouni et al. (2017) find that analyst following increases with more voluntary disclosure policies of the firm. Since non-GAAP earnings metrics are a form of voluntary disclosures, I expect that analyst following is higher for firms that disclose non-GAAP earnings metrics. The first hypothesis I will test is therefore:

> Hypothesis 1: Analyst following is higher for firms that report non-GAAP earnings metrics

Lang & Lundholm (1996) also find that more informative disclosures lead to a higher accuracy of analysts' earnings forecasts. Other studies also find that analysts' earnings forecasts are more accurate for firms that have more voluntary disclosures (Hope, 2003; Lakhal, 2009; Dhaliwal et al., 2012; Hamrouni et al., 2017). Therefore, I also expect this to be the case for non-GAAP earnings metrics. The second hypothesis is thus as follows:

> Hypothesis 2: Analysts' earnings forecasts are more accurate for firms that report non-GAAP earnings metrics

Another finding of Lang & Lundholm (1996) is that more informative disclosures lead to lower dispersion among analysts. This finding is consistent with Hope (2003) and Lakhal (2009). Therefore, I also expect dispersion among analysts' earnings forecasts to be lower for firms that disclose non-GAAP earnings metrics. The third hypothesis is thus as follows:

Hypothesis 3: Dispersion among analysts' earnings forecasts is lower for firms that report non-GAAP earnings metrics

There are two incentives for firms to use non-GAAP earnings metrics. They could use them to inform their investors and give a better view of the future performance of the company, or they could use them to mislead investors, so that there firm looks better and attracts more investors (Bradshaw & Sloan, 2002; Lougee & Marquardt, 2004; Choi & Young, 2015). Knowing that more informative disclosures lead to higher analyst following (Lang & Lundholm, 1996), I expect that firms that use non-GAAP earnings metrics with an incentive to inform investors to have more analyst following than those firms that use non-GAAP earnings metrics with an incentive to mislead investors. The fourth hypothesis is therefore:

Hypothesis 4: Analyst following is higher for firms that disclose non-GAAP earnings metrics with an incentive to inform investors than for firms that disclose non-GAAP earnings metrics with an incentive to mislead investors

The above reasoning also applies for the accuracy of analysts' earnings forecasts. More informative disclosures lead to more accurate analysts' earnings forecasts (Lang & Lundholm, 1996). The fifth hypothesis is therefore:

Hypothesis 5: Analysts' earnings forecasts are more accurate for firms that disclose non-GAAP earnings metrics with an incentive to inform investors than for firms that disclose non-GAAP earnings metrics with an incentive to mislead investors

More informative disclosures lead to lower dispersion among analysts' earnings forecasts (Lang & Lundholm, 1996). Following the reasoning above, I expect dispersion among analysts to be lower for firms with an incentive to inform investors. The sixth hypothesis is therefore:

Hypothesis 6: Dispersion among analysts' earnings forecasts is lower for firms that disclose non-GAAP earnings metrics with an incentive to inform investors than for firms that disclose non-GAAP earnings metrics with an incentive to mislead investors

Libby boxes of these hypotheses are provided in Appendix 1.

5. Research design

In this chapter, I provide an overview of how the hypotheses are tested. First off, I discuss the independent, dependent and control variables I use. Thereafter, I work out how I test the hypotheses and what model I use. Finally, I discuss how I select my sample.

5.1 Variable definition

Following my earlier stated hypotheses, I test the effects of non-GAAP earnings metrics on analyst following, analysts' earnings forecast accuracy and analysts' earnings forecast dispersion. The independent variable, being non-GAAP earnings metrics, is discussed first, followed by the first dependent variable, analyst following, along with its control variables. I then discuss the second dependent variable, analysts' earnings forecast accuracy, and its control variables. Finally, I discus the third dependent variable, analysts' earnings forecast dispersion, and its control variables. An overview of all variables is provided in Table 1.

5.1.1 Non-GAAP earnings metrics

For the first two hypotheses, I test the effects of non-GAAP earnings metrics. The most optimal way to determine if a firm discloses non-GAAP earnings metrics is by looking at press releases. Since this is a very time-consuming task, I use a different method. To see if firms disclose non-GAAP earnings metrics, I compare the Actual earnings from the I/B/E/S database with that of GAAP earnings from the Compustat database. This method is used in different prior research (Doyle et al., 2003; Heflin & Hsu, 2008; Doyle et al., 2013). It is, however, not the most clean option. Gu & Chen (2004) mention that the I/B/E/S Actual EPS is the non-GAAP EPS calculated by analysts, and not by management. They also note that studies that use a small hand-collected sample find that non-GAAP EPS and Actual EPS from I/B/E/S differ in 30-40% of the cases (Johnson & Schwartz, 2001; Bhattacharya et al., 2003). However, I only need to know whether non-GAAP EPS reported by management is higher or lower than the GAAP EPS. Doyle et al. (2013) also look at the direction of the non-GAAP EPS compared to the GAAP EPS. They use the Actual EPS from I/B/E/S as a proxy for non-GAAP EPS reported by management as well and test whether using a sample of hand-collected non-GAAP EPS disclosures would lead to different results. They find that using the hand-collected sample leads to similar results, both qualitatively and quantitatively. I therefore follow Doyle et al. (2013)

and use the Actual EPS from I/B/E/S to determine if a firm discloses non-GAAP earnings metrics and whether these metrics are used to inform or mislead investors.

I create the dummy variable NG, which is one for firms that disclose non-GAAP earnings metrics, and zero otherwise. The value of one is given to firms with a difference between the Actual EPS from I/B/E/S and the GAAP EPS from Compustat.

Since I make a distinction between informative and misleading non-GAAP earnings metrics in my fourth, fifth and sixth hypotheses, the next step is determining if the incentive for reporting is informative or misleading. Since it is very difficult to know the real motive of a company for reporting non-GAAP earnings measures, I use the conclusions of Choi & Young (2015). As earlier mentioned, their research leads to the conclusion that when GAAP earnings are higher than expected, non-GAAP earnings tend to be informative. When the GAAP earnings are lower than expected, the non-GAAP earnings tend to have a misleading incentive. Following this, I create the dummy variable ING which is one when GAAP EPS is higher than the non-GAAP EPS, and zero if it is lower. I use the Actual EPS from I/B/E/S as a proxy for non-GAAP EPS, and give the value of one to firms that have a GAAP EPS from Compustat that is higher than the Actual EPS from I/B/E/S.

5.1.2 Analyst following

For the first and fourth hypotheses, I test the effects on analyst following. The amount of analysts following a firm is directly available from the I/B/E/S database. For the amount of analysts following a firm, I use the variable #ANALYSTS. Since I want to know the effects on analyst following, I control for several other factors.

Based on Bhushan (1989), Lang & Lundholm (1996) and Barth et al. (2001), firm size is associated with analyst following. Larger firms have more analyst following. Therefore, I will control for firm size by defining the variable SIZE, which is the logarithm of market value of equity. This is similar to the aforementioned studies of Bhushan (1989), Lang & Lundholm (1996) and Barth et al. (2001).

Firms with more growth tend to have more interest from investors, which attracts more analysts (Lehavy et al., 2011). Barth et al. (2001) also control for growth. From their results, this variable is significantly different from zero. Therefore, I also use this variable and define it the same way as Barth et al. (2001) did, being a firm’s sales growth of the prior five years. When there is no data available of the prior five years, sales growth is calculated with the prior four or three years, which is consistent with Barth et al. (2001) and Lehavy et al. (2011). The variable GROWTH is therefore calculated as in Barth et al. (2001):

$$GROWTH = \left(\frac{sales_{t-1}}{sales_{t-(i+1)}}\right)^{\frac{1}{i}} - 1$$

Where i is a number that can take the value $3 \leq i \leq 5$.

As earlier mentioned, Barth et al. (2001) argue that analyst following is higher for firms with more intangible assets, since these assets are not always fully taken into account in the firm's financial statements. Firms with a lot of research and development have a higher analyst following. Analyst following is also higher for firms with more advertising expenses (Barth et al., 2001). Therefore, I define a control variable for research and development (RD) in the same way as Barth et al. (2001), namely the ratio of research and development expenses to operating expenses. The control variable for advertising expenses (ADV) is the ratio of advertising expenses to operating expenses (Barth et al., 2001).

5.1.3 Analysts' earnings forecast accuracy

For the second and fifth hypotheses, I test the effects on analysts' earnings forecast accuracy. Several measures for analysts' earnings forecast accuracy are used in prior research. Since I test the effects of non-GAAP metrics on the accuracy of analysts combined instead of individual analysts, I use the same measure as Lang & Lundholm (1996) to measure the accuracy of analyst forecast (ACCURACY). This measure is also used in other studies (Guan et al., 2006). To calculate analysts' earnings forecast accuracy, Lang & Lundholm (1996) take the negative of the absolute value of the analyst forecast error. This number is then divided by the stock price. This leads to the following formula:

$$ACCURACY = -(|EPS_t - AF_t|)/P_t$$

Where:

EPS_t = Actual earnings per share in year t

AF_t = The median analyst forecast in year t

P_t = Price per share in year t

Since a value of ACCURACY that is closer to zero means a higher accuracy, I use the negative absolute value so that a higher value means a higher analysts' earnings forecast accuracy. To identify the effects of non-GAAP earnings metrics on analysts' earnings forecast accuracy, I control for several other factors that may affect analysts' earnings forecast accuracy.

Larger firms provide in general more and better information, which is beneficial for analyst in making their earnings forecasts (Hutton et al., 2012). Also Lang & Lundholm (1996) find that firm size is positively related to analysts' earnings forecast accuracy. I therefore include firm size (SIZE) as a control variable for analysts' earnings forecast accuracy. Its definition is, as earlier mentioned, the logarithm of the market value of equity.

As earlier mentioned, Barth et al. (2001) find that firms that experience high growth have more analyst following. Hutton et al. (2012) argue that this growth however, results in less accurate forecasts, since it is more difficult to determine the firm's future cash flows. I therefore include GROWTH as a control variable for analysts' earnings forecast accuracy.

Although prior research does not say anything about the effects of research and development or advertising expenses on analysts' earnings forecast accuracy, I include RD and ADV as control variables as well. These variables might affect analysts' earnings forecast accuracy, since more intangibles might make it harder for analyst to provide an accurate forecast.

Lang & Lundholm (1996) also include a control variable for an earnings surprise. Actual earnings are likely to differ from expected earnings when the firm introduces a major new product. This would likely result in lower consensus among analysts. If the difference between EPS and prior year's EPS is bigger, forecast accuracy is expected to be lower. Lang & Lundholm (1996) find that there is a significant relation between analysts' earnings forecast accuracy and earnings surprise. Therefore, I also use the earnings surprise (EARNSUR) as a control variable and define it in the same way as Lang & Lundholm (1996):

$$EARNSUR = (|EPS_t - EPS_{t-1}|)/P_{t-1}$$

Where:

EPS_t = Earnings per share of year t

EPS_{t-1} = Earnings per share of year t-1

P_{t-1} = Share price at the beginning of the fiscal year

I also include the number of analysts (#ANALYST) as a control variable. Lys & Soo (1995) find that more competition between analysts results in higher analysts' earnings forecast accuracy. They use analyst following as a proxy for competition between analysts. Since more analysts make predictions for a firm, the average of these predictions is more likely to be close to the actual earnings of the firm.

Table 1
Variable definitions

Variable	Definition	Database
NG	Dummy variable that is 1 in case a firm discloses non-GAAP earnings metrics, and 0 zero if a firm does not. A firm is expected to disclose non-GAAP earnings metrics when EPS from Compustat and Actual EPS from I/B/E/S differ.	Compustat and I/B/E/S
ING	Dummy variable that is 1 in case a firm discloses informative non-GAAP earnings metrics, and is 0 if a firm discloses misleading non-GAAP earnings metrics. The incentive for disclosing non-GAAP earnings metrics is expected to be informative when EPS from Compustat is higher than the Actual EPS from I/B/E/S.	Compustat and I/B/E/S
#ANALYST	Amount of analysts following a firm	I/B/E/S
ACCURACY	Accuracy of the earnings forecasts made by analysts, measured by the negative of the absolute value of the forecast error, divided by the share price.	Compustat and I/B/E/S
DISP	Standard deviation of analysts' earnings forecasts	I/B/E/S
SIZE	The size of the firm, measured by the logarithm of the market value of equity.	Compustat
GROWTH	Average growth of the firm over prior five years.	Compustat
RD	Ratio of research and development expense to operating expense	Compustat
ADV	Ratio of advertising expense to operating expense	Compustat
EARNSUR	Earnings surprise, calculated as the absolute value of the difference between EPS of year t and year t-1, divided by the share price.	Compustat

5.1.4 Analysts' earnings forecast dispersion

For the third and sixth hypotheses, I test the effects on the dispersion among analysts' earnings forecasts. For this, I use the standard deviation of analysts' earnings forecasts, which is consistent with prior research (Lang & Lundholm, 1996). This number is directly available from the I/B/E/S database. For this, I define the variable DISP, and use several control variables to test the effects of non-GAAP earnings metrics. As dispersion is closely related to analysts' earnings forecast accuracy, I use the same control variables as I do with analysts' earnings forecast accuracy.

5.2 Model

Since I want to know the relation between the dependent and independent variables, I use a regression model. More specifically, I use ordinary least squares (OLS) regressions to test my hypotheses. This leads to the following regression formulas:

For hypotheses 1 through 3, I use the following regression:

$$Dep.Var. = \alpha + \beta_1 NG + \beta_2 SIZE + \beta_3 GROWTH + \beta_4 RD + \beta_5 ADV + \beta_6 EARNSUR + \beta_7 \#ANALYST + \varepsilon$$

Where *Dep.Var.* is the dependent variable, which is #ANALYST for hypothesis 1, ACCURACY for hypothesis 2 and DISP for hypothesis 3. For hypothesis 1, #ANALYST is not included as control variable.

For hypotheses 4 through 6, I use the following regression:

$$Dep.Var. = \alpha + \beta_1 ING + \beta_2 SIZE + \beta_3 GROWTH + \beta_4 RD + \beta_5 ADV + \beta_6 EARNSUR + \beta_7 \#ANALYST + \varepsilon$$

Where *Dep.Var.* is the dependent variable, which is #ANALYST for hypothesis 4, ACCURACY for hypothesis 5 and DISP for hypothesis 6. For hypothesis 4, #ANALYST is not included as control variable.

I use the statistical software Stata to perform my statistical tests.

5.3 Sample selection

I obtain data for my research from two databases, being Compustat and I/B/E/S. I extract data from these databases through Wharton Research Data Services (WRDS). To combine the two databases, I use the official Ticker provided in both Compustat and I/B/E/S. Combining this ticker with the fiscal year, I create a unique code for each firm-year observation. Since these official Tickers can change over time, I extracted data from both databases at the same time. Separate additional extractions for several control variables are made using the unique identifiers of each database, which do not change over time.

The sample selection is shown in table 2. First, I extract all data of firms with sales higher than $ 1 million from Compustat in the period between January 2010 and December 2016. Consistent with prior research, I do not include firms with sales less than $ 1 million to prevent potential outliers due to small firms (Barth et al., 2001). I choose the period between January 2010 and December 2016 because several regulations issued by the SEC in the early 2000's resulted in changes in my dependent variables (Irani & Karamanou, 2003; Bagnoli et al., 2008). Choosing this period also gives a better picture of the current situation. To make sure all data is in the same currency, I only use firms that report data in United States Dollars (USD). The extraction from Compustat results in a total of 8,580 firms with 43,549 firm-year observations.

Table 2

Sample selection

	Firms	**Firm-years**
Firms with sales > $ 1 million in Compustat with fiscal years ending between January 2010 and December 2016	8,580	43,549
Less:		
Observations with no available EPS data		-1,962
Observations with no available shares outstanding data		-692
Observations with no available share price data or share price of 0		-2,557
Observations with no available data on sales in prior years		-5,320
Observations with no available EPS data in prior year		-19
Observations with no available share price data or share price of 0 in prior year		-42
Potential sample from Compustat data	6,547	32,957
Less:		
Observations with no actual EPS data from the I/B/E/S Actuals file		-11,316
Final sample	4,514	21,641

From this extraction, I drop observations that have no information on EPS, since I need this information for my independent variables, to calculate accuracy, and for the control variable EARNSUR. I also drop observations with no information on shares outstanding and share price, since I need this information to control for firm size. Because I control for growth firms, observations with no sales data in prior years are also dropped. Observations with no data on prior year EPS and prior year share price are dropped as well, since I need this information for the control variable EARNSUR. Last, but not least, I drop observations with no actual EPS data in the I/B/E/S Actuals file. This results in a final sample of 4,514 firms and 21,641 firm-years.

5.4 Summary

To test my hypotheses, I use OLS regressions to find a relation between my variables. The independent variable is the disclosure of (informative) non-GAAP earnings metrics. For this, I use a dummy variable that is 1 if a firm discloses (informative) non-GAAP earnings metrics and zero otherwise. I test the effects of these two independent variables on the dependent variables. The dependent variables are analyst following, analysts' earnings forecast accuracy and analysts' earnings forecast dispersion. Analyst following, which is the amount of analysts following a firm, is directly available from the I/B/E/S database. The accuracy of the forecasts made by these analysts is calculated by the negative of the difference between EPS and the median analyst forecast, divided by the share price. For analysts' earnings forecast dispersion, I use the standard deviation of analysts' earnings forecasts, which is also directly available from the I/B/E/S database. I control for several other factors. The size of the firm and its sales growth in prior years are both included in all regressions. For analyst following, I also include intangible assets by using advertising expense and research and development expense as a proxy. For analysts' earnings forecast accuracy and analysts' earnings forecast dispersion, I include a control variable for the earnings surprise, since Lang & Lundholm (1996) find a significant relation between these variables. Based on Lys & Soo (1995), I also include analyst following as a control variable for analysts' earnings forecast accuracy.

I collect my data from the Compustat and I/B/E/S databases. I only include firms with at least $ 1 million of sales, to prevent potential outliers due to small firms. Because of regulations in the early 2000's, I choose a period that is several years away from these events, since Irani & Karamanou (2003) and Bagnoli et al. (2008) find that these regulation affect my dependent variables. I therefore extract data from the period of January 2010 through December 2016. After dropping observations due to missing data, my final sample consists of 4,514 firms with 21,641 firm-years.

6. Results

In this chapter, I analyze my data. I start off by providing descriptive statistics and account for outliers. I perform unpaired t-tests to provide initial insight in the relation between my variables. I then use OLS regressions to control for other factors and test my hypotheses.

6.1 Descriptive statistics

Taking a first look at my sample, some extreme values for the variables ACCURACY and DISP jump out. These values are caused by some outliers. Because these outliers do not reflect the rest of the sample, but do cause inferences in my tests, I decide to drop observations that have a value that is lower than -5 for ACCURACY. This is about 1% of the data (215 observations). Summary statistics of my variables after dropping the outliers is provided in table 3.

Table 3

Summary statistics after controlling for outliers

Variable	N	Mean	Std. Dev.	Min	Max
NG	21,426	0.83	0.37	0	1
ING	17,803	0.45	0.50	0	1
#ANALYSTS	21,426	8.11	7.50	0	55
ACCURACY	21,134	-0.08	0.32	-4.94	0
DISP	21,134	0.08	0.36	0	23.54
SIZE	21,426	7.27	1.92	0.52	13.35
GROWTH	21,426	0.13	0.41	-8.53	19.75
ADV	21,426	0.01	0.04	0	0.75
RD	21,426	0.06	0.13	-0.01	1.79
EARNSUR	21,426	0.70	45.69	0	6,006.25

Summary statistics are provided for the dependent, independent and control variables after controlling for outliers. Variable descriptions are provided in table 1.

Of these variables, NG and ING are dummy variables. NG has a value of 1 when a company discloses non-GAAP earnings metrics. This is the case for 17,803 of the observations. There are 3,623 observations where firms do not disclose a non-GAAP earnings metrics, so NG has the value of zero. 7,963 of the 17,803 observations are firms that disclose informative non-GAAP earnings, resulting in the value 1 for ING. This automatically means that the other 9,840 observations disclose misleading non-GAAP earnings.

Another difference that can be noticed in table 3, is the lower sample size for ACCURACY and DISP. This is caused by 292 firm-year observations that have an analyst following of zero. For these observations, I cannot compute a value for analysts' earnings forecast accuracy and analysts' earnings forecast dispersion. Therefore, the sample for hypothesis 1 has 21,426 firm-year observations, where hypotheses 2 and 3 have 21,134 firm-year observations.

On average, firms are followed by eight analysts and forecasts for these firms have an average accuracy of -0.08. The dispersion between analysts has a mean of 0.08. Since dispersion is the standard deviation of the estimates made by analysts, this number shows that analysts, in general, agree with each other.

For my hypotheses, I compare the amount of analysts, accuracy of earnings forecasts and dispersion among analysts between two groups. One being firms that disclose non-GAAP earnings metrics and the other firms that do not. Performing an unpaired t-test provides insights in the differences in means between the two groups. These results are provided in table 4.

Table 4

Mean comparison

	Non-GAAP discloser, NG=1		**No non-GAAP discloser, NG=0**			
Variable	**N**	**Mean**	**N**	**Mean**	**Difference**	***t*-statistic**
#ANALYSTS	17,803	8.72	3,623	5.11	-3.61	-26.91*
ACCURACY	17,593	-0.09	3,541	-0.03	0.06	10.36*
DISP	17,593	0.08	3,541	0.08	-0.01	-1.09

Unpaired t-tests are performed with #ANALYSTS, ACCURACY and DISP as dependent variables. Variable descriptions are provided in table 1. * indicates significance at the 1% level confidence level.

As discussed earlier, ACCURACY and DISP have less firm-year observations due to an anlyst following of zero. This is also visible in table 4. Of the 17,803 observations that disclose non-GAAP earnings metrics, 210 have no analyst following.

Table 4 shows that analyst following is significantly higher for firms that disclose non-GAAP earnings metrics and would therefore confirm hypothesis 1. When looking at accuracy of analysts' earnings forecasts, we can also observe a significant difference. However, this difference is not as expected. I hypothesized that accuracy would be higher for firms that disclose non-GAAP earnings metrics. Based on the mean comparison, it seems that accuracy is lower for firms that disclose non-GAAP earnings metrics. No significant difference is observed for the dispersion among analysts.

When zooming in on the firms that disclose non-GAAP earnings metrics and looking at the difference between firms with an informative and misleading incentive to disclose non-GAAP earnings metrics, we can also perform an unpaired t-test to get some insights in the differences between the means of the two groups. Table 5 provides the results of this test.

Table 5
Mean comparison

	Informative Non-GAAP discloser, ING=1		**Misleading non-GAAP discloser, ING=0**			
Variable	**N**	**Mean**	**N**	**Mean**	**Difference**	***t*-statistic**
#ANALYSTS	7,963	8.14	9,840	9.19	1.05	8.98*
ACCURACY	7,870	-0.09	9,723	-0.08	0.00	0.50
DISP	7,870	0.09	9,723	0.08	-0.01	-1.96**

Unpaired t-tests are performed with #ANALYSTS, ACCURACY and DISP as dependent variables. Variable descriptions are provided in table 1. * indicates significance at the 1% level confidence level. ** indicates significance at the 5% confidence level.

The results of this test is not as expected. Hypothesis 4 expects a larger analyst following for firms with informative non-GAAP earnings metrics. Based on this test, we see that firms with misleading non-GAAP earnings metrics have significantly larger analyst following. Forecasts are also a little bit more accurate for firms that disclose misleading non-GAAP earnings metrics, but this difference is not significant. Dispersion among analysts is lower for firms that disclose misleading non-GAAP earnings metrics, meaning that there is less uncertainty among analysts.

These unpaired t-tests provide an initial insight in the relation between the dependent and independent variables. However, these tests do not control for several other factors that might explain the difference. In the next section, the relation is tested using OLS regressions as specified in section 5.2.

6.2 Empirical analysis

I use OLS regressions to test my hypotheses. An important assumption when dealing with OLS regressions is that the variables are not correlated. To test for this, I generate a Pearson correlation matrix and test for the variation inflation factors (VIF). The correlation matrix can be found in appendix 3 and the VIF tables can be found in appendix 4. Based on the numbers in the correlation matrix and the VIF tables, I assume that there is no multicollinearity issue with my data.

6.2.1 Using non-GAAP earnings metrics

For the first three hypotheses, I use NG as the independent variable in the OLS regressions specified in section 5.2. Results of these OLS regressions of these hypotheses are provided in table 6.

Table 6

Regression results hypotheses 1, 2 and 3

Variable	**Pred.**	**#ANALYSTS**	**Pred.**	**ACCURACY**	**Pred.**	**DISP**
NG	+	0.506* (0.000)	+	-0.122* (0.000)	-	0.009 (0.214)
SIZE	+	2.368* (0.000)	+	0.041* (0.000)	-	0.015* (0.000)
GROWTH	+	0.665* (0.000)	+	-0.004 (0.418)	-	0.000 (0.938)
ADV	+	13.157* (0.000)	-	0.180* (0.002)	+	-0.111 (0.104)
RD	+	6.567* (0.000)	-	-0.225* (0.000)	+	0.109* (0.000)
EARNSUR	+/-	-0.001 (0,411)	+/-	-0.001* (0.000)	+/-	0.000 (0.576)
#ANALYSTS			+	-0.001* (0.000)	+/-	-0.004* (0.000)
Intercept		-11.598* (0.000)		-0.219* (0.000)		-0.034 (0.519)
Year FE’s		Included		Included		Included
Industry FE’s		Included		Included		Included
Observations		21,426		21,134		21,134
R^2		40.50%		8.41%		2,02%

OLS regression are performed with ANALYSTS, ACCURACY and DISP as dependent variable. Fixed effects for year and industry are included to control for unobserved factors in time and industry. Variable descriptions are provided in table 1. * indicates significance at the 1% confidence level. Corresponding p-values are provided in the parentheses.

Following hypothesis 1, I expected analyst following to be higher for firms that report non-GAAP earnings metrics. Following the results provided in table 6, I can conclude that this is the case. While controlling for firm size, growth in the prior three to five years, and intangible assets, firms that report non-GAAP earnings metrics have significantly higher analyst following. The coefficient of the variable of interest, NG, is 0.506. This shows that firms that report non-GAAP earnings metrics have almost one more analyst following than firms which do not report non-GAAP earnings metrics. Also the size of the firm, growth in the prior three to five years, and intangible assets show a significant relation with analyst following. Their coefficients are as expected. Larger firms, growth firms, and firms with more intangible assets have more analyst following, which is consistent with prior research (Bhushan, 1989; Lang & Lundholm, 1996; Barth et al., 2001).

In hypothesis 2, I expected analysts' earnings forecasts to be more accurate for firms that report non-GAAP earnings metrics. However, the results from the OLS regression show a different relation. Analysts' earnings forecasts are significantly less accurate for firms that disclose non-GAAP earnings metrics. The coefficient of the variable of interest, NG, is -0.122. It appears that the additional information provided by firms, the non-GAAP earnings metrics, alters the expectations of analysts. These expectations are further away from the actual EPS, resulting in lower accuracy. From this, it seems that analysts are misled by the non-GAAP earnings metrics. All control variables also show a significant relation with analysts' earnings forecast accuracy. Accuracy is higher for larger firms and lower for growth firms, which is consistent with prior research (Lang & Lundholm, 1996; Hutton et al., 2012). Consistent with Lang & Lundholm (1996), I find that there is a negative relation between analysts' earnings forecast accuracy and earnings surprise. However, contrary to Lys & Soo (1995), I find that more analyst following results in lower accuracy.

Hypothesis 3 expected lower dispersion among analysts, since more disclosures would mean more information and thus lower uncertainty among analysts. However, no significant relation is observed between analyst dispersion and the disclosure of non-GAAP earnings metrics by firms. From table 6, it is visible that the coefficient of the variable NG is 0.009 for DISP, which is not significant. Also no significant relation is found between dispersion and the control variables, with the exception of firm size (0.015) and RD (0.109). Larger firms have significantly more dispersion among analysts, which is not consistent with Lang & Lundholm (1996).

6.2.2 Informative versus misleading non-GAAP earnings metrics

Prior research shows that there are two incentives for firms to disclose non-GAAP earnings metrics. They could use them to inform their investors and give a better view of the future performance of the company, or they could use them to mislead investors, so that there firm looks better and attracts more investors (Bradshaw & Sloan, 2002; Lougee & Marquardt, 2004; Choi & Young, 2015). I therefore stated the fourth, fifth and sixth hypothesis, where I test whether this different incentive results in different results. For this, I defined the variable ING, which is 1 when a firm discloses informative non-GAAP earnings metrics and zero otherwise. The results of the regressions for the fourth, fifth and sixth hypothesis are presented in table 7.

Table 7

Regression results hypotheses 4, 5 and 6

Variable	**Pred.**	**#ANALYSTS**	**Pred.**	**ACCURACY**	**Pred.**	**DISP**
ING	+	-0.422* (0.000)	+	-0.009 (0.072)	-	0.007 (0.213)
SIZE	+	2.496* (0.000)	+	0.047* (0.000)	-	0.013* (0.000)
GROWTH	+	1.060* (0.000)	+	-0.002 (0.829)	-	0.001 (0.922)
ADV	+	13.275* (0.000)	-	0.227* (0.001)	+	-0.102 (0.155)
RD	+	7.883* (0.000)	-	-0.482* (0.000)	+	0.173* (0.000)
EARNSUR	+/-	-0.001 (0,577)	+/-	-0.001* (0.000)	+/-	0.000 (0.641)
#ANALYSTS			+	-0.002* (0.000)	+/-	-0.003* (0.000)
Intercept		-11.924* (0.000)		-0.364* (0.000)		-0.011 (0.845)
Year FE's		Included		Included		Included
Industry FE's		Included		Included		Included
Observations		17,803		17,593		17,593
R^2		39,68%		9,88%		2,17%

OLS regression are performed with ANALYSTS, ACCURACY and DISP as dependent variable. Fixed effects for year and industry are included to control for unobserved factors in time and industry. Variable descriptions are provided in table 1. * indicates significance at the 1% confidence level. Corresponding p-values are provided in the parentheses.

Based on table 7, the regression coefficient for ING on #ANALYSTS is -0.422, meaning that if a firm discloses informative non-GAAP earnings metrics, analyst following is on average 0.422 lower. This is not consistent with the fourth hypothesis. I expected analyst following to be higher for firms that disclose informative non-GAAP earnings metrics, since Lang &

Lundholm (1996) find that more informative disclosures lead to higher analyst following. A possible explanation for this is that investors are able to make better predictions themselves and that there is less demand for analyst services. Less demand for analyst services results in less analyst following a firm (Bhushan, 1989). The relation between analyst following and the control variables all show a significant positive relation, with the exception of EARNSUR. The coefficient of this control variable is -0.001 and is not significant. This is similar to the results of the regression for hypothesis 1. Larger firms, growth firms, and firms with more intangible assets have more analyst following, which is consistent with prior research (Bhushan, 1989; Lang & Lundholm, 1996; Barth et al., 2001).

Following Lang & Lundholm (1996), I expected that firms with more informative non-GAAP earnings metrics have higher analysts' earnings forecast accuracy. The coefficient of the variable ING is -0.009 when regressing on ACCURACY, which is not significant. Therefore, I find no significant relation between the incentive to disclose non-GAAP earnings metrics and accuracy of analysts' earnings forecasts. I therefore cannot accept hypothesis 5. Similar to the result of hypothesis 2, I find significant relations between the control variables and analysts' earnings forecast accuracy, with the exception of GROWTH, which is not significant in both hypotheses.

For the final hypothesis, I expected dispersion among analysts to be lower for firms with informative non-GAAP earnings metrics. Table 7 shows that there is no significant relation between DISP and ING, the coefficient being 0.007.

Overall, I can only accept hypothesis 1. Hypotheses 3, 5 and 6 are rejected due to the absence of a significant relation between the variables. In the case of hypotheses 2 and 4, a significant relation is observed, but in the opposite direction of what I expected.

6.3 Summary

In this chapter I provide descriptive statistics of my initial sample. These statistics show that my initial sample consists of some extreme observations. I therefore delete 215 observations that have a value that is lower than -5 for ACCURACY. This results in a sample of 21,426 observations for hypotheses 1. For hypotheses 2 and 3, the sample consists of 21,134 observations, due to observations that have analyst following of zero and therefore no data on accuracy and dispersion. In total, 17,803 firms disclose non-GAAP earnings metrics, of which

7,963 disclose informative non-GAAP earnings metrics. Therefore, the sample for hypothesis 4 consists of 17,803 observations. The sample for hypotheses 5 and 6 is 17,593, due to observations that have analyst following of zero and therefore no data on accuracy and dispersion

I perform unpaired t-tests to find that analyst following is significantly higher and analysts' earnings forecasts are significantly less accurate for firms that disclose non-GAAP earnings metrics. I do not find a significant relation between analyst dispersion and the disclosure of non-GAAP earnings metrics. I then make a distinction between informative and misleading non-GAAP earnings metrics and perform another unpaired t-test. I find that analyst following is significantly lower and analyst dispersion is significantly higher for firms that disclose informative non-GAAP earnings metrics. I do not find a significant difference for analysts' earnings forecast accuracy.

I use OLS regressions to control for other factors that may cause the difference in my independent variables. These OLS regressions show the same results as the unpaired t-tests. Analyst following is significantly higher and analysts' earnings forecasts are significantly less accurate for firms that disclose non-GAAP earnings metrics. Firms that disclose informative non-GAAP earnings metrics have less analyst following.

Based on these results, I can only accept hypothesis 1. The other hypotheses are rejected due to no significant relation in hypotheses 3, 5 and 6, or an opposite significant relation for hypotheses 2 and 4.

7. Conclusion

The main goal of this thesis is finding an answer to the question: "Does the disclosure of non-GAAP earnings metrics by firms influence financial analysts' earnings forecasts?" For this, I focus on sell-side analysts and look at three attributes, namely analyst following, analysts' earnings forecast accuracy and dispersion among analysts' earnings forecasts. I also distinguish between two motives for firms to disclose non-GAAP earnings metrics. Since prior research shows that more voluntary disclosures by firms lead to higher analyst following, more accurate earnings forecasts and less dispersion among analysts (Lang & Lundholm, 1996; Healy et al., 1999; Hope, 2003; Lakhal, 2009; Dhaliwal et al., 2012, Hamrouni et al., 2017), I expect the same trend for firms that disclose non-GAAP earnings metrics. My results show that this is not the case in all attributes. Analyst following is significantly higher for firms that disclose non-GAAP earnings, but analysts are significantly less accurate in their earnings forecasts. I do not find a significant relation between non-GAAP earnings metrics and analyst dispersion. When distinguishing between the firm's motives for disclosing non-GAAP earnings metrics, I find that informative non-GAAP earnings metrics have lower analyst following. I do not find a significant relation between the disclosing motive and analysts' earnings forecast accuracy or between the disclosing motive and analysts' earnings forecast dispersion. These findings are also not what I expected. I hypothesized that analyst following would be higher, earnings forecasts would be more accurate and that there would be less dispersion among analysts, based on research on informative disclosures by Lang & Lundholm (1996).

To come back to my research question. Yes, the disclosure of non-GAAP earnings metrics influences financial analysts. The disclosure of non-GAAP earnings metrics by firms attracts more analysts. I find that analysts are less accurate in their forecasts, so it seems that analysts' earnings forecasts are influenced by the non-GAAP earnings metrics. I believe that there are two possible reasons for this. The first is that analysts are misled by the non-GAAP earnings metrics, the other is that analyst do not fully incorporate informing non-GAAP earnings metrics. Since I find no significant difference in accuracy between the two motives, I assume the lower accuracy is a combination of the two possible causes. The incentive for non-GAAP earnings also has an effect on analyst following. Informative non-GAAP earnings metrics have less analyst following than misleading non-GAAP earnings metrics. A possible explanation for this is that investors are able to make better predictions themselves when non-GAAP earnings metrics are informative and that there is less demand for analyst services. Less demand for analyst services results in less analyst following a firm (Bhushan, 1989). This would mean that investors are able to identify whether non-GAAP earnings are informative.

This thesis contributes to the existing literature in that it is, as far as I know, the first study that looks at the effects of non-GAAP earnings metrics on analyst attributes, while making a distinction between the two motives for disclosing non-GAAP earnings metrics. It shows that analysts have difficulty in identifying the underlying motive for disclosing non-GAAP earnings metrics. This is important information for standard setters and firms, but also for investors using the analyst forecasts.

My research has several limitations. First off, I use the difference between the EPS provided by Compustat and the I/B/E/S actual EPS as an indicator for non-GAAP earnings metrics. Since prior research shows that this is a good way to determine whether a firm discloses non-GAAP earnings metrics, it is not 100% accurate (Doyle et al., 2003; Heflin & Hsu, 2008; Doyle et al., 2013). Although I do not expect that this would affect my results, there is a small chance it does. There is also a possibility that there are control variables that I do not use, but could explain differences in my dependent variables.

Where this thesis focuses on EPS, there are many other ways of disclosing non-GAAP earnings metrics. Future research might focus more on these other metrics and look if there is an effect on analysts. Using a sample of hand collected data might also be a more accurate way to test for effects on analysts, although this would require a lot of work. Future research could also focus on what would be a good way to reduce to use of misleading non-GAAP earnings metrics.

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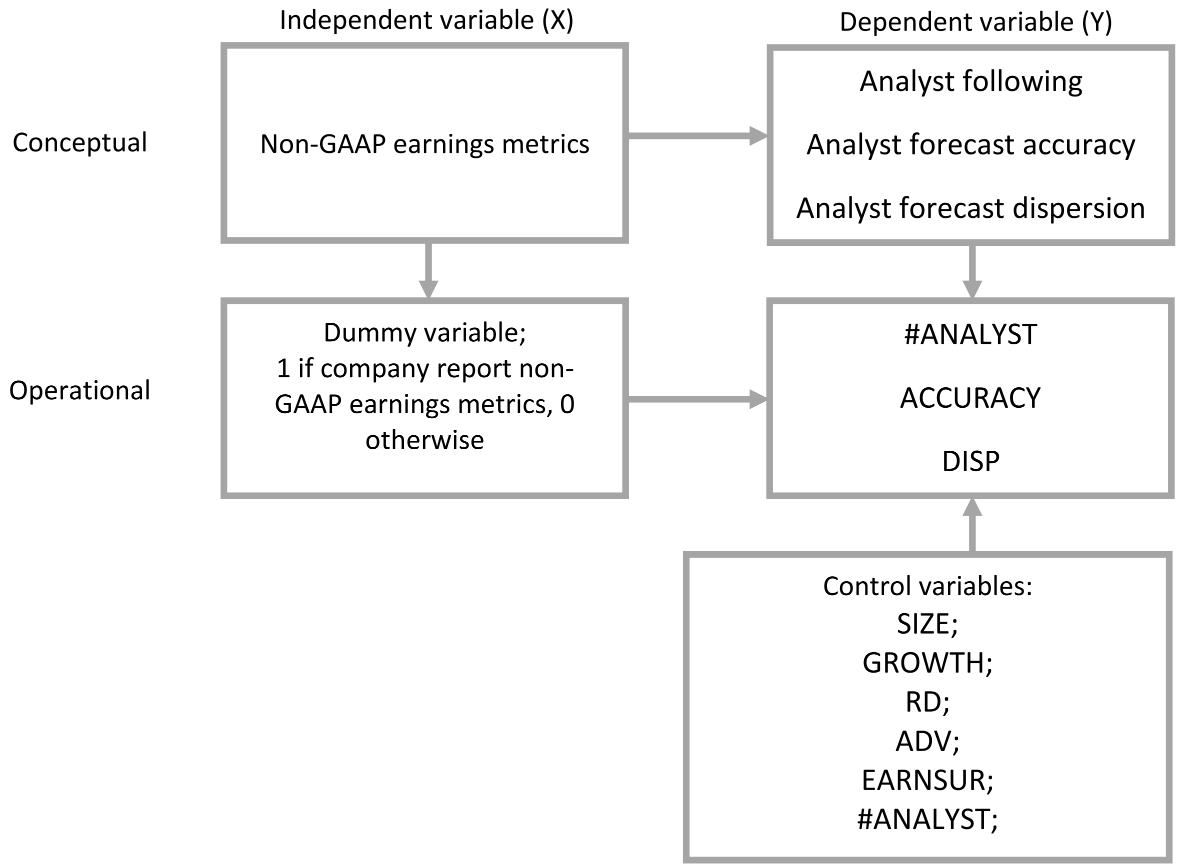
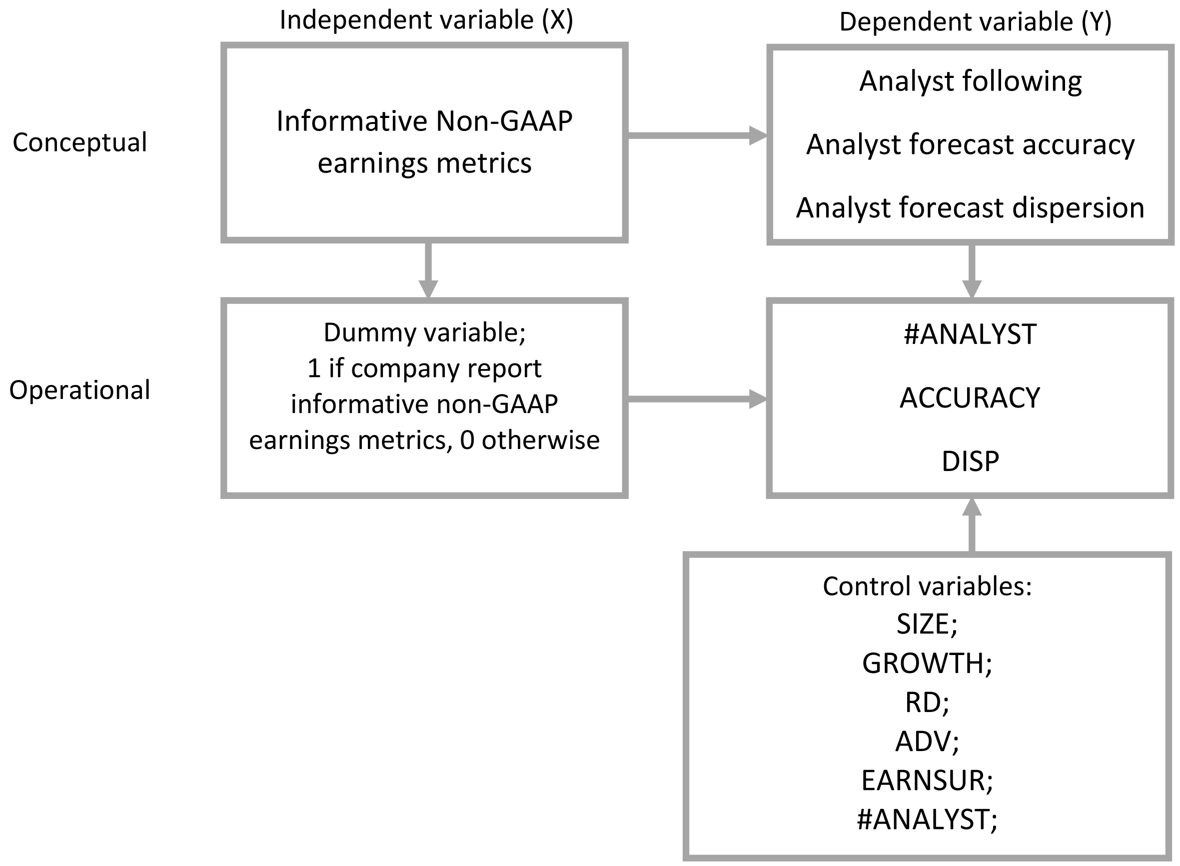
9. Appendices

9.1 Libby boxes

Hypotheses 1, 2 and 3



Hypothesis 4, 5 and 6



9.2 Summary Table

Year	Author	Research Question	Population	Methodology	Results
Non-GAAP earnings measures					
2000	Schrand & Walther	What benchmark is used to compare current earnings?	Archival study. US firms that sold PPE in the years 1988 through 1994. Total of 130 observations.	Analysis of the treatment of gains or losses from sale of PPE in prior period.	Managers strategically lower the earnings from prior period by reporting different components separately in the case of a gain on sale of PPE. In case of a loss, no such separation was made. This means managers strategically choose their benchmark to make the earnings look better.
2002	Bradshaw & Sloan	Does the use of non-GAAP and difference between GAAP and non-GAAP earnings show an increase over the past years?	Archival study. 98.647 firm-quarter observations in the years 1985 through 1997.	Time trend regressions are used to see whether the use of non-GAAP and difference between GAAP and non-GAAP has increased.	Non-GAAP earnings metrics are used more often and the difference between these and GAAP earnings has increased. Non-GAAP earnings are often larger than the GAAP earnings.
2004	Lougee & Marquardt	What characteristics distinguish firms that include pro forma earnings in their press releases from those that do not, and do investor response to those firms differ?	Archival study. 249 press releases from 1997 through 1999.	Regression analysis is used to find characteristics of firms that report non-GAAP earnings metrics.	Firms that report GAAP earnings that are less informative, are more likely to report non-GAAP earnings. When GAAP earnings are less informative or GAAP earnings show a positive earnings surprise, non-GAAP earnings are more relevant and provide more information. When the opposite is the case, non-GAAP earnings are used to mislead investors.

2005	Bowen et al.	To what extent are managers deliberate in the emphasis they place on alternative performance metrics in press releases?	Archival study. 1.188 press releases from Q2, 2001 through Q3, 2002.	The level of emphasis and relative emphasis are measured to see how non-GAAP metrics are used.	Firms emphasize metrics that are more value-relevant and portray a favorable firm performance. Media coverage affects decisions of management in placing emphasis. In 2002, a shift towards emphasis on GAAP is observed.
2006	Marques	What are the effects of the SEC interventions on non-GAAP reporting?	Archival study. 4.234 press releases from 2001 through 2003	Comparison is made between three different time periods.	After the SEC regulations, less firms disclose non-GAAP earnings. Investors have a positive market reaction to non-GAAP earnings.
2008	Heflin & Hsu	What are the effects of the SEC interventions on non-GAAP reporting?	Archival study. 2.138 firms with 42.760 firm-quarter observations from March 2000 through February 2005.	Comparison is made between two different time periods	Non-GAAP disclosures declined after regulation G. Differences between GAAP and non-GAAP declined. Lower probability that firms meet or beat forecasts.
2008	Kolev et al.	What are the effects of the SEC interventions on the quality of exclusions from non-GAAP earnings?	Archival study. 104.954 firm-quarter observations from Q2, 1998 through Q3, 2004.	Comparing the quality before and after implementation of SEC interventions.	There is a significant increase in the quality of exclusions from non-GAAP earnings after SEC regulations.
2013	Doyle et al.	Do managers use non-GAAP exclusions to meet or beat analyst forecasts, and what are the effects on the market?	Archival study. 237.617 firm-quarter observations from 1988 through 2009	Regression analysis is performed to find a relation between the use of non-GAAP earnings metrics and the meeting/beating analysts' earnings forecasts.	Firms are more likely to meet or beat analyst forecasts when non-GAAP earnings are higher than GAAP earnings. The market shows lower ERC's for those firms, indicating that they see through the misleading non-GAAP.

2015	Isidro & Marques	What is the influence of countries' institutional and economic factors on non-GAAP disclosures?	Archival study. 1.301 press releases from 316 firms. Fiscal years 2003 through 2007.	Regression analysis is performed to find a relation between institutional and economic factors and the use of non-GAAP earnings metrics.	Managers are more likely to use non-GAAP earnings to meet or beat earnings benchmarks in countries with efficient law and enforcement, strong investor protection, developed financial markets and good communication.
2015	Choi & Young	When are non-GAAP earnings informative or misleading?	Archival study. Firms that are included at least once as the largest 500 firms in the UK in 1993, 1994, 1996, 2001. 3.914 firm-year observations.	Regression analysis is performed to find the incentive for disclosing non-GAAP earnings metrics.	When GAAP exceeded expectations, disclosure probability and transitory items were positively related, and thus informative. When GAAP fell short of expectations, there was a weaker relation, thus strategic.
Financial Analysts					
- **Analyst following**					
1989	Bhushan	What are the main determinants of the number of analyst following a firm?	Archival study. 1.409 firms in 1985.	Regression analysis is performed between analyst following and several variables that might determine analyst following.	Ownership structure of the firm, firm size, return variability of the firm, number of lines of business of the firm, and the correlation between the firm's return and the market return have a significant effect on analyst following.
2001	Barth et al.	What is the relation between analyst following and firms' intangible assets?	Archival study. 10.631 firm-year observations in 1983 through 1994.	Regression analysis is performed between analyst following and several variables that might determine analyst following.	Firms with larger R&D and advertising costs relative to their industry have more analyst following. Analyst following is also higher with firm size, growth, trading volume, equity issuance, and perceived mispricing. Analyst following is lower with size of analysts brokerage house and effort.

- **Analysts' earnings forecast accuracy**					
1988	O'Brien	What are the advantages of different composite forecasts?	Archival study. 508 firms, 3.556 firm-years from 1975 through 1981.	Three different composite forecasts are used to find the most accurate one.	The most current forecast is as accurate as either the mean or median of the forecasts.
1999	Clement	What causes differences in analysts' earnings forecast accuracy?	Archival study. 1.219.979 forecasts of 6.468 analysts for 9.707 firms in the period of 1983 through 1994.	Regression analysis is used to find what causes differences in analysts' earnings forecast accuracy.	Analysts' earnings forecast accuracy increases with experience and employer size. It decreases with number of firms and industries followed.
1999	Jacob et al.	What influences analysts' earnings forecast accuracy?	750.633 forecasts of 3.515 analysts for 4.357 firms in the period from 1981 through 1992.	Regression analysis is used to find what causes differences in analysts' earnings forecast accuracy.	Forecast horizon, number of companies followed, forecast frequency, broker-industry specialization, broker size and outgoing broker-analyst turnover are associated with forecast accuracy.
2001	Brown	How important is past analyst forecast accuracy?	Archival study. 123.670 observations from 1986-1998.	Two different models are used to find which analyst forecasts are most accurate.	The past accuracy model performs as well as the analyst characteristics model.
2003	Brown & Mohd	Can analyst characteristics plus forecast age be used to form a more accurate consensus estimate than one based on forecast age, the control variable of the analyst characteristic models?	Archival study. 172.837 observations from 1987-1999	Regression analysis is used to find which consensus estimate is more accurate.	The model with analyst characteristics does not outperform the model with only forecast age.

-	**After Reg FD**				
2006	Ke & Yu	Do analysts issue biased forecasts to please firm management?	Archival study. U.S.-based analysts. 228.904 firm-analyst-year observations between 1983-2000.	Regression analysis is used to find whether analysts issue biased forecasts.	Analysts who initially issue optimistic forecasts, but pessimistic forecast right before the announcement are less likely to be fired, are more experienced and employed by larger brokerage firms.
2008	Bagnoli et al.	What is the effect of Reg FD on the competitiveness of all-star analysts?	Archival study. Turnover in the top three rankings between 1998 and 2003.	Tests are performed on turnover rates to find whether Reg-FD had an effect on all-stars.	Turnover of analyst increased significantly in the All-American ranking in the year following Reg FD.
2015	Brown et al.	What inputs do analysts use and what incentives do they face when making earnings forecasts and stock recommendations?	Survey. 365 analyst who were active in 2012.	A survey is used to provide insight in the decision-making of analysts.	Private communication with management is a more useful input to analysts' earnings forecasts and stock recommendations than their own primary research. Also issuing earnings forecasts and stock recommendations that are well below the consensus often leads to an increase in analysts' credibility.
2017	Keskek et al.	Has the relation between analyst characteristic and analyst forecast accuracy changed after Reg FD?	Archival study. 150.438 observations from 1995 through 2010.	Regression analysis is used to find a relation between Reg FD and analyst characteristics.	Analyst characteristics are no longer important after Reg FD. Prior year accuracy shows an increase in importance.

Financial Analysts and non-GAAP earnings metrics					
1996	Lang & Lundholm	What are the relations between the disclosure practices of firms, the number of analysts following each firm and properties of the analysts' earnings forecasts?	Archival study. Companies in the United States. 2272 firm-years between 1985-1989	Regression analysis is used to look at the relation between several analyst attributes and the informativeness of disclosures.	Firms with more forthcoming disclosures in their industry have a greater analyst following, more consensus among analysts' earnings forecasts, more accurate forecasts and less variable forecast revisions
2003	Hope	Does the quantity of annual report disclosures have an effect on the accuracy of analysts' earnings forecasts?	Archival study. 1.309 observations of 890 firms of years 1991 and 1993.	Regression analysis is used to look at the relation between analysts' earnings forecast accuracy and the amount of disclosures.	More firm-level disclosures in the annual report leads to higher earnings forecast accuracy.
2009	Lakhal	Does corporate disclosure policy change financial analysts' behaviour?	Archival study. 154 French-listed firms between 1998 and 2001.	Regression analysis is used to look at the relation between several analyst attributes and the disclosure policy of firms.	Voluntary earning disclosures positively influence analyst following. Voluntary disclosures also improve the accuracy of analyst forecasts and reduce market uncertainty.
2012	Dhaliwal et al.	What is the relation between nonfinancial information and analysts' earnings forecast accuracy?	Archival study. 7.108 observations from 1.297 firms in the period from 1994 through 2007.	CSR reports are used as proxy for nonfinancial disclosures to test for their effects on analysts' earnings forecast accuracy.	Using CSR reports as proxy for nonfinancial disclosures, they find that nonfinancial disclosures are related to lower forecast error.
2017	Hamrouni et al.	Does a high-level of voluntary disclosures attract more sell-side analysts?	Archival study. 155 French-listed firms from 2004 through 2012.	Regression analysis is used to look at the relation between analyst following and voluntary disclosures.	The number of analysts increases with the amount of voluntary disclosures.

2004	Frederickson & Miller	Do pro forma disclosures influence analysts' stock price adjustments?	Experiment. 24 M.B.A.s and 18 analysts. Study in the U.S.	Regression analysis of experimental results to find a relation between non-GAAP earnings metrics and investors.	Analysts were not influenced by the disclosing of pro forma earnings, M.B.A.s, which are a proxy for nonprofessional investor, were.
2006	Elliott	Are investors influenced by pro forma emphasis and reconciliations in earnings announcements?	Experiment. 89 M.B.A.s and 55 analysts. Study in the U.S.	Comparison between two (experimental) situations.	Emphasis placed by management on pro forma earnings influences nonprofessional investors' judgments. In case of reconciliation, this effect is mitigated.
2007	Allee et al.	What is the effect of pro forma earnings disclosure on investors with different levels of sophistication	Archival study. 4.928 announcements in the period 1998-2003 in the U.S.	Regression analysis on the relation between non-GAAP earnings metrics and investors.	Existence of pro forma earnings in the announcement affect less-sophisticated investors. More-sophisticated users trade less or in the opposite directions of the earnings surprise. Also emphasis of the pro forma earnings influences less-sophisticated investors but have no influence on more-sophisticated investors.
2007	Andersson & Hellman	Does pro forma reporting bias analyst forecasts?	Experiment. 36 financial analysts. Study concerned a Swedish firm.	Comparison between two (experimental) situations.	Analyst with non-GAAP information made significantly higher forecasts than those with only GAAP information.

9.3 Correlation matrix

Correlation Matrix

N=21.426

	#ANALYSTS	ACCURACY	DISP	NG	ING	SIZE	GROWTH	ADV	RD	EARNSUR
#ANALYSTS	1,0000									
ACCURACY	0,0751*	1,0000								
DISP	-0,0109	-0,2266*	1,0000							
NG	0,1809*	-0,0711*	0,0075	1,0000						
ING	-0.0672*	-0,0038	0,0148**	.	1,0000					
SIZE	0,5901*	0,1875*	0,0485*	0,2530*	-0,0202*	1,0000				
GROWTH	0,0245*	-0,0249*	0,0050	-0,0423*	-0,0189**	-0,0466*	1,0000			
ADV	0,0758*	0,0336*	-0,0251*	0,0302*	-0,0097	0,0329*	0,0014	1,0000		
RD	0,0294*	-0,0925*	0,0104	-0,1588*	-0,0933*	-0,1054	0,1022*	-0,0287*	1,0000	
EARNSUR	-0,0119	-0,0977*	0,0042	0,0035	0,0140	-0,0064	-0,0299*	0,0006	-0,0053	1,0000

Correlation matrix between all dependent, independent and control variables. Variable descriptions are provided in table 1. * indicates significance at the 1% confidence level. ** indicates significance at the 5% confidence level.

9.4 VIF tables

Hypotheses 1, 2 and 3

Variable	VIF	1/VIF
NG	1.12	0.891
SIZE	1.76	0.569
GROWTH	1.03	0.974
ADV	1.05	0.955
RD	1.32	0.760
EARNSUR	1.00	0.999
#ANALYSTS	1.70	0.587

VIF test for hypothesis 1, 2 and 3. Variable descriptions are provided in table 1.

Hypotheses 4, 5 and 6

Variable	VIF	1/VIF
ING	1.07	0.935
SIZE	1.67	0.598
GROWTH	1.03	0.968
ADV	1.05	0.955
RD	1.24	0.809
EARNSUR	1.00	0.998
#ANALYSTS	1.68	0.594

VIF test for hypothesis 4, 5 and 6. Variable descriptions are provided in table 1.