ABSTRACT

Title of dissertation:	ESSAYS ON INFORMATION PRODUCTION AND DIFFUSION IN FINANCIAL MARKETS
	Stefano Collina Doctor of Philosophy, 2019
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This dissertation contains two essays that study the information produced by equity analysts and how the diffusion, or lack thereof, of this information affects financial markets.

In the first essay, "Does the Precision of Equity Analysts Matter? Evidence from the Textual Content of Analysts' Reports", I propose that analyst's precision and opinion jointly explain a range of market outcomes, including returns, volume, and volatility, of the publication of an analyst report. I construct a novel measure of precision based on textual analysis of equity analysts' reports. I find that for pessimistic reports, higher precision is associated with a significantly larger negative price reaction. Moreover, the higher precision is associated with higher abnormal turnover, higher volatility, and lower change in uncertainty. However, precision is not significantly or only weakly correlated with market reaction for optimistic reports. I argue that this dichotomy is a result of the well-known optimism bias of equity analysts and of a tendency of analysts to inflate the precision of more optimistic

reports. I also show that the relation between precision and price reaction varies depending on the information environment and on textual characteristics of the analyst report.

In the second essay, "Information Asymmetry, Agency Conflicts, and the Cost of Capital", I study the causal relation between information asymmetry and the cost of capital employing the exogenous increase in information asymmetry caused by the loss of equity analysts due to brokers' closures or mergers, In particular, I focus on understanding how information asymmetry differentially affects the cost of debt and the cost of equity and how managerial and debt agency conflicts affect this relation. I find that an increase in information asymmetry results in higher cost of equity (debt) when the shock is greater and when incentives to engage in debt-equity wealth transfers are low (high). These results suggest that for some firms, differently from what usually assumed, the cost of debt can actually be more sensitive than the cost of equity. I argue that these findings are consistent with the hypothesis that an information asymmetry increase is not necessarily costly for shareholders, since it can facilitate debt-equity wealth transfers that can reduce equity risk.

ESSAYS ON INFORMATION PRODUCTION AND DIFFUSION IN FINANCIAL MARKETS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2019

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Dedication

To my husband Zeus, for his endless love and support

Acknowledgments

Several people, directly and indirectly, made this dissertation possible and I owe my gratitude to all of them.

First and foremost, I would like to thank Profs. Steve Heston, Laurent Fresard, and Nagpurnanand Prabhala for their availability and for their invaluable guidance and advice. I am also indebted to my other, present and past, dissertation committee members Profs. Maria Cecilia Bustamante, Mark Loewenstein, Russell Wermers, Julien Cujean, and Pablo Slutzky for their help and availability. I also want to extend my gratitude to Prof. John Chao, of the Economics department, for sitting on my committee as Dean's representative and for his valuable comments.

I am also grateful to other faculty members for their advice and feedback. In particular, I would like to thank Profs. Gurdip Bakshi, Francesco D'Acunto, Michael Faulkender, William Mullins, Alberto Rossi, Shrihari Santosh, Geoffrey Tate, Liu Yang as well as all the participants of the finance department brownbag seminars for the helpful comments.

I would also like to thank all the people in the PhD program that have, in different ways, helped me through the years. Thanks to Donald Bowen, Ruyun Feng, Bo Hu, Danmo Lin, and Jinming Xue for their valuable feedback and suggestions. A great thank also to Justina Blanco for her continuous support and help; she is truly irreplaceable.

Finally, my family deserve huge thanks. Thanks to my husband, Zeus, who has continuously cared for, supported, and encouraged me; in the brightest as well as in the darkest times. I feel extremely lucky to have him by my side during this journey. Thanks to my parents who have always believed in me; I would not be here if they had not supported me since I was a little kid. Thanks to all my family and my in-laws, to who is still with us and who has prematurely departed, for their love and support.

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Chapter 1: Does the Precision of Equity Analysts Matter? Evidence from the Textual Content of Analysts' Reports

1.1 Introduction

Equity sell-side analysts have been widely studied in financial and accounting literature. This is unsurprising since analysts play an important role in producing information for financial markets. The research produced by analysts includes numerical or categorical output such as earnings forecasts and buy or sell recommendations. However, analysts also produce extensive textual output in the form of reports. These reports are read and used by market participants to form their expectations and to set prices. In this paper, I focus on the textual output produced by equity analysts.

The primary features of an analyst report, and of any analyst output, are the tone – or analyst's opinion – and the precision. While opinions of analysts and the tone of reports have been objects of research in several works (e.g., Bradshaw 2011; Huang et al. 2014), studies that discuss the precision of a single analyst's output are scarce since analysts largely do not provide any information about their precision. But in models on information diffusion in financial markets (e.g., Kim and Verrecchia 1991; Subramanyam 1996), precision is an important dimension. Precision captures the informativeness of a signal and investors use it to weight an analyst opinion.

This paper studies the precision of equity analyst reports, i.e., the uncertainty and noise of the information contained in an analyst report. I employ textual analysis to construct a measure of precision based on the words present in the text of analysts' reports. This text-based measure can be calculated in a consistent way for any sufficiently-long analyst report and it does not require analysts to provide a numerical measure of precision. I employ the "uncertainty" word list of Loughran and McDonald (2011) to define the measure of precision as the percentage of sentences not containing any of these words. I also use the Loughran and McDonald (2011) dictionaries to construct a measure of tone defined as the difference between the frequency of positive and negative words.

I study the relation between the precision of the information contained in analyst reports and market outcomes, including returns, volume, and volatility, of their publication. Models of information diffusion suggest that investors consider a more precise report to be more informative and thereby place more weight on the analyst report and respond more strongly to its publication. In other words, precision has a multiplicative effect on price reaction, i.e., it amplifies or dampens the investors' response to the publication of a new report.[1] The extent of this relation depends also on the precision of previously held information: A higher precision

[1]Intuitively, the multiplicative nature of the precision effect also means that precision plays a limited role if a report is considered largely uninformative per se (e.g., a non-opinionated report), since the response would be null or weak to begin with.

of priors would mean that a new signal, independently from its precision, is less important for investors and that, as a result, these reports would be weighted less and priors weighted more. All of these would lead to report's precision being less important. A further result of information diffusion models is that precision has a similar multiplicative effect on such other measures of market reaction as volume and volatility.

A key limitation of these arguments is their assumption that investors observe the true, undistorted opinion and precision of the analyst. The well-known optimism bias of analysts means that optimistic opinions are considered of limited informativeness per se and, more generally, that the informativeness of a report depends on its degree of bias in addition to its precision.[2] In other words, a more precise, especially optimistic, report may be not significantly more informative if it is also highly or more biased. Furthermore, investors only observe a noisy and possibly distorted signal about precision. Thus, a more precise report could be not more informative if the signal about precision is distorted upward, i.e., if analysts, consciously or not, inflate the precision of their information and, hence, the signal poorly reflects the true precision. Moreover, the main argument assumes that investors have unlimited attention and are able to fully assess the precision of an analyst report. Instead, investors may not pay attention or may pay extra attention to just some reports or to just some parts of these, resulting in a weaker (or stronger) relation between precision and investors' reaction for them.

[2] For example, see Lin and McNichols (1998), Michaely and Womack (1999), Jackson (2005), Barber et al. (2007)

Following the above arguments, I hypothesize that the precision of an analyst report is positively related to the magnitude of the price and market reaction to its publication. I also argue that the relation between price reaction and precision as well as the stronger price reaction to more precise reports are not quickly reversed, as non-informational trading theories (e.g., DeLong et al. 1990; Tetlock 2007, 2011) would imply. I also hypothesize that the relation between precision and price and market reaction is weaker for optimistic reports because of the optimism bias of analysts. For instance, Womack (1996) and Malmendier and Shantikumar (2007) show that investors consider optimistic analysts' opinions to have limited informativeness and that they weakly react to them. I also hypothesize that this weaker relation for optimistic reports is driven by the existence of a positive correlation between report textual precision and report tone, suggesting that textual precision is inflated for more positive reports and that it does not fully reflect true precision.

I also test whether the relation between precision and price reaction is stronger for reports issued during periods of higher firm uncertainty. Indeed, besides the aforementioned role of the precision of priors, this relation could arise because investors pay more attention to analysts' output when uncertainty is higher (Loh and Stulz 2017). The relation between precision and price reaction should also depend on what part of the report is used to measure the report's tone and precision. Specifically, I argue that a strong tone at the beginning of a report would drive the investors' attention away from the rest of the report, resulting in a weaker role of precision. The last portion of a report, often employed to discuss risks and model assumptions, could better capture the precision perceived by limited-attention investors and better explain their reaction to the publication of a new report.

My sample comprises of analyst reports regarding 290 S&P500 firms published between 2003 and 2015. I study the relation between precision and price reaction, defined as the cumulative abnormal returns between the day the report was issued and one to six trading days afterward. I also study abnormal turnover, realized volatility, and change in the implied volatility of at-the-money options with 30 days to maturity.

I focus on reports published on days when the analyst issued an earnings forecast in order to exclude reports that may be deemed not important by investors and, hence, that may not be read by several investors. For the main analysis, I also exclude any report published in the five days centered around earnings announcements or management guidance issuance, in order to avoid capturing the reaction to major overlapping events. I sort each report into three *Tone* categories: pessimistic (bottom 25th percentile), neutral, and optimistic (top 25th percentile). Furthermore, for each month, I also sort each of these reports into three *Precision* categories: low (bottom sextile), medium, and high precision (top sextile).

I observe that precision peaks on days when earnings or management guidance are announced, while it decreased sharply during the 2008-2009 financial crisis. These results suggest that the measure is related to the availability of clear and high-quality information about a firm. Consistent with the idea that precision also captures firm-level uncertainty, I find that precision is related to idiosyncratic volatility and other proxies such as firm size and number of analysts covering the firm. I also find a positive relation between precision and tone, i.e., optimistic reports are disproportionately more highly precise and disproportionately less lowly precise than pessimistic ones. This relation suggests that analysts inflate the precision of more optimistic reports, possibly to embellish them.

I also find that precision is positively related to the ex-post accuracy of the simultaneously issued earnings forecasts, i.e., more precise reports also appear to be more accurate. However, I find that high precision is weakly related to higher accuracy for more optimistic reports; this is consistent with the idea that analysts inflate their precision for these reports.

I find an economically and statistically significant relation between price reaction and precision for pessimistic reports. Indeed, high precision is associated with a larger negative price reaction of between 40 and 95 bps than low precision, depending on time horizon and empirical specification. On the other hand, this relation, as well as the overall price reaction, is largely insignificant for optimistic reports. This finding is consistent with the idea that investors, at least partially, see through the optimism bias and precision inflation of optimistic reports and, hence, discount them accordingly. These results, especially for longer horizons, are robust to alternative *Precision* sorting, to using stricter definitions of included dates, and to controlling for report topics. I also find that the magnitude of the difference in price reaction is larger for the longer horizons and that the price reaction to highly precise pessimistic reports is largely unchanged, even at horizons of one trading week or longer. The absence of a significant reversal is consistent with the idea that the larger price reaction is due to a higher informativeness and not only due to overreaction driven by sentiment or behavioral-biases-induced trading (e.g., Tetlock

2007, 2011).

I also find a relation similar to the one between precision and price reaction for other measures of market reaction. Indeed, higher precision is associated with a significantly higher abnormal turnover and with higher realized volatility, suggesting that the publication of higher quality reports is associated with increased market activity. On a different note, I find that greater precision is associated with a smaller change in implied volatility, suggesting that more precise reports are associated with a reduction or, at least, no increase in uncertainty. As observed for price reaction, all these relations appear to be especially significant for pessimistic reports.

I also find that the relation between price reaction and precision is stronger when firm uncertainty is higher. Indeed, the difference in price reaction between high and low precision pessimistic reports is around 1 percent higher when idiosyncratic volatility is above the median. Consistent with theoretical models, this finding can be explained by the fact that a highly precise signal is particularly valuable when uncertainty about a firm is higher, i.e., when its relative precision is also high. Furthermore, this result is also consistent with the fact that investors pay more attention to analysts during periods of higher uncertainty (Loh and Stulz 2017) and hence they are able to better discern the degree of precision of the reports.

Consistent with the hypothesis that investors' attention could affect the relation between informativeness and precision, I observe that the portion of an analyst report used to measure tone and precision matters. The relation between precision and price reaction is weaker if the tone is calculated based on the first 30 sentences. This result suggests that investors pay less attention to report precision when the beginning of a report displays a strong opinion. This is especially true for pessimistic reports since strong negative opinions could be interpreted by investors as a good-enough signal (Joos and Piotroski 2016). Instead, especially at longer horizons, I find that the relation is stronger if precision is measured based on the last 30 sentences of the reports. Indeed, for long reports, the last pages often contain information that is of direct use for assessing precision (e.g., discussions about risk or modeling choices); limited-attention investors may focus specifically on these parts.

1.1.1 Literature and Contributions

My main contribution is to the literature about the informativeness of analyst reports and, more generally, to that of professional financial forecasters. Consistently with both the literature that claims that analysts do not produce informative output (e.g., Altınkılıc et al. 2009, 2013) and research that argues that analysts produce valuable content (e.g., Bradley et al. 2014; Li et al. 2015), I find that a sizable number of reports are largely uninformative, but also that some reports, especially highly precise pessimistic reports, contain useful information. Indeed, I observe that the publication of these latter reports is associated with a significant and persistent larger price reaction and, more generally, market reaction (abnormal turnover and volatility). In particular, I show that informativeness varies not only along a measure of analyst opinion (e.g., Womack 1996), but also along a measure of analyst precision. These results suggest that the research studying the informativeness of analysts' output should take into account both the analyst's opinion and the analyst's precision. These findings also suggest that analysts' precision is a variable of interest for researchers using analysts' output to answer broader questions, such as the literature that uses analysts' disappearance as a shock to information asymmetry (e.g., Kelly and Ljungqvist 2012; Derrien and Kecskec 2013), since analysts' precision is related to the value of this output for investors.

I also bring new evidence to the literature about the characteristics of analysts' output. While earnings forecasts and recommendations have been largely analyzed in existing literature, there is limited research about analysts' reports. We have very limited knowledge of the characteristics of analysts' precision. Similarly to what observed by Joos and Piotroski (2016) about the "alternative scenarios" provided by some brokers, I find that precision is related to a series of firm characteristics related to uncertainty as well as to ex-post earnings forecast accuracy. However, I also find that (textual) precision is correlated with optimism, suggesting that not are only analysts' opinions distorted upward (e.g., McNichols and O'Brien 1997), but also that precision is characterized by a similar distortion for more optimistic opinions. A better knowledge of analyst reports is especially important given the industry trend toward a business model where investors have to directly purchase these reports.

This study also contributes to the growing literature about the textual content of analysts' reports. Current literature has focused on the tone of analysts' reports (Asquith et al. 2005; Huang et al. 2014), their novelty with respect to conference calls (Huang et al. 2017), and the use of misleading wording (Bellstam 2017). My work adds results concerning the degree of precision or uncertainty that stems from the text of analysts' reports. This measure captures a more general definition of uncertainty than measures of "assertiveness" (Huang et al. 2014) and "weaseling" (Bellstam 2017). Moreover, I provide further evidence concerning the existence of a significant relation between the textual content of analysts' reports and different market variables, such as turnover, realized volatility, and implied volatility, besides the commonly used price reaction. Finally, differently from part of the existing research, I show the importance of identifying what part of analysts' reports is employed to calculate textual measures. Indeed, my results vary depending on whether the full text or only some specific parts are employed, consistent also with the idea that investors' limited attention plays a role in the relation between textual content and investors' reaction.

Finally, this paper contributes to the literature about uncertainty in financial and accounting documents. Existing research has studied uncertainty in documents produced by management such as 10-Ks (Loughran and McDonald 2011), IPO-related filings (Loughran and McDonald 2013), earnings announcements (Demers and Vega 2014), and earnings conference calls (Huang et al. 2017). I show that textual analysis and, specifically, the dictionaries of Loughran and McDonalds (2011) can be used to measure uncertainty in analysts' reports. My results also suggest that the same methodology can be extended to other information produced by media or professional forecasters such as credit analysts.

The rest of the paper is structured as follows. In Section 2, I present my main hypotheses. Section 3 focuses on the construction of my data, while Section 4 discusses the construction of the textual measures as well as their characteristics.

Section 5 discusses the main results concerning the relation between precision and price reaction and Section 6 discusses the relation with other market variables. In Section 7, I study the price reaction precision relation varies and in Section 8, I present some robustness results. Finally, I conclude the paper in Section 9.

1.2 Hypotheses Development

While much of the existing literature has focused on the point estimates produced by equity analysts, precision also matters (e.g., Kim and Verrecchia 1991; Subramanyam 1996). Bayesian investors use precision to "weight" a signal they receive about a stochastic payoff, such as firm fundamentals. Investors place more weight on signals that are more precise and, hence, more informative. A consequence is that the magnitude of the price reaction to a signal about firm fundamentals, such as an analyst report, is increasing in its precision. Precision has a multiplicative effect on the price reaction to the publication of a report: High precision amplifies this reaction and low precision dampens it.[3] Intuitively, this multiplicative effect also means that precision plays a limited role when the signal is perceived to be not informative per se, such as a non-opinionated report, since the price reaction is null or weak to begin with.

Hypothesis 1: The magnitude of the price reaction to an analyst report publication is increasing in its precision.

Much of the literature about the relation between analysts output and returns (e.g., Huang et al. 2014) focuses on very short-term market reaction measures. I also examine longer horizons in order to distinguish between informational trading and sentiment or behavioral-driven trading (Tetlock 2007, 2011; Heston and Sinha 2017). Indeed, theories suggest that substantial price reaction can be generated

[3] In other words, report's precision "modulates" the relation between tone and investors' response.

in the short term by sentiment trading (e.g., DeLong et al. 1990 or Campbell et al. 1993), by behavioral-biases-induced trading (e.g., overconfidence, Barberis 2018) or by salience (e.g., Merton 1987 with Duffie 2010), these reactions, however, are reversed at longer horizons. For instance, existing literature has observed that, particularly less sophisticated, investors overreact to bad news (Tetlock 2007) or to stale information (Tetlock 2011); in these scenarios, returns are fully reversed or almost reversed within a trading week.

Consistent with this argument, if more precise reports are actually more informative, then their effect on prices should not be very short lived. Similarly, the relation between precision and price reaction should not disappear within a few trading days horizon.

Hypothesis 1a: The relation between price reaction and precision is not reversed within a trading week.

Theoretical models suggest that precision is related not only to price reaction but also to other measures of market reaction. For instance, Kim and Verrecchia (1991) argue that precision is positively related to both trading volume[4] and volatility (as in variance of price change); the higher the quality of the information released, the stronger the reaction of traders. In other words, both turnover and volatility should, at least temporarily, increase after more precise information is released. However, it is worth pointing out that volume cannot be employed to rule out sentiment or behavioral motives since theory suggests that they also produce substantial volume (e.g., Tetlock 2007).

[4] The main assumption is that there is disagreement about precision before the information is released.

Hypothesis 1b: Turnover and stock volatility reaction to an analyst report publication are increasing in its precision.

One of the main assumptions behind the previous hypotheses is that the reports reflect the actual expectations of the analysts, i.e., there is no bias in their opinions. This assumption means that, for instance, optimistic reports actually reflect optimistic information. However, existing literature about equity analysts has highlighted the existence of an optimism bias of analysts (e.g., McNichols and O'Brien 1997; Michaely and Womack 1999) that has partially persisted even after regulations were implemented in the early 2000s (e.g., Jackson 2005, Barber et al. 2007). Furthermore, literature has highlighted the fact that investors are able to see through the bias and, accordingly, heavily discount and react less strongly to optimistic opinions (Womack 1996; Malmendier and Shantikumar 2007; Huang et al. 2014).

The existence of this bias means that optimistic reports may actually reflect only neutral or weakly positive information. For instance, Malmendier and Shantikumar (2007) found that sophisticated investors treat positive stock recommendations as neutral. In this case, the analyst opinion itself would be considered by investors not particularly informative and precision, given the multiplicative nature of its effect, would play a limited role.

Another main assumption is that investors know the true precision of the signal. However, investors only observe a noisy signal about the precision of the signal, for instance, from the text of the report. My results highlight the existence of a positive correlation between the report's textual precision and the report's tone: Optimistic and, to a lesser extent, neutral reports appear to be more precise than pessimistic ones. This correlation suggests that analysts, consciously or as a result of "overprecision" (Moore and Healy 2008), inflate the precision of their reports when they are more optimistic. Consequently, more (textually) precise optimistic reports are not necessarily more precise and more informative. Investors who can see through this precision inflation will discount the observed precision and will not react more strongly.

Hypothesis 2: The relation between price reaction and report precision is weaker for optimistic reports.

The previous hypothesis concerning volume and volatility can be generally extended to account for this dichotomy between optimistic and pessimistic reports. In particular, if the signal about precision that investors receive is of poor quality due to precision inflation, then the relation between precision and volume or volatility should be similar to the relation between precisions and price reaction, i.e., less strong. However, it is also worth mentioning that, even if the relation with price reaction is weaker, this is not necessarily true for volume; an increase in volume can also be spurred by disagreement about the interpretation of a signal (e.g., Kandel and Person 1995, Kim and Verrecchia 1994, 1997).

Hypothesis 2a: The relation between volume or volatility and report precision is weaker for optimistic reports.

Investors' reactions to a signal depend not only on the precision of the signal but also on the precision of their priors. When uncertainty is low and investors have prior information that is highly precise, signals are generally not valuable and investors put more weight on their priors. Thus, investors largely ignore new signals and signal's precision, as well as its multiplicative effect, matter less. In other words, the magnitude of the relation between price reaction and precision is increasing in uncertainty[5].

The relation between precision and price reaction may also be affected by

[5]For instance, in Subramanyam (1996) the sensitivity of price reaction to precision is decreasing in the precision of the payoff of the risky asset

investors' attention. A now quite extensive line of accounting and finance research has highlighted the role that inattention plays in explaining different empirical facts (Barberis 2018). Since analysts largely do not provide information about their precision, investors have to read and analyze their reports to understand how precise they are. An inattentive investor may not be able to fully capture the degree of a report's precision and, hence, not react according to it. For instance, research has highlighted that investors pay more attention to financial information (Ouimet and Tate 2017) and, specifically, to analysts' output (Loh and Stulz 2017) in periods of higher uncertainty.

Hypothesis 3b: The relation between price reaction and report precision is stronger when firm uncertainty is higher.

The fact that investors' attention plays a role in the relation between price reaction and report content suggests that stylistic characteristics of the reports may affect the price reaction to differentially precise reports. Indeed, recent papers have shown that text characteristics (e.g., Huang et al. 2014; Zhou 2018) affect investors' reaction to new information. In particular, part of this research has highlighted the importance of focusing on some specific parts of a text such as the title or headline (e.g., Huang et al. 2014; Umar 2017) since investors may focus their attention only on these.

Some reports produced by analysts are significantly long; investors with limited-attention may focus only on specific parts of these. For instance, the first page or two usually represents a summary of the analyst's opinion. Limited-attentive investors may focus specifically on this part of the report to gauge the analyst's opinion. If the tone is strong enough, the investors may partially disregard its precision. This phenomenon is particularly important for pessimistic opinions, since a strong negative opinion could already be considered highly informative (Joos et al. 2016).

Hypothesis 4a: The relation between price reaction and report precision is *weaker if the analyst displays a strong opinion, especially a pessimistic opinion, at the beginning of the report.*

The ending part of reports often contains conclusions, discussions about modeling choices, risks involved with the forecast, and general firm characteristics. Limited-attentive investors may focus specifically on this last part of the report to gauge the report's precision, since this is the part where analysts are more prone to discuss the uncertainty surrounding their analysis. In other words, the last part of the report may better capture the report's degree of precision and, possibly, the precision perceived by limited-attentive investors.

Hypothesis 4b: The relation between price reaction and report precision is stronger if precision is measured based on the ending of the report.

Here it is important to mention that attention may also play a role against this hypothesis. Indeed, inattentive and less sophisticated investors may just focus on the first part and disregard the ending of these longer reports. In this scenario, the relation may be actually weaker.

1.3 Data

I start with all non-financial firms that are in the S&P500 at the end of 2015 or were in the S&P500 for at least four years during the period between 2003 and 2015. The choice of the starting date is two-fold. First, I will base my full analysis on a post-RegFD and post-Global Research Settlement period. Second, the quality of textual data in older reports is lower since many are just scanned copies; hence, it is hard to extract the text. I obtain equity analysts reports from the Thomson One Investext database. This database is not comprehensive since not all brokers are included for all the periods, but it covers a significant part of the universe of reports.[6] I also exclude firms with fewer than 100 reports. Firms appear in the

[6] My assumption is that my reports sample is representative of the whole universe. At the best of my knowledge, there is no reason why it should not be.

Thomson One database with name, ticker and CUSIP. Since CUSIP is the most reliable identifier, I use it to match reports to other data. However, Thomson One does not store the CUSIP for all firms. To be conservative, I exclude firms for which Thomson One does not report the CUSIP.[7] This selection leaves me with 290 firms for which data is ample and easy to match with other sources.

I match the reports to I/B/E/S brokers and analyst names[8] as well as to further data about the recommendation and forecasts they issued during the sample period. It is possible to match approximately 95% of the available reports via Investext. I use this matched database to construct my final sample. In particular, I focus on reports published on days when an analyst issued an annual earnings forecast.[9] The idea is to exclude reports that could be considered not particularly important and that are probably only read by a limited number of investors. I further exclude reports that are either too short for a reliable textual analysis or for which it is not feasible to extract the textual content; the result is a final sample of approximately 115,000 reports. Before computing the textual measures, I clear from these reports all disclaimer sections, numerical tables, and other parts that do not contain relevant content, such as contact information.

I obtain S&P500 components as well as stock returns data from CRSP. Balance sheet data is obtained from Compustat. Information about earnings announcements, management guidance announcements, and other data about analysts and brokers is obtained from I/B/E/S. Information about analysts' awards is obtained from issues of *Euromoney*. The economic uncertainty index is obtained from *policyuncertainty.com*.

[7]Matching data via names is feasible for some firms, but not always reliable.

[8]See Appendix B for more details about sample construction

[9]If quarter forecasts are used, the results are largely similar (around 90% are issued contemporaneously with annual forecasts), but the sample is smaller. Results are also largely similar if recommendation-only reports or reports issued within two days from the forecast issuance are included

1.4 Textual Measures

1.4.1 Precision

It is possible to obtain firm-level measures of uncertainty based on the forecasts issued by multiple analysts, such as the dispersion of analysts' forecasts (Diether et al. 2002; Johnson 2004; Zhang 2006). However, it is difficult to measure the precision of a specific forecast or opinion. Analysts largely provide only point forecasts or categorical recommendations and not the confidence interval of these. An exception is the "alternative scenarios" framework for earnings or target prices, usually a "bull" and a "bear" scenario, that some brokers (such as Morgan Stanley and Barclays) have started to provide in some of their reports. The major problems are that these measures are available only for a few brokers and that their actual implementation varies even within the same broker. Furthermore, even if the range of scenarios appears to be correlated with firm uncertainty (Joos and Piotroski 2016), these scenarios appear often to be used to display how strongly optimistic the analyst is. The scenarios also appear to be characterized by the same optimism bias of point estimates (Joos and Piotroski 2017), i.e., high certainty about positive outcomes mainly tends to reflect a large bias.

In this paper, I propose a novel, text-based measure of precision of analysts' reports. The benefit of using a text-based methodology is that it can be employed to measure precision consistently. Also, It does not rely on analysts providing some numerical measure of precision. No assumption is required regarding whether investors pay attention to, are familiar with, and are able to interpret specific parts of these reports, as is the case with measures like "alternative scenarios". To the best of my knowledge, this is the first paper that proposes a report-level measure of analysts' precision with such characteristics.

It is worth mentioning here two papers that introduced text-based measures related to precision and how these differ from the measure suggested in this paper. The first is the measure of "assertiveness" suggested by Huang et al. (2014). While it is reasonable to assume some correlation between assertiveness and precision, this measure is mainly geared toward identifying reports using a strong language (employing words like "lowest," "never," and "strongly") and, hence, reports that want to convey a particularly strong optimistic or pessimistic opinion.[10] The second is the measure of analysts' "weaseling" introduced by Bellstam (2017), i.e., a measure of how extensively an analyst uses elusive and possibly misleading language. While there is some overlap between what can be classified as weaseling and what can be classified as uncertainty (Zerva et al. 2017), weaseling could, for instance, be used to "soften" the language. More importantly, lack of precision is expressed in other ways, not just via weaseling.

To construct my measure of precision, I use a "bag-of-words" methodology.[11] This methodology relies on the creation of a "dictionary" of words that convey some particular message and on the construction of a measure based on the frequency of these words. To measure precision, I rely on the financial dictionaries proposed by Loughran and McDonald (2011). Specifically, I use their "uncertainty" dictionary, i.e., a set of words that are usually associated with different aspects of uncertainty. For instance, this dictionary has been used to study uncertainty in 10-Ks (Loughran and McDonald 2011), IPO-related filings (Loughran and McDonald 2013), earnings announcements (Demers and Vega 2014), and earnings conference calls (Huang et al. 2017).[12]

I identify sentences that contain any of these uncertainty words and define

[10]Xiao and and Zang (2017) finds a strong relation between assertiveness and strong opinions.

[11]For examples of papers using a similar approach, see Tetlock (2007), Loughran and McDonald (2011), and Huang et al. (2014)

[12]Demers and Vega (2014) is methodologically the closest to my paper. Indeed, the authors use textual measures of optimism and uncertainty to study whether they explain the price reaction to earnings announcements.

precision as one minus the frequency of these sentences.[13]

$PrecisionC = 1 - \frac{UncertainSentences}{TotalSentences}$

Appendix C contains some examples of paragraphs containing multiple sentences with uncertainty words. It is interesting to notice that some reports have sections specifically aimed at discussing uncertainty factors potentially affecting their estimates and valuations.

1.4.2 Tone

To construct a measure of the report's tone, I choose a text-based measure. Specifically, I use the Loughran and McDonald (2011) financial dictionaries to identify positive and negative words. I define tone as the difference between the frequency of positive and negative words. Similar results are obtained by using the differences in frequencies relative to the total number of positive and negative words.

$ToneC = \frac{PosWords - NegWords}{TotalWords}$

I classify the reports into three bins based on this measure of tone. I classify reports as pessimistic if in the bottom 25th percentile, as optimistic if in the top 25th percentile and as neutral if between the 25th and 75th percentiles. The choice of the thresholds assures that reports classified as pessimistic or optimistic really reflect a significantly negative or positive view about a firm[14]. I obtain similar results if the threshold for optimistic reports is chosen in order to mirror the tone threshold for pessimistic reports.

Summary statistics about the two measures are reported in Table 1 (Panel A). It is interesting to note that the positive median suggests that $ToneC$ tends to be positive more frequently than negative, even if my sample includes the period during and around the 2008-2009 financial crisis. This result is consistent with the

[13] I use sentences since it is the primary language unit to express an opinion (Huang et al. 2014) and, given the low frequency of these uncertainty words, it produces a less noisy measure. The results are similar if words frequency is used, especially if a stricter constraint on minimum number of words is applied.

[14] Cumulative abnormal returns are non-significant for pessimistic-leaning reports and significant only for very short horizons for optimistic-leaning reports

idea that analysts are disproportionately optimistic.

1.4.3 Determinants of Precision

I examine how the measure of precision ($PrecisionC$) varies across time and cross-sectionally.

I examine whether precision varies along the business cycle and across the earnings reporting cycle. It is reasonable to expect that precision is higher when macro uncertainty is low as well as when management has recently released valuable information such as earnings or guidance. In these time periods, analysts have access to more information about a firm and, hence, their reports should be more precise.

It is interesting to point out that the precision measure appears to have an upward trend, i.e., the precision of analysts' reports has increased over time. This is unimportant for the main results since my precision sorting is made within a month.

Figure 1 shows the average precision around days when earnings or management guidance are announced. Consistently with the previous argument, it can be observed that precision peaks on those dates and, then, starts to decrease in the following days. The results are even more striking if looking at the frequency of high or low precision, i.e., the frequency of reports whose precision is in the top or bottom sextile. Figure 1 also reports these results and shows that, while the frequency of high precision reports peaks on those dates, the frequency of low precision reports reaches its minimum. To summarize, the results suggest that, indeed, analysts' reports appear to be more precise right after analysts obtain information about a firm.

Figure 2 shows the average value of the detrended precision measure. It shows that precision dipped between late 2008 and early 2009, i.e., at the height of the global financial crisis. This is consistent with the argument that higher macro uncertainty should lead to lower precision. Interestingly, the dip is mainly driven by neutral and, particularly, by optimistic reports. This is not surprising since it is reasonable to assume that uncertainty was particularly high for any non-negative forecast.

I next examine the cross-sectional determinants of precision. I run a series of regressions of my measure on month fixed effects as well as on industry, analyst, and firm fixed effects. The results are reported in Table 2. First it is interesting to note that both time, industry, and firm fixed effects explain only a small fraction of the variation in precision. The analyst fixed effect appears to explain a significant part of the variation in precision, around 30 percent. This result suggests that some analysts are more precise than others due to certain characteristics or a particular writing style.

Given these results, I investigate what firm characteristics and, especially, what analyst characteristics are related to precision. Table 3 presents a series of results for regressions of the precision measure on different firm, analyst, and opinion characteristics. Different sets of fixed effects are included as well as a control for days close to earnings/guidance announcements. First, the results suggest that there is a positive relation between the number of analysts covering a firm and precision. This could be explained by the fact that firms covered by several analysts are usually characterized by lower uncertainty since more information is available to the markets. I also observe a significant and negative coefficient for idiosyncratic volatility.[15] This result is not surprising and it confirms that analyst precision varies with firm uncertainty.

The second set of results concerns characteristics of the analyst. There is a clear and positive relation with analysts' absolute experience, i.e., more experienced analysts appear to issue more precise reports. This result goes hand in hand with the idea that experience is related to forecasting performance (e.g., Clement 1999). The negative relation between broker size and precision is instead puzzling. These

[15] Idiosyncratic volatility is the standard deviation of the residuals of fitting a Fama-French plus momentum model.

results further confirm the need to include analysts fixed effects.

I also estimate similar specifications for analysts' opinion characteristics: boldness (deviation from consensus), staleness (cosine similarity with reports about the same firm published in the previous 90 days), and tone. "Bold" reports are associated with higher precision, suggesting that analysts write more precise reports when in possession of some private information that is not in line with consensus. A similar conclusion can also be drawn by the strong negative relation with staleness of the report, suggesting that analysts' precision does not stem purely from herding. I also examine the relation between precision and the incidence of numbers in a report; I find a strong positive relation, suggesting that more precise reports are indeed more quantitative in nature. This result is consistent with the results of Zhou (2018) for corporate disclosures and with the idea that a lack of numbers is used to mask uncertainty about a statement or forecast.

An equally interesting result is the strong relation between tone and precision. Particularly, optimistic tone is associated with a precision that is between 2.7% and 3.8% higher than that of pessimistic reports.[16] In other words, optimistic reports appear to be disproportionately more precise, while pessimistic reports appear to be disproportionately less precise. Given the well-known optimism bias of analysts, these results suggest the possible existence of a second layer of distortion. Indeed, when producing more optimistic reports, analysts appear to inflate the precision of their information. This behavior is consistent with the idea that there are incentives for analysts to produce flattering and strong reports (e.g., Lin and McNichols 1998; Hong and Kubik 2003; Barber et al. 2007), while downplaying pessimistic opinions.

Table 4 reports regressions where two dummies are used to identify reports

[16] The definition of tone as used here is slightly different from that used in the rest of the paper due to the fact that a small subset of words appear in both the "negative" and "uncertain" lists (e.g., the word "volatile"). To avoid capturing any by-construction effect, I exclude these words when calculating the measure of tone used here. Not surprisingly, the results are marginally stronger if they are included.

in the top or bottom sextile in terms of precision. The results of the linear probability models are again largely consistent with what was previously found about the relation between precision and the different firm, analyst, and report characteristics. Particularly striking is the result for the difference between pessimistic and optimistic reports, where there is a difference of 5-6 percent in the probability of a report being in one of the top/bottom categories. Given a baseline probability of observing a highly or lowly precise report of around 17 percent, this means that the probability of optimistic reports being of high (low) precision is 30-35 percent higher (lower) than pessimistic reports.

1.4.4 Precision and Ex-Post Accuracy

The previous subsections focused on questions concerning the cross-sectional and time-series determinants of precision. I now examine the relation between precision and ex-post accuracy.

Table 5 (Panel A) reports the results of a series of regressions for different measures of earnings forecasts error and standardized $PrecisionC$ as well as for a series of controls for analyst and firm characteristics (e.g., Stickel 1992 ; Clement 1999), and for forecast age (Brown and Mohd 2003).[17] Regardless of the measure used, the results suggest that precision and forecast error are negatively related. For instance, one standard deviation increase in precision is associated with smaller earnings-per-share errors of around 1 cent. Table 5 (Panel B) reports similar results

[17] Forecast error is equal to forecast EPS minus actual EPS. "Scaled" means scaled by stock price. "Proportional" means as a proportion of the average forecast error of all forecasts. "Relative" means relative to average forecast error of all forecasts issued in the previous or next 90 days, scaled by forecast standard deviation.

where the previously defined high/low precision dummies are employed as well as their interaction with the $Tone$ variable. High precision is associated with smaller forecast error and, albeit at a lower extent, low precision is associated with higher forecast error. However, this relation is much weaker and, generally, not statistically significant for optimistic and, to a lesser extent, neutral reports. In other words, high precision optimistic reports do not appear be much more accurate than medium precision reports and, for some specifications, than low precision ones. This empirical evidence is again consistent with the idea that the precision of optimistic reports is somewhat inflated.

Finally, Table 6 reports some other results for the relation between $Tone$, forecast error, and bias. First, neutral and optimistic reports appear to be significantly more positively biased than pessimistic reports, suggesting that the well-known optimism bias of analysts' forecasts also extends to the textual content of their reports. Second, neutral and optimistic reports appear overall to be more accurate ex-post. This result is consistent with the finding of Xiao and Zang (2017) that analysts tend not to incorporate into the earnings forecasts the negative information discussed in the reports, resulting in a larger forecast error.

1.5 Analyst Precision, Price Reaction, and Report Informativeness

The main question this paper tries to answer is whether there is a relation between the analysts' report precision, the magnitude of the price reaction to its publication, and, more generally, the informativeness of the output they produce.

Following existing finance and accounting literature, I use abnormal returns around the issuance of an analyst report to measure price reaction and, more generally, the report's informativeness. To avoid capturing the effect of overlapping events, I excluded from the empirical specifications all the reports published in the five trading days centered on earnings announcements and management guidance days. Other corporate news is published in other periods, but earnings announcements and guidance (as well as leaks happening the days before) are definitely the major sources of information on which analysts can piggyback.

I study the relation between cumulative abnormal returns that are calculated for different horizons around the issuance of an analyst reports, and two categorical variables: $Tone$ and $Precision$. I run the following empirical specification for each report j about firm i published at time t:

$$CAR[t, t+n]_{i,t,j} =$$

$$\alpha + \beta Tone_j + \gamma Precision_j + \delta Tone_j \times Precision_j + \mathbf{v} Controls_{i,j,t} + \epsilon_{i,j,t}$$

CARs are estimated using the Carhart (1997) model for $n = 1, 2, 4, 6$.[18] The $Tone$ measure is constructed as previously defined, s.t. it is equal to 0, 1, or 2 for, respectively, neutral, pessimistic and optimistic reports. $Precision$ is constructed based on a monthly sort of the $PrecisionC$ measure previously defined in three bins; reports in the bottom sextile are classified as low precision, reports in the top sextile as high precision and all other reports as medium precision. $Precision$ is equal to 0, 1 or 2 for, respectively, low, medium or high precision.

The list of control variables is reported in Appendix A; control variables vary depending on the specification and also include the interactions between these variables and both $Tone$ and $Precision$. The controls includes different firm and analysts characteristics related to investors' reaction as well as a control for overall

[18] Results are stronger if using a simple market model

uncertainty (Baker et al. 2016).[19] All variables are winsorized at 1 percent and, excluding prior-CAR and analyst opinion change variables, are standardized. Summary statistics for the non-standardized variables are reported in Table 1 (Panel B). All regressions also include fixed effects; specifically I use analyst-firm pair fixed effect. Results are comparable if using analyst and firm fixed effects.

Table 7 reports the results of variations of this specification. The first two columns include fixed effects as well as the aforementioned controls. Column 2, in particular, includes also controls for the change in recommendation or change in earnings forecasts. Differently, column 3 includes no controls or fixed effects.

First, it is important to notice that $Tone$ is, at least at the shorter horizons, a predictor of the direction the market moves, consistent with Huang et al. (2014). More interesting is the result for the interaction between $Tone$ and $Precision$. Consistently with the first hypothesis, at the two-day horizon and for pessimistic reports, the interaction coefficient is significant and between -40 and -47 bps. This result suggests that high precision is associated with a significantly stronger price reaction - and, hence, with report informativeness - for pessimistic reports. The interaction coefficient rises by about 50 percent at the three-day horizon. The results are stronger when fixed-effects are included, suggesting that the variation in precision within analyst-firm matters more.

I do not observe a significant relation for positive reports, where precision appears to have a largely non-significant effect of, at best, around 6 bps. This result is consistent with the second hypothesis that the presence of overoptimism as well as an inflation in precision for optimistic reports results in textual precision not being a strong predictor of report informativeness. The interpretation is that investors, at least partially, "see through" these systematic distortions and discount

[19] For examples, see Stickel (1995), Gleason and Lee (2003), Jegadeesh and Kim (2010), and Loh and Stulz (2011)

the analysts' opinion and precision accordingly. Generally speaking, and consistent with the literature about analysts' bias, the price reaction to optimistic reports appears to be limited.

Table 8 reports the results for longer CAR horizons: five and seven days, respectively. The results are largely similar, but the magnitude of the precision effect for pessimistic reports tends to be greater. The price reaction for highly precise pessimistic reports appears to be unchanged within a trading week and only slightly lower at the longer seven-day horizon. These results support the hypothesis that the price reaction to highly precise reports and the relation between price reaction and precision are not short-lived and are not immediately reversed, suggesting that more precise pessimistic reports are indeed more informative. On the other hand, the price reaction to low precision pessimistic reports is significant only at very short horizons. This result suggests that while investors appear to trade according to report precision, there is some degree of overreaction to these low precision pessimistic reports, similar to what has been observed in literature about news and sentiment (e.g., Tetlock 2007).

As a robustness check, Table 9 reports the results where reports are sorted into precision classification based on quartiles instead of sextiles. The results are again largely consistent with the main results, just slightly weaker in terms of magnitude, and are consistent with the fact that the difference in precision is smaller. In particular, the price reaction to highly precise pessimistic reports is unchanged even at the longest horizon. Furthermore, although not reported, these main results are also robust when running separate regressions for pessimistic and optimistic reports.

1.6 Analyst Precision, Turnover, and Volatility

The previous section established a relationship between report precision and price reaction, especially for more pessimistic reports. In this section, I investigate whether precision is related to volume and volatility. I test the hypothesis that the diffusion of more precise information is associated with higher volume and volatility.

1.6.1 Precision and Turnover

I calculate abnormal turnover as the difference between the log turnover and the average log turnover in the five days before the report is issued. The results, especially for pessimistic reports, are largely similar, if not stronger, if a longer window is used to calculate the average or if the predicted value from a regression of log turnover on market log turnover is used instead of the average (Umar 2017).

Specifically, I run the following empirical specification for each report j about firm i published at time t:

$$CAT[t, t+n]_{i,t,j} =$$

$$\alpha + \beta Tone_j + \gamma Precision_j + \delta Tone_j \times Precision_j + \mathbf{v}Controls_{i,j,t} + \epsilon_{i,j,t}$$

Where CAT is Cumulative Abnormal Turnover and is calculated for $n = 1, 2, 4, 6$. Controls are the same as in the main specification plus the abnormal turnover in the prior five trading days. For the longer five and seven-day horizons, I also provide the results excluding any observation whose event window overlaps with earnings or guidance announcements.[20]

Table 10 reports the results. At the two-day horizon, the coefficient of the interaction between $Tone$ and $Precision$ is significant between 0.13 and 0.15, suggesting that higher precision is associated with larger turnover. Similar to what was observed for the price reaction, there is also a dichotomy between pessimistic and

[20]The robustness check section discusses this potential issue for the main price reaction result

optimistic reports; high precision pessimistic reports are associated with a stronger and longer lasting market reaction than are high precision optimistic reports. Indeed, abnormal turnover for optimistic reports is significant only in the first two trading days and the results for these reports are not very robust to alternative specifications.

1.6.2 Precision and Volatility

I next study the relation between precision and stock volatility. I estimate the following empirical specification for each report j about firm i published at time t:

$$CSAR[t, t+n]_{i,t,j} =$$
$$\alpha + \beta Tone_j + \gamma Precision_j + \delta Tone_j \times Precision_j + \mathbf{v}Controls_{i,j,t} + \epsilon_{i,j,t}$$

Where $CSAR$ is the sum of squared abnormal returns and was calculated for $n = 1, 2, 4, 6$. Controls are the same as in the main specification and idiosyncratic volatility. As for the turnover specifications, for the longer five and seven-day horizons, I also provide the results excluding any observation whose event window overlaps with earnings or guidance announcements.[21]

The results are reported in Table 11. At the two days horizon, the interaction coefficient between *Tone* and *Precision* is positive and significant for pessimistic report. This result suggests that high precision is associated with an increase in stock volatility and increased market activity around the issuance of these more precise reports. As observed for price reaction, the phenomenon is non-significant for optimistic ones.

[21] The results for the two to three-day horizons are slightly stronger if the same restriction is applied

Next I calculate the change in the implied volatility of 30-day standardized at-the-money options from OptionMetrics around the publication of an analyst report. Following existing literature (e.g., Billings et al. 2015), I calculate the average of the implied volatility of call and put options. Specifically I define abnormal volatility as the difference between the natural log of implied volatility at different horizons after a report's publication and the log implied volatility two days before the publication date.

Table 12 reports the results of a series of empirical specifications similar to the previous ones but for this measure of abnormal implied volatility. Besides the covariates included in previous specifications, I also control for market change in volatility by using the change in VIX in the same period. I also restrict the sample such that there is no overlap between any earning/guidance announcement and the event window - even at longer horizons - since the former can have a significant effect on uncertainty.[22] The results suggest the existence of a negative and significant relation between precision and volatility for pessimistic reports. Albeit not statistically significant, the results also suggest the existence of a similar relation for neutral reports. On the other hand, similar to what has been observed for other specifications, the effect appears to be largely non-significant for optimistic reports. To summarize, the diffusion of highly precise pessimistic reports is associated with a smaller increase in firm uncertainty or even a partial resolution of it.[23]

1.7 Variation in the Relation between Precision and Price Reaction

An interesting question is whether the results observed in the previous section

[22] The results are largely similar if this restriction is not applied.

[23] I take an agnostic approach regarding the overall effect of the publication of a report on firm uncertainty. While in a purely Bayesian framework a new signal would always decrease uncertainty, it is possible that new information increases uncertainty if perceived as premonitory of future possible surprises (e.g., Rogers et al. 2009).

vary. I focus on two main factors that could affect the relative informativeness of highly precise reports. First, the reaction to highly precise reports will tend to depend on the general information environment. Precise reports are more valuable particularly if uncertainty about a firm is high, while investors can just rely on their priors and public information when uncertainty is low. Second, I test whether the effect of precision is greater when investors are more attentive to the whole report text. While the analyst opinion can be obtained from published numerical outputs, precision requires the reading of the entire report. Therefore, precision should play a bigger role when precision or tone are obtained from specific parts of the report text.

1.7.1 Precision and Firm Uncertainty

An interesting question is how analyst precision interact with overall firm-level uncertainty. To identify periods of high or low firm uncertainty, I estimate idiosyncratic volatility as the standard deviation of the residuals of the aforementioned Carhart (1997) model. Then, I classify a report as being produced during a period of low firm uncertainty if idiosyncratic volatility is below the median [24]. The $FirmU$ dummy variable takes value 0 if the observation corresponds to a period of low firm uncertainty as previously defined. Specifically, I ran the following specification for each report j about firm i published at time t:

$$CAR[t,t+n]_{i,t,j} =$$

$$\alpha + \beta Tone_j + \gamma Precision_j + \delta Tone_j \times Precision_j + \zeta Tone_j \times FirmU_{i,t} +$$

$$\eta Precision_j \times FirmU_{i,t} + \theta Tone_j \times Precision_j \times FirmU_{i,t} + \mathbf{v}Controls_{i,j,t} + \epsilon_{i,j,t}$$

Differently from the main specification, I sort $Precision$ according to quartiles

[24] The results are conceptually the same if I use quartiles, but significance is affected due to lower power. Results are also quantitatively similar, albeit smaller in magnitude, if observations are sorted within year.

instead of sextiles. This choice allows me to reduce possible issues related to power or to a small set of observations driving the results. The results are similar, especially at the longer horizons, to ones obtained using sextiles, but minimum bin size is significantly larger: The smallest bin, low uncertainty-low precision-optimistic, contains around 500 observations.

Table 13 reports the results for different horizons, where the interactions between the control variables and the $FirmU$ dummy are added as controls. These results are largely consistent with the hypothesis, when they are pessimistic. Indeed, higher firm uncertainty is associated with a larger effect of precision for pessimistic reports of between 70 and 150 bps. Table 14 reports the results for similar empirical specifications where analysts' disagreement is used instead of idiosyncratic volatility. This measure has been used in the literature as a measure of uncertainty (e.g., Johnson 2004); not surprisingly, it is correlated with volatility. The results, albeit weaker, are largely consistent with the ones obtained using the $FirmU$ dummy.

1.7.2 Tone, Precision, and Sentence Position

My main analysis takes an agnostic view regarding where the positive or negative words are located as well where the sentences containing uncertainty words are positioned. Here I run empirical specifications similar to the main ones, but I change the portion of the report used to calculate tone and precision. Indeed, consistently with the idea of limited-attentive investors, it is possible to hypothesize that the effects of these two variables should be stronger if calculated based on specific parts of the report. On one hand, the beginning of a report usually consists of a summary of the analyst's opinion. A strong opinion, especially one that is pessimistic, [25], would make investors focus on this and place less importance on precision. On

[25] A pessimistic opinion could be perceived as highly informative per se (Joos et al. 2016).

the other hand, the endings of longer reports are usually employed by analysts to discuss the forecasting models, risks and uncertainties concerning these along with general discussions about firm characteristics and trends. In other words, investors with limited attention would focus on this part to gauge the level of precision.

I focus on the first 30 sentences of each report to calculate an alternative measure of $Tone$ and the last 30 sentences to calculate an alternative measure of $Precision$. These correspond, respectively, to approximately the first and last two pages of a report.[26] It is important to point out that all thresholds for tone and precision classification are the same as those used in the main specifications.

Table 15 reports the results where tone from the first 30 sentences is used, while precision is the same used in the main specification. The results are qualitatively similar, but, consistent with the hypothesis, the precision effect for pessimistic reports is significantly weaker at around 15-20 bps. A strong opinion at the beginning of a report sways the attention of investors away from precision. Alternatively, a strong negative tone in the beginning of the report is perceived as a signal that the analyst has some strong information and precision becomes somewhat less relevant. A possible issue is that, by using just the first 30 sentences, some pessimistic or optimistic reports are mislabeled as neutral. While part of the weaker results can be ascribed to this, unreported regressions on only pessimistic reports suggest that the effect of precision is indeed weaker, especially at shorter horizons.

Table 16 reports the results where precision from the last 30 sentences is used, while tone is the same used in the main specification. The results for the longer four, seven-day and, especially, two-week horizons are stronger than in the main specification.[27] This result suggests that the last part of the report is the section that better measures (perceived) precision. However, at shorter horizons, the relation

[26] Choosing a higher threshold (40-50), yields results closer to the main results.

[27] The interaction coefficient is only marginally statistically significant at this latter horizon for the main specification.

between price reaction and precision is actually weaker than the relation in the main specification. This result could stem from some inattentive investors ignoring the concluding parts of the reports, instead of focusing on them. These investors' choices would, hence, lead to some overreaction to low precision reports.

1.8 Robustness

In this section, I present the results of checks for robustness checks for the main price reaction results.

1.8.1 Alternative Restrictions to Observations

In the main results, I follow existing literature and exclude days around earnings announcements and around the issuance of management guidance. While these are the major groups of possibly problematic events, there could be other confounding news events. In this subsection, I define three progressively stricter definitions of possible confounders. First, I exclude any observation on days when more than 50 percent of the analysts covering a firm issued a forecast. For the second definition, I exclude days when more than five analysts issued a forecast, i.e., corresponding to 20-30 percent of analysts issued a forecast. For the last and most conservative forecast, I focus only on days where no more than three analysts issued a forecast, i.e., 10-20 percent.[28] In these two restrictions, I also exclude days when more than one analyst changed a recommendation since these usually occur due to firm news (Loh and Stulz 2011).

The results for all the restrictions are reported in Table 17. The first additional restriction has a relatively small effect on both the magnitude and significance of the main results. The effect of using the two more restrictive definition is stronger, but the results are still statistically significant at the three, five, and seven-day horizons. In particular, the effect of the restrictions is larger for shorter horizons compared to the effect for longer ones, suggesting that when analyst activity is limited, investors

[28] The results are similar in magnitude, but noisier, when using a two analysts threshold.

take more time to process the information about report precision.

1.8.2 Longer Horizons and Overlapping Events

In the main results, I exclude reports issued fewer than three days before earnings or management guidance announcements. This choice does not prevent a partial overlap between these events and the longer horizons' five and seven-day event windows. On one hand, this helps in understanding whether informativeness and not just sentiment varies along with the precision measure. Indeed, earnings or guidance announcements should tend to reverse any short-term non-informational price reaction. On the other hand, it makes it harder to properly separate the price reaction in response to the report publication from the price reaction to these major corporate news announcements.

Table 18 reports the results for the longer five and seven-day horizons where only reports published at least seven days before an earnings/guidance announcement are included. The results are nearly identical to the ones obtained with the full sample. It is also worth mentioning that this also largely holds for other empirical specifications for price reaction, such as the ones presented in previous section.

1.8.3 Crisis and Tone Thresholds

The construction of the $Tone$ variable assumes that the threshold between pessimistic, neutral, and optimistic reports is fixed across time. However, as aforementioned, it is reasonable to assume that the signal communicated by a neutral report could vary across time. Existing literature (e.g. Malmendier and Shantikumar 2007) has highlighted the fact that neutral opinions of analysts are considered as mildly negative signals by larger traders and positive ones are considered as neutral, due to the well-known optimistic bias of analysts. This should perhaps be especially true during periods of crisis.

I run an alternative version of the main specification where I classify neutral reports as pessimistic and optimistic reports as neutral if issued during “bad times”. I use NBER recession dates to identify “bad times” in my sample. Specifically, the period between December 2007 and June 2009 is classified as such.

The results, reported in Table 19, are actually stronger than the main results. High precision effect for pessimistic reports jumps to 75-99 bps depending on the horizon. Furthermore, even medium precision is associated with a generally significant, albeit smaller, effect of around 30-40 bps, or around half the effect observed for high precision.

1.8.4 Anomalous Measures

While the large majority of observations take a wide range of values for $ToneC$ and $PrecisionC$, some observations have extreme values. In particular, some reports have a value of precision equal to 1, suggesting that there was no sentence containing uncertain words. Similarly, some reports contains no positive or negative words. While these values could actually reflect the characteristics of the reports, they may correspond to reports not actually discussing a firm. I estimate the same main price reaction specifications but exclude these observations. Results are reported in Table 20 and, despite the smaller sample, are largely equivalent. This suggests that neither of these two groups of possibly anomalous measures is driving the results.

1.8.5 Alternative Precision Sorting

In the main specification, the $Precision$ categorical variable is constructed based on monthly sorting. Here, I present results where the high and low precision thresholds are constructed based on all the reports published in the previous 30 days. In other words, the sorting is based only on reports accesible to investors at the time a report was issued. The results are reported in the first part of Table

21 and are largely equivalent to the baseline ones. Furthermore, in the second part of Table 21, I report results for the same sample where also $Tone$ is constructed in a similar manner based on previously issued reports and where I also exclude fixed effects. While slightly weaker at some horizons, the results are again largely consistent with the baseline ones.

1.9 Conclusions

In this paper, I study the relation between the precision of the textual content of equity analysts' report and the informativeness of those reports. In particular, I study whether the magnitude of the price, and more generally market, reaction to the publication of a report is increasing in report precision. I test whether investors put more "weight" on more precise reports and whether the price reaction is greater for highly precise optimistic or pessimistic reports. Because this relation could be negatively affected by analysts' distortions and biases as well as by investors' priors, I hypothesize that the relation between price reaction and precision is weaker when an analyst's opinion and precision are more strongly distorted and when investors' priors are more precise. Finally, I test whether due to investors' limited attention, the placement of sentences within a report affects investors' ability to correctly process the information and, as a consequence, the precision effect.

To measure precision at the analyst report level, I employ textual analysis to construct a novel, text-based measure of precision. I find that precision is related to different proxies for firm uncertainty such as idiosyncratic volatility, the availability of high quality information about a firm (e.g., days when earnings are announced) as well as to the ex-post accuracy of earnings forecasts. Precision is also positively correlated with the sentiment (tone) of the report, i.e., more optimistic reports also appear to be more precise. This finding suggests that analysts inflate the precision of more positive reports, possibly as a result of their well-known distorted incentives to produce flattering reports.

I find that high precision is associated with a larger and persistent price reaction for pessimistic reports, suggesting that more precise reports are also more informative. I also find that high precision is associated with higher abnormal turnover, higher realized volatility, and a smaller change in implied volatility. All these results support the hypothesis that highly precise pessimistic report are associated with increased market activity.

On the other hand, I find a weak and largely non-significant relation for the more biased optimistic reports. These results suggest that investors are at least partially able to see through the analysts' distortions and consequently discount their opinions and their reports' textual precision accordingly.

Concerning pessimistic reports, I also find that the relation between precision and price reaction is stronger for reports issued during periods of higher uncertainty. This result for firm uncertainty is consistent with the argument that investors put limited weight on analysts reports when their prior information is highly precise. Furthermore, this finding is also consistent with the idea that investors pay more attention to analysts during these periods and, hence, are better able to assess their precision.

Finally, I observe a relation between the effect of precision on price reaction and the part of an analyst report used to measure tone or precision; this relation is consistent with the idea that limited-attention affects the relation between precision and investors' reaction. Indeed, I find that the relation is weaker when tone is measured based on the first 30 sentences of a report, but it is stronger when precision is measured based on the last 30 sentences. I argue that these results are due to (1) investors focusing mainly on tone and less on precision when it is strongly presented in the first part of the report or (2) investors focusing on parts of the reports, such as the ending, that more often contain direct information about the risks related to the analysts' estimates.

This study provides evidence about the characteristics of analysts' precision as well as the relation between precision and financial markets, but it also opens several questions for future research. First, it would be interesting to have a better understanding of how precision is related to other variables and how it is affected by incentive, regulatory, or macroeconomic factors. This is particularly interesting because the industry is moving toward a business model where investors must purchase reports and, hence, the ability to value a report is key. More generally, this can provide further information about what characteristics or incentives drive the production of high or low informativeness ouput in financial markets. In other work in progress, I provide further evidence about how precision and precision determinants changed after the implementation of the Global Research Settlement and related regulations (e.g., Kadan et al. 2009, Guan et al. 2017, Corwin et al. 2017).

It would also be interesting to employ machine learning and natural language processing to improve the understanding of analyst precision as well as to refine the textual measure of precision. For instance, in Appendix D, I use a Latent Dirilecht Allocation (LDA) algorithm to provide results concerning the relation between precision, market outcomes, and the topics of the reports. In other work in progress, I am working on a naive Bayes classifier to obtain a measure of precision that does not depend on a predefined dictionary. It would also be interesting to use similar classification algorithms to obtain measures capturing different types of (lack of) precision.

Finally, it would be interesting to employ the same methodology to study the output produced and disseminated by other information providers such as media or, especially, credit analysts. I leave this to future work.

1.10 Tables

Table 1.1: **Summary Statistics**
This table reports summary statistics about the two textual measures as well as several of the covariates used in the analyses. Definitions of the variables are presented in Appendix A.

PANEL A

	Mean	StDev	25th	Median	75th
ToneC	0.003	0.021	-0.009	0.003	0.016
PrecisionC	0.738	0.12	0.667	0.75	0.824
Observations	98,914				

PANEL B

	Mean	StDev	25th	Median	75th
Size	9.26	1.25	8.36	9.18	10.15
Book-to-Market	0.41	0.26	0.23	0.35	0.54
Policy Uncertainty	119.84	45.75	87.42	108.51	146.12
Length	3.85	0.88	3.18	3.76	4.42
Broker Size	3.95	0.8	3.33	4.14	4.58
Number of Analysts	2.94	0.44	2.71	3	3.26
Absolute Experience	3.75	0.91	3.26	3.97	4.48
Relative Experience	2.52	1.26	1.79	2.77	3.47
Deviation from Consensus	-0.01	0.2	-0.02	0	0.02
ABS(Deviation from Consensus)	0.09	0.21	0.01	0.02	0.06
Observations	98,914				

Table 1.2: **Precision Fixed Effects**
This table reports the percentage of variance in Precision explained by different fixed effects. Industry is Fama-French 12 industries.

VARIABLES	(1) PrecisionC	(2) PrecisionC	(3) PrecisionC	(4) PrecisionC	(5) PrecisionC
Observations	98,914	98,914	98,832	98,914	98,038
Adjusted R-squared	0.019	0.026	0.320	0.062	0.383
Month FE	YES	YES	YES	YES	YES
Industry FE	NO	YES	NO	NO	NO
Analyst FE	NO	NO	YES	NO	NO
Firm FE	NO	NO	NO	YES	NO
Analyst-Firm FE	NO	NO	NO	NO	YES

Table 1.3: **Precision Determinants**

This table reports the results of different regressions of Precision (in percentage points) on a set of different firm and analysts characteristics. Earnings is a dummy equal to one if the report is published within two days from an earnings or management guidance announcement. Staleness is the maximum cosine similarity between a report and any report published about the same firm in the previous 90 days. Standard errors are double clustered at analyst and firm level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) PrecisionC	(2) PrecisionC	(3) PrecisionC	(4) PrecisionC	(5) PrecisionC	(6) PrecisionC
Size	-0.067	0.141	-0.117			
	(-0.38)	(1.26)	(-0.24)			
Book-to-Market	-0.154	-0.205**	-0.094			
	(-1.00)	(-1.98)	(-0.73)			
Id Volatility	-0.968***	-0.787***	-0.336***			
	(-7.31)	(-8.55)	(-3.83)			
Number of Analysts	0.404**	-0.177	-0.061			
	(2.48)	(-1.65)	(-0.43)			
Absolute Experience				0.674***	0.527***	-1.104
				(3.14)	(2.65)	(-0.56)
Relative Experience				0.238	-0.001	1.750
				(1.20)	(-0.01)	(1.42)
Broker Size				-0.892***	-0.777***	-0.350
				(-4.53)	(-3.79)	(-1.18)
Observations	98,914	98,832	98,038	98,459	98,459	97,620
Adjusted R-squared	0.008	0.359	0.419	0.010	0.106	0.413
Earnings	NO	YES	YES	NO	YES	YES
Month FE	NO	YES	YES	NO	YES	NO
Analyst FE	NO	YES	NO	NO	NO	NO
Firm FE	NO	NO	NO	NO	YES	NO
Analyst-Firm FE	NO	NO	YES	NO	NO	YES

	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	PrecisionC	PrecisionC	PrecisionC	PrecisionC	PrecisionC	PrecisionC
Abs(Dev Consensus)	0.163	0.234***	0.178***			
	(1.37)	(3.58)	(3.30)			
Pessimistic	-1.944***	-1.366***	-1.228***			
	(-9.45)	(-7.57)	(-10.67)			
Optimistic	1.909***	1.618***	1.453***			
	(8.72)	(9.37)	(13.86)			
Staleness				-1.840***	-1.707***	-1.198***
				(-13.01)	(-12.80)	(-14.43)
Log(# of numbers)				2.344***	1.791***	1.689***
				(14.05)	(11.78)	(16.68)
Observations	98,914	98,914	98,038	94,699	94,699	93,837
Adjusted R-squared	0.013	0.108	0.424	0.038	0.123	0.431
Earnings	NO	YES	YES	NO	YES	YES
Month FE	NO	YES	YES	NO	YES	YES
Analyst FE	NO	NO	NO	NO	NO	NO
Firm FE	NO	YES	NO	NO	YES	NO
Analyst-Firm FE	NO	NO	YES	NO	NO	YES

Table 1.4: **High and Low Precision Determinants**
This table reports the results of different regressions of High Precision and Low Precision dummy variables on a set of different firm and analysts characteristics. High (Low) is equal to one if PrecisionC is in the top (bottom) sextile. Earnings is a dummy equal to one if the report is published within two days from an earnings or management guidance announcement. Staleness is the maximum cosine similarity between a report and any report published about the same firm in the previous 90 days. Standard errors are double clustered at analyst and firm level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) High Precision	(2) High Precision	(3) Low Precision	(4) Low Precision
Size	0.009**	0.002	0.003	0.002
	(2.07)	(0.12)	(0.62)	(0.17)
Book-to-Market	-0.005	-0.005	-0.003	-0.005
	(-1.43)	(-1.45)	(-0.78)	(-1.38)
Id Volatility	-0.013***	-0.004*	0.015***	0.008***
	(-4.06)	(-1.82)	(4.10)	(2.84)
Number of Analysts	-0.003	0.002	-0.007*	-0.001
	(-0.75)	(0.55)	(-1.80)	(-0.32)
Absolute Experience	0.012**	-0.050	-0.009*	-0.113
	(2.36)	(-0.34)	(-1.87)	(-0.88)
Relative Experience	0.003	0.055	-0.002	-0.025
	(0.61)	(1.45)	(-0.38)	(-0.59)
Broker Size	-0.024***	-0.009	0.018***	0.010
	(-4.81)	(-1.22)	(3.49)	(1.23)
Abs(Dev Consensus)	0.007***	0.001	-0.006***	-0.005***
	(3.34)	(0.55)	(-2.91)	(-3.05)
Staleness	-0.049***	-0.039***	0.025***	0.018***
	(-13.21)	(-15.45)	(8.13)	(8.00)
Log(# of numbers)	0.017***	0.008***	-0.058***	-0.057***
	(3.82)	(2.66)	(-15.51)	(-19.14)
Pessimistic	-0.018***	-0.013***	0.035***	0.026***
	(-3.92)	(-4.03)	(6.24)	(6.74)
Optimistic	0.046***	0.038***	-0.032***	-0.028***
	(8.40)	(10.39)	(-6.51)	(-8.71)
Observations	94,265	93,440	94,265	93,440
Adjusted R-squared	0.045	0.248	0.061	0.258
Earnings	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Analyst-Firm FE	NO	YES	NO	YES

Table 1.5: **Precision and Ex-Post Accuracy**

This table reports the results of regressions of different measures of earnings forecast accuracy on Precision. Panel A includes the standardized value of Precision, while Panel B contains two dummies for High (Low) Precision. Controls include size, B/M, number of analysts, idiosyncratic volatility, absolute and relative analyst experience, deviation from consensus, broker size, and distance from earnings announcement. Standard errors are double clustered at analyst and firm level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A VARIABLES	(1) Abs Error	(2) Abs Error (Scaled)	(3) Proportional Abs Error (Scaled)	(4) Relative Abs Error
PrecisionC (standardized)	-0.012***	-0.048***	-0.029***	-0.014***
	(-2.72)	(-2.60)	(-6.44)	(-3.84)
Observations	97,539	97,539	97,539	97,539
Adjusted R-squared	0.352	0.273	0.237	0.081
Year FE	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Panel B VARIABLES	(1) Abs Error (Scaled)	(2) Proportional Abs Error (Scaled)	(3) Relative Abs Error
High Precision	-0.090***	-0.051***	-0.045***
	(-3.43)	(-4.20)	(-2.99)
Low Precision	0.029	0.021*	0.025
	(1.06)	(1.76)	(1.56)
Neutral×High Precision	0.063**	0.038***	0.029
	(2.09)	(2.65)	(1.65)
Optimistic×High Precision	0.077**	0.036**	0.035*
	(2.32)	(2.25)	(1.90)
Neutral×Low Precision	0.008	0.004	0.006
	(0.32)	(0.30)	(0.35)
Optimistic×Low Precision	0.010	0.014	0.012
	(0.33)	(0.86)	(0.59)
Observations	97,539	97,539	97,539
Adjusted R-squared	0.524	0.294	0.075
Year FE	YES	YES	YES
Analyst-Firm FE	YES	YES	YES
Controls	YES	YES	YES

Table 1.6: **Tone, Bias, and Ex-Post Accuracy**
This table reports the results of regressions of different measures of bias and earnings forecasts accuracy on Tone. Controls include size, B/M, number of analysts, idiosyncratic volatility, absolute and relative analyst experience, deviation from consensus, broker size, and distance from earnings announcement. Standard errors are double clustered at analyst and firm level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Error	(2) Error (Scaled)	(3) Abs Error	(4) Propor. Abs Error (Scaled)	(5) Propor. Abs Error (Scaled)	(6) Relative Abs Error
Neutral	0.039***	0.137***	-0.016***	-0.086***	-0.026***	0.007
	(4.89)	(4.50)	(-3.68)	(-6.23)	(-3.48)	(0.81)
Optimistic	0.080***	0.230***	-0.025***	-0.127***	-0.061***	-0.016
	(7.10)	(5.49)	(-3.91)	(-6.89)	(-6.15)	(-1.58)
Observations	97,539	97,539	97,539	97,539	97,539	97,539
Adjusted R-squared	0.202	0.192	0.478	0.544	0.294	0.075
Year FE	YES	YES	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Table 1.7: **Price Reaction and Analyst Report Precision**
This table reports the relation between price reaction (Cumulative Abnormal Returns multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,1]	(3) CAR[0,1]	(4) CAR[0,2]	(5) CAR[0,2]	(6) CAR[0,2]
Tone = 1, Pessimistic	-0.442***	-0.250	-0.563***	-0.268	-0.081	-0.467***
	(-2.77)	(-1.59)	(-4.45)	(-1.47)	(-0.45)	(-3.24)
Tone = 2, Optimistic	0.417**	0.290	0.357**	0.363*	0.229	0.275*
	(2.13)	(1.57)	(2.34)	(1.74)	(1.13)	(1.77)
Precision = 1, Medium	-0.165	-0.147	-0.095	-0.099	-0.081	-0.038
	(-1.42)	(-1.29)	(-1.09)	(-0.77)	(-0.64)	(-0.39)
Precision = 2, High	-0.219	-0.218	-0.132	-0.127	-0.125	-0.099
	(-1.52)	(-1.53)	(-1.22)	(-0.80)	(-0.80)	(-0.88)
Pessimistic×Medium	**-0.176**	**-0.224**	**-0.133**	**-0.266**	**-0.309**	**-0.148**
	(-0.99)	**(-1.28)**	**(-0.89)**	**(-1.31)**	**(-1.53)**	**(-0.86)**
Pessimistic×High	**-0.395**	**-0.466***	**-0.342**	**-0.609****	**-0.677*****	**-0.491****
	(-1.63)	**(-1.96)**	**(-1.52)**	**(-2.30)**	**(-2.59)**	**(-2.07)**
Optimistic×Medium	**0.028**	**0.043**	**-0.075**	**-0.029**	**-0.014**	**-0.046**
	(0.13)	**(0.21)**	**(-0.44)**	**(-0.13)**	**(-0.07)**	**(-0.27)**
Optimistic×High	**-0.070**	**-0.062**	**-0.133**	**-0.050**	**-0.049**	**-0.000**
	(-0.32)	**(-0.29)**	**(-0.66)**	**(-0.21)**	**(-0.21)**	**(-0.00)**
Observations	21,361	21,361	21,361	21,361	21,361	21,361
R-squared	0.216	0.236	0.013	0.205	0.222	0.009
Controls	YES	YES	NO	YES	YES	NO
Rev Controls	NO	YES	NO	NO	YES	NO
Analyst-Firm FE	YES	YES	NO	YES	YES	NO

Table 1.8: **Price Reaction and Analyst Report Precision - Longer Horizons**

This table reports the relation between price reaction (Cumulative Abnormal Returns multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,4]	(2) CAR[0,4]	(3) CAR[0,4]	(4) CAR[0,6]	(5) CAR[0,6]	(6) CAR[0,6]
Tone = 1, Pessimistic	-0.207	-0.042	-0.515***	0.144	0.303	-0.224
	(-0.96)	(-0.19)	(-2.78)	(0.58)	(1.22)	(-1.10)
Tone = 2, Optimistic	0.253	0.115	0.179	0.224	0.118	0.254
	(0.96)	(0.45)	(0.89)	(0.75)	(0.41)	(1.15)
Precision = 1, Medium	-0.140	-0.125	-0.168	-0.066	-0.055	-0.037
	(-0.99)	(-0.89)	(-1.40)	(-0.38)	(-0.32)	(-0.26)
Precision = 2, High	-0.146	-0.140	-0.166	-0.036	-0.030	0.027
	(-0.78)	(-0.76)	(-1.20)	(-0.16)	(-0.14)	(0.16)
Pessimistic×Medium	**-0.152**	**-0.175**	**0.029**	**-0.376**	**-0.393**	**-0.175**
	(-0.64)	**(-0.74)**	**(0.13)**	**(-1.35)**	**(-1.41)**	**(-0.73)**
Pessimistic×High	**-0.627****	**-0.697****	**-0.466**	**-0.882****	**-0.959*****	**-0.722****
	(-1.98)	**(-2.23)**	**(-1.61)**	**(-2.48)**	**(-2.70)**	**(-2.20)**
Optimistic×Medium	**0.122**	**0.130**	**0.042**	**-0.023**	**-0.019**	**-0.180**
	(0.44)	**(0.48)**	**(0.19)**	**(-0.08)**	**(-0.06)**	**(-0.76)**
Optimistic×High	**0.055**	**0.049**	**-0.061**	**-0.110**	**-0.097**	**-0.347**
	(0.18)	**(0.16)**	**(-0.23)**	**(-0.32)**	**(-0.28)**	**(-1.22)**
Observations	21,361	21,361	21,361	21,361	21,361	21,361
R-squared	0.201	0.212	0.005	0.199	0.206	0.002
Controls	YES	YES	NO	YES	YES	NO
Rev Controls	NO	YES	NO	NO	YES	NO
Analyst-Firm FE	YES	YES	NO	YES	YES	NO

Table 1.9: **Price Reaction and Analyst Report Precision - Precision Quartiles**

This table reports the relation between price reaction (Cumulative Abnormal Returns multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly quartiles. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.338**	-0.191	-0.184	0.097
	(-2.45)	(-1.24)	(-1.03)	(0.46)
Tone = 2, Optimistic	0.274*	0.173	0.121	0.102
	(1.84)	(1.06)	(0.61)	(0.42)
Precision = 1, Medium	-0.087	-0.049	-0.140	-0.062
	(-0.83)	(-0.43)	(-1.09)	(-0.42)
Precision = 2, High	-0.084	-0.009	-0.106	0.006
	(-0.73)	(-0.07)	(-0.70)	(0.04)
Pessimistic×Medium	**-0.074**	**-0.121**	**0.111**	**0.008**
	(-0.44)	**(-0.64)**	**(0.51)**	**(0.03)**
Pessimistic×High	**-0.393****	**-0.576*****	**-0.613****	**-0.935*****
	(-2.02)	**(-2.66)**	**(-2.35)**	**(-3.05)**
Optimistic×Medium	**0.132**	**0.117**	**0.237**	**0.118**
	(0.83)	**(0.68)**	**(1.08)**	**(0.46)**
Optimistic×High	**-0.118**	**-0.084**	**-0.096**	**-0.251**
	(-0.65)	**(-0.44)**	**(-0.39)**	**(-0.85)**
Observations	21,361	21,361	21,361	21,361
R-squared	0.235	0.221	0.213	0.207
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.10: **Turnover and Analyst Report Precision**
This table reports the relation between turnover (Cumulative Abnormal log Turnover) response to the publication of an analyst report and its precision. Abnormal log turnover is measured as the difference between log turnover and the average log turnover in the previous five trading days. "NOLH" excludes observations whose 7 days event window overlap with an earnings or guidance announcement. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, prior-CAT, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CAT[0,1]	CAT[0,2]	CAT[0,4]	CAT[0,4]	CAT[0,6]	CAT[0,6]
Tone = 1, Pessimistic	-0.059*	-0.092**	-0.132*	-0.177**	-0.130	-0.198*
	(-1.77)	(-2.07)	(-1.84)	(-2.23)	(-1.33)	(-1.85)
Tone = 2, Optimistic	-0.065	-0.048	-0.036	-0.002	-0.011	0.020
	(-1.60)	(-0.86)	(-0.41)	(-0.02)	(-0.09)	(0.16)
Precision = 1, Medium	0.021	0.037	0.074	0.031	0.077	0.008
	(0.72)	(0.94)	(1.20)	(0.45)	(0.93)	(0.09)
Precision = 2, High	-0.022	-0.026	-0.030	-0.054	-0.067	-0.124
	(-0.60)	(-0.52)	(-0.40)	(-0.65)	(-0.64)	(-1.10)
Pessimistic×Medium	**0.071***	**0.109****	**0.146***	**0.198****	**0.147**	**0.221***
	(1.93)	**(2.20)**	**(1.87)**	**(2.30)**	**(1.38)**	**(1.89)**
Pessimistic×High	**0.151*****	**0.232*****	**0.344*****	**0.376*****	**0.389*****	**0.464*****
	(3.14)	**(3.59)**	**(3.44)**	**(3.46)**	**(2.87)**	**(3.15)**
Optimistic×Medium	**0.031**	**0.036**	**0.029**	**0.004**	**0.031**	**0.007**
	(0.75)	**(0.61)**	**(0.32)**	**(0.04)**	**(0.25)**	**(0.05)**
Optimistic×High	**0.134*****	**0.157****	**0.198***	**0.178**	**0.213**	**0.231**
	(2.75)	**(2.29)**	**(1.87)**	**(1.54)**	**(1.43)**	**(1.44)**
Observations	21,255	21,255	21,255	18,519	21,255	18,519
R-squared	0.263	0.259	0.268	0.281	0.284	0.293
NOLH			NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES	YES	YES

Table 1.11: **Volatility and Analyst Report Precision - Realized Volatility**
This table reports the relation between realized volatility (Cumulative Squared Abnormal Returns, multiplied by 100) response to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. "NOLH" excludes observations whose 7 days event window overlap with an earnings or guidance announcement. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, report length, and idiosyncratic volatility. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CSR[0,1]	(2) CSR[0,2]	(3) CSR[0,4]	(4) CSR[0,4]	(5) CSR[0,6]	(6) CSR[0,6]
Tone = 1, Pessimistic	-0.024	-0.018	0.012	-0.028	0.026	-0.017
	(-1.63)	(-1.16)	(0.54)	(-1.41)	(1.01)	(-0.76)
Tone = 2, Optimistic	-0.014	-0.006	0.017	-0.008	0.012	-0.014
	(-0.66)	(-0.27)	(0.62)	(-0.30)	(0.39)	(-0.49)
Precision = 1, Medium	-0.010	-0.005	0.020	0.001	0.018	-0.002
	(-0.90)	(-0.45)	(1.42)	(0.10)	(1.02)	(-0.12)
Precision = 2, High	-0.000	-0.000	0.021	0.001	0.020	0.001
	(-0.02)	(-0.01)	(1.20)	(0.03)	(0.92)	(0.05)
Pessimistic×Medium	**0.054*** **	**0.049** **	**0.015**	**0.055** **	**0.010**	**0.054* **
	(2.88)	**(2.44)**	**(0.58)**	**(2.18)**	**(0.34)**	**(1.89)**
Pessimistic×High	**0.066** **	**0.068** **	**0.045**	**0.086** **	**0.024**	**0.066* **
	(2.52)	**(2.41)**	**(1.32)**	**(2.47)**	**(0.63)**	**(1.73)**
Optimistic×Medium	**-0.003**	**-0.005**	**-0.028**	**-0.005**	**-0.017**	**0.006**
	(-0.13)	**(-0.23)**	**(-0.96)**	**(-0.20)**	**(-0.51)**	**(0.18)**
Optimistic×High	**-0.012**	**-0.014**	**-0.024**	**-0.005**	**-0.024**	**-0.005**
	(-0.54)	**(-0.59)**	**(-0.84)**	**(-0.18)**	**(-0.72)**	**(-0.16)**
Observations	21,361	21,361	21,361	18,605	21,361	18,605
R-squared	0.316	0.338	0.372	0.391	0.391	0.409
NOLH			NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES	YES	YES

Table 1.12: **Volatility and Analyst Report Precision - Uncertainty**
This table reports the relation between volatility (percentage change in implied volatility of 30-days ATM option) response to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Controls include size, B/M, number of analysts, uncertainty index, prior- CAR, absolute and relative analyst experience, deviation from consensus, broker size, report length, and change in the VIX. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) aIVOL1	(2) aIVOL2	(3) aIVOL4	(5) aIVOL6
Tone = 1, Pessimistic	0.159	0.523	0.271	0.405
	(0.47)	(1.42)	(0.56)	(0.79)
Tone = 2, Optimistic	-0.358	0.410	0.198	0.064
	(-0.81)	(0.83)	(0.33)	(0.11)
Precision = 1, Medium	**-0.190**	**-0.092**	**-0.290**	**-0.238**
	(-0.73)	**(-0.32)**	**(-0.77)**	**(-0.65)**
Precision = 2, High	**-0.098**	**-0.255**	**-0.583**	**-0.646**
	(-0.27)	**(-0.69)**	**(-1.22)**	**(-1.34)**
Pessimistic×Medium	**-0.244**	**-0.487**	**-0.412**	**-0.560**
	(-0.80)	**(-1.40)**	**(-0.97)**	**(-1.24)**
Pessimistic×High	**-0.925*** **	**-0.955***	**-1.196***	**-1.374*** **
	(-2.06)	**(-1.94)**	**(-1.86)**	**(-2.12)**
Optimistic×Medium	**-0.292**	**-0.459**	**-0.468**	**-0.364**
	(-0.69)	**(-0.98)**	**(-0.82)**	**(-0.63)**
Optimistic×High	**0.259**	**-0.225**	**-0.069**	**-0.037**
	(0.52)	**(-0.40)**	**(-0.10)**	**(-0.05)**
Observations	17,995	17,995	17,995	17,995
R-squared	0.465	0.476	0.448	0.494
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Abnormal VIX	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.13: **Variation in the Relation between Price Reaction and Precision – Firm Uncertainty**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly quartiles. Firm Uncertainty is equal to one if idiosyncratic volatility is above median. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Coefficients of the interaction between Firm Uncertainty and Tone and between Firm Uncertainty and Precision are not reported for compactness. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	CAR[0,1]	CAR[0,2]	CAR[0,4]	CAR[0,6]
Tone = 1, Pessimistic	-0.481***	-0.344**	-0.340*	-0.164
	(-3.76)	(-2.44)	(-1.89)	(-0.77)
Tone = 2, Optimistic	0.064	-0.010	0.141	0.157
	(0.38)	(-0.05)	(0.65)	(0.61)
Precision = 1, Medium	-0.124	-0.073	-0.117	-0.130
	(-1.04)	(-0.55)	(-0.79)	(-0.76)
Precision = 2, High	-0.039	0.035	-0.079	-0.170
	(-0.27)	(0.22)	(-0.43)	(-0.83)
Firm Uncertainty	0.076	0.077	0.198	-0.014
	(0.43)	(0.38)	(0.82)	(-0.05)
Pessimistic×Medium×Firm Uncertainty	**-0.415**	**-0.277**	**-0.204**	**-0.292**
	(-1.41)	**(-0.85)**	**(-0.54)**	**(-0.64)**
Pessimistic×High×Firm Uncertainty	**-0.694****	**-0.788****	**-1.087****	**-1.485*****
	(-1.97)	**(-2.07)**	**(-2.40)**	**(-2.80)**
Optimistic×Medium×Firm Uncertainty	**-0.205**	**-0.153**	**0.089**	**0.174**
	(-0.67)	**(-0.46)**	**(0.21)**	**(0.35)**
Optimistic×High×Firm Uncertainty	**-0.320**	**-0.495**	**-0.496**	**-0.882**
	(-0.86)	**(-1.18)**	**(-0.99)**	**(-1.51)**
Observations	21,361	21,361	21,361	21,361
R-squared	0.243	0.229	0.219	0.212
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.14: **Variation in the Relation between Price Reaction and Precision – Analysts' Disagreement**
This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly quartiles. High Disagreement is equal to one if analysts' disagreement (standard deviation of analysts' EPS forecasts) is above median. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Coefficients of the interaction between High Disagreement and Tone and between High Disagreement and Precision are not reported for compactness. Standard errors are double clustered at analyst and industry-week level. tstats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.557***	-0.358*	-0.648**	-0.480
	(-2.96)	(-1.67)	(-2.55)	(-1.58)
Tone = 2, Optimistic	0.158	0.205	0.282	0.318
	(0.80)	(0.92)	(0.99)	(0.97)
Precision = 1, Medium	0.008	0.068	0.018	0.117
	(0.05)	(0.42)	(0.10)	(0.51)
Precision = 2, High	-0.188	-0.100	-0.284	-0.068
	(-1.09)	(-0.53)	(-1.29)	(-0.26)
High Disagreement	0.043	0.075	0.005	0.061
	(0.24)	(0.39)	(0.02)	(0.22)
Pessimistic×Medium×High Disagreement	**0.052**	**0.236**	**-0.011**	**-0.177**
	(0.17)	**(0.67)**	**(-0.03)**	**(-0.36)**
Pessimistic×High×High Disagreement	**-0.477**	**-0.524**	**-0.929***	**-1.264****
	(-1.39)	**(-1.41)**	**(-1.94)**	**(-2.32)**
Optimistic×Medium×High Disagreement	**-0.079**	**0.216**	**0.601**	**0.591**
	(-0.25)	**(0.64)**	**(1.44)**	**(1.20)**
Optimistic×High×High Disagreement	**-0.156**	**-0.139**	**-0.124**	**0.066**
	(-0.44)	**(-0.37)**	**(-0.27)**	**(0.12)**
Observations	21,361	21,361	21,361	21,361
R-squared	0.243	0.229	0.219	0.213
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.15: **Variation in the Relation between Price Reaction and Precision – Tone Position**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Tone is measured based on the first 30 sentences reports. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.341**	-0.171	-0.111	0.158
	(-2.38)	(-1.02)	(-0.52)	(0.65)
Tone = 2, Optimistic	0.248	0.213	0.086	-0.002
	(1.53)	(1.12)	(0.36)	(-0.01)
Precision = 1, Medium	-0.197*	-0.144	-0.194	-0.179
	(-1.67)	(-1.07)	(-1.29)	(-0.97)
Precision = 2, High	-0.263*	-0.168	-0.265	-0.195
	(-1.71)	(-0.98)	(-1.26)	(-0.82)
Pessimistic×Medium	**-0.186**	**-0.234**	**-0.117**	**-0.275**
	(-1.10)	**(-1.22)**	**(-0.49)**	**(-0.97)**
Pessimistic×High	**-0.308**	**-0.482***	**-0.546***	**-0.734****
	(-1.27)	**(-1.83)**	**(-1.71)**	**(-2.11)**
Optimistic×Medium	**0.164**	**0.137**	**0.268**	**0.288**
	(0.97)	**(0.71)**	**(1.09)**	**(1.04)**
Optimistic×High	**0.008**	**-0.005**	**0.350**	**0.314**
	(0.04)	**(-0.02)**	**(1.17)**	**(0.92)**
Observations	21,361	21,361	21,361	21,361
R-squared	0.236	0.222	0.213	0.206
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.16: **Variation in the Relation between Price Reaction and Precision – Precision Position**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Precision is measured based on the last 30 sentences of the reports. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]	(5) CAR[0,10]
Tone = 1, Pessimistic	-0.363**	-0.319*	-0.136	0.189	0.311
	(-2.25)	(-1.78)	(-0.64)	(0.79)	(1.03)
Tone = 2, Optimistic	0.329*	0.276	0.182	0.116	0.305
	(1.78)	(1.42)	(0.74)	(0.40)	(0.87)
Precision = 1, Medium	-0.044	0.050	0.082	0.152	0.100
	(-0.42)	(0.42)	(0.58)	(0.90)	(0.48)
Precision = 2, High	-0.076	0.025	0.106	0.226	0.191
	(-0.54)	(0.16)	(0.59)	(1.08)	(0.71)
Pessimistic×Medium	**-0.065**	**0.023**	**-0.014**	**-0.200**	**-0.254**
	(-0.36)	**(0.11)**	**(-0.06)**	**(-0.75)**	**(-0.76)**
Pessimistic×High	**-0.386***	**-0.524****	**-0.767****	**-1.037*****	**-0.998****
	(-1.69)	**(-2.05)**	**(-2.50)**	**(-2.88)**	**(-2.19)**
Optimistic×Medium	**0.001**	**-0.069**	**0.057**	**-0.002**	**-0.432**
	(0.01)	**(-0.34)**	**(0.22)**	**(-0.01)**	**(-1.18)**
Optimistic×High	**-0.161**	**-0.128**	**-0.063**	**-0.175**	**-0.506**
	(-0.70)	**(-0.54)**	**(-0.20)**	**(-0.48)**	**(-1.09)**
Observations	21,361	21,361	21,361	21,361	21,361
R-squared	0.235	0.221	0.212	0.206	0.201
Controls	YES	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES	YES

Table 1.17: **Price Reaction and Analyst Report Precision – Events Restrictions**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. The first restriction excludes days when more than 50% of analyst covering a firm issued an earnings forecast. The second restriction limits the sample to days when five or less forecasts were issued and the third restriction when three or less. Both excludes days when more than one recommendation revision was issued. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.183	-0.008	0.010	0.367
	(-1.19)	(-0.05)	(0.05)	(1.49)
Tone = 2, Optimistic	0.175	0.145	0.085	0.055
	(0.92)	(0.70)	(0.32)	(0.18)
Precision = 1, Medium	-0.111	-0.045	-0.075	0.006
	(-1.04)	(-0.37)	(-0.54)	(0.03)
Precision = 2, High	-0.167	-0.061	-0.036	0.071
	(-1.26)	(-0.41)	(-0.20)	(0.33)
Pessimistic×Medium	**-0.204**	**-0.307**	**-0.147**	**-0.383**
	(-1.20)	**(-1.57)**	**(-0.63)**	**(-1.39)**
Pessimistic×High	**-0.380***	**-0.575****	**-0.572***	**-0.925*****
	(-1.73)	**(-2.33)**	**(-1.90)**	**(-2.67)**
Optimistic×Medium	**0.070**	**-0.020**	**0.082**	**-0.043**
	(0.34)	**(-0.09)**	**(0.29)**	**(-0.14)**
Optimistic×High	**0.026**	**0.019**	**0.075**	**-0.053**
	(0.12)	**(0.08)**	**(0.25)**	**(-0.15)**
Observations	20,826	20,826	20,826	20,826
R-squared	0.230	0.217	0.211	0.205
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

VARIABLES	(5) CAR[0,1]	(6) CAR[0,2]	(7) CAR[0,4]	(8) CAR[0,6]
Tone = 1, Pessimistic	-0.124	0.036	0.061	0.386
	(-0.82)	(0.20)	(0.29)	(1.63)
Tone = 2, Optimistic	0.126	0.091	0.067	0.052
	(0.66)	(0.43)	(0.25)	(0.17)
Precision = 1, Medium	-0.134	-0.072	-0.099	-0.037
	(-1.24)	(-0.57)	(-0.69)	(-0.21)
Precision = 2, High	-0.123	0.004	0.019	0.127
	(-0.92)	(0.02)	(0.10)	(0.57)
Pessimistic×Medium	**-0.115**	**-0.211**	**-0.063**	**-0.278**
	(-0.70)	**(-1.10)**	**(-0.28)**	**(-1.06)**
Pessimistic×High	**-0.348**	**-0.565****	**-0.625****	**-0.835****
	(-1.62)	**(-2.29)**	**(-2.11)**	**(-2.41)**
Optimistic×Medium	**0.119**	**0.004**	**0.062**	**-0.115**
	(0.58)	**(0.02)**	**(0.22)**	**(-0.37)**
Optimistic×High	**0.085**	**0.026**	**0.026**	**-0.061**
	(0.39)	**(0.11)**	**(0.08)**	**(-0.17)**
Observations	19,896	19,896	19,896	19,896
R-squared	0.237	0.222	0.214	0.210
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

VARIABLES	(9) CAR[0,1]	(10) CAR[0,2]	(11) CAR[0,4]	(12) CAR[0,6]
Tone = 1, Pessimistic	-0.088	0.094	0.096	0.471*
	(-0.58)	(0.51)	(0.44)	(1.89)
Tone = 2, Optimistic	-0.002	-0.083	-0.199	-0.288
	(-0.01)	(-0.40)	(-0.72)	(-0.96)
Precision = 1, Medium	-0.157	-0.135	-0.147	-0.054
	(-1.41)	(-1.03)	(-0.98)	(-0.29)
Precision = 2, High	-0.164	-0.056	-0.032	0.048
	(-1.18)	(-0.35)	(-0.16)	(0.20)
Pessimistic×Medium	**-0.089**	**-0.225**	**-0.059**	**-0.336**
	(-0.54)	**(-1.15)**	**(-0.26)**	**(-1.22)**
Pessimistic×High	**-0.337**	**-0.565****	**-0.606****	**-0.934****
	(-1.51)	**(-2.23)**	**(-1.97)**	**(-2.58)**
Optimistic×Medium	**0.274**	**0.236**	**0.355**	**0.226**
	(1.43)	**(1.11)**	**(1.26)**	**(0.75)**
Optimistic×High	**0.198**	**0.238**	**0.354**	**0.345**
	(0.91)	**(0.97)**	**(1.11)**	**(0.96)**
Observations	18,026	18,026	18,026	18,026
R-squared	0.245	0.227	0.222	0.217
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.18: **Price Reaction and Analyst Report Precision - Long Horizons no Overlap**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. tstats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	CAR[0,4]	CAR[0,6]
Tone = 1, Pessimistic	-0.042	0.269
	(-0.19)	(1.07)
Tone = 2, Optimistic	0.152	0.129
	(0.59)	(0.44)
Precision = 1, Medium	-0.130	-0.119
	(-0.85)	(-0.67)
Precision = 2, High	-0.124	0.018
	(-0.63)	(0.08)
Pessimistic×Medium	**-0.220**	**-0.372**
	(-0.87)	**(-1.29)**
Pessimistic×High	**-0.702****	**-0.922****
	(-2.04)	**(-2.43)**
Optimistic×Medium	**0.067**	**0.040**
	(0.24)	**(0.13)**
Optimistic×High	**-0.105**	**-0.218**
	(-0.35)	**(-0.63)**
Observations	18,605	18,605
R-squared	0.227	0.222
Controls	YES	YES
Rev Controls	YES	YES
Analyst-Firm FE	YES	YES

Table 1.19: **Price Reaction and Analyst Report Precision - Neutral Reports and Crisis**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are sorted into three Tone categories based on quartiles and monthly sorted into three Precision categories based on sextiles (top, bottom, and four middle). Neutral reports are classified as Pessimistic and Optimistic as Neutral if published during the 2008-09 financial crisis. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.109	0.032	0.102	0.271
	(-0.83)	(0.20)	(0.55)	(1.26)
Tone = 2, Optimistic	0.290	0.311	0.270	0.112
	(1.56)	(1.54)	(1.09)	(0.40)
Precision = 1, Medium	-0.037	0.023	0.001	0.041
	(-0.34)	(0.18)	(0.01)	(0.24)
Precision = 2, High	0.008	0.103	0.057	0.021
	(0.05)	(0.64)	(0.31)	(0.10)
Pessimistic×Medium	**-0.327****	**-0.385****	**-0.335**	**-0.520****
	(-2.17)	**(-2.14)**	**(-1.57)**	**(-2.12)**
Pessimistic×High	**-0.760*****	**-0.926*****	**-0.905*****	**-0.888*****
	(-3.87)	**(-3.80)**	**(-3.23)**	**(-2.75)**
Optimistic×Medium	**-0.070**	**-0.151**	**-0.042**	**-0.104**
	(-0.35)	**(-0.72)**	**(-0.16)**	**(-0.36)**
Optimistic×High	**-0.259**	**-0.239**	**-0.154**	**-0.025**
	(-1.22)	**(-1.05)**	**(-0.53)**	**(-0.08)**
Observations	22,040	22,040	22,040	22,040
R-squared	0.233	0.218	0.209	0.204
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

Table 1.20: **Price Reaction and Analyst Report Precision - Abnormal Measures**

This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Reports with Precision equal to 1 and reports containing no positive or negative words are excluded. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.324*	-0.105	-0.066	0.265
	(-1.88)	(-0.55)	(-0.29)	(0.98)
Tone = 2, Optimistic	0.151	0.161	0.142	0.163
	(0.82)	(0.80)	(0.54)	(0.55)
Precision = 1, Medium	-0.213	-0.146	-0.191	-0.119
	(-1.61)	(-1.02)	(-1.17)	(-0.60)
Precision = 2, High	-0.239	-0.108	-0.089	-0.023
	(-1.47)	(-0.61)	(-0.42)	(-0.09)
Pessimistic×Medium	**-0.111**	**-0.194**	**-0.010**	**-0.224**
	(-0.61)	**(-0.93)**	**(-0.04)**	**(-0.76)**
Pessimistic×High	**-0.480***	**-0.683****	**-0.746****	**-0.935****
	(-1.95)	**(-2.50)**	**(-2.32)**	**(-2.53)**
Optimistic×Medium	**0.215**	**0.134**	**0.202**	**0.037**
	(1.08)	**(0.65)**	**(0.73)**	**(0.12)**
Optimistic×High	**0.078**	**0.038**	**-0.006**	**-0.099**
	(0.36)	**(0.16)**	**(-0.02)**	**(-0.28)**
Observations	20,137	20,137	20,137	20,137
R-squared	0.233	0.218	0.209	0.204
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

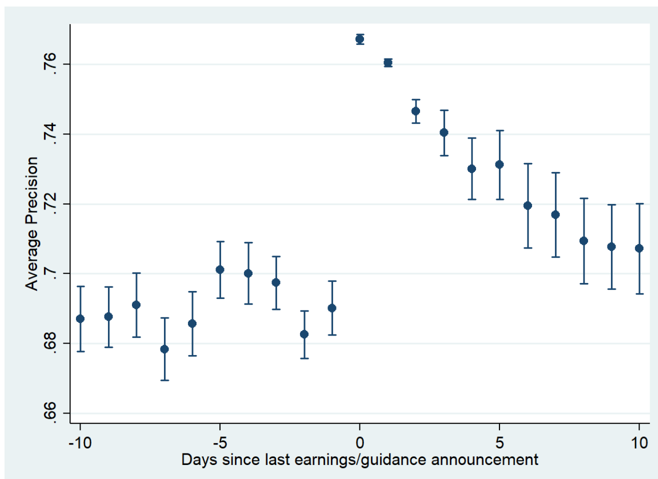
Table 1.21: **Price Reaction and Analyst Report Precision - Alternative Sorting**
This table reports the relation between price reaction (Cumulative Abnormal Returns, multiplied by 100) to the publication of an analyst report and its precision. In the first table, reports are sorted into three Tone categories based on quartiles and monthly sorted into three Precision categories based on sextiles (top, bottom, and middle four) of the distribution of the reports issued in the previous 30 days. In the second table, also Tone is constructed based on previously issued reports. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, and report length. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.327**	-0.133	-0.087	0.249
	(-2.01)	(-0.73)	(-0.42)	(1.02)
Tone = 2, Optimistic	0.200	0.204	0.207	0.121
	(1.07)	(0.98)	(0.80)	(0.41)
Precision = 1, Medium	-0.112	0.038	-0.000	0.044
	(-0.90)	(0.27)	(-0.00)	(0.25)
Precision = 2, High	-0.181	0.046	0.033	0.109
	(-1.24)	(0.28)	(0.17)	(0.49)
Pessimistic×Medium	**-0.103**	**-0.205**	**-0.074**	**-0.249**
	(-0.57)	**(-1.02)**	**(-0.32)**	**(-0.92)**
Pessimistic×High	**-0.409***	**-0.650****	**-0.689****	**-1.076*****
	(-1.75)	**(-2.56)**	**(-2.26)**	**(-2.99)**
Optimistic×Medium	**0.214**	**0.100**	**0.111**	**0.079**
	(1.05)	**(0.45)**	**(0.40)**	**(0.25)**
Optimistic×High	**0.039**	**0.011**	**0.002**	**-0.069**
	(0.18)	**(0.05)**	**(0.01)**	**(-0.20)**
Observations	21,287	21,287	21,287	21,287
R-squared	0.236	0.222	0.213	0.207
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.370***	-0.270*	-0.323*	-0.055
	(-2.75)	(-1.79)	(-1.75)	(-0.26)
Tone = 2, Optimistic	0.080	0.012	-0.020	0.049
	(0.48)	(0.07)	(-0.09)	(0.19)
Precision = 1, Medium	-0.086	-0.016	-0.183	-0.065
	(-0.83)	(-0.13)	(-1.34)	(-0.41)
Precision = 2, High	-0.154	-0.065	-0.145	0.042
	(-1.29)	(-0.49)	(-0.92)	(0.23)
Pessimistic×Medium	**-0.127**	**-0.145**	**0.052**	**-0.093**
	(-0.82)	**(-0.84)**	**(0.25)**	**(-0.38)**
Pessimistic×High	**-0.392***	**-0.582****	**-0.536***	**-0.913*****
	(-1.84)	**(-2.55)**	**(-1.94)**	**(-2.79)**
Optimistic×Medium	**0.124**	**0.129**	**0.231**	**0.028**
	(0.65)	**(0.64)**	**(0.95)**	**(0.10)**
Optimistic×High	**-0.025**	**0.100**	**0.120**	**-0.116**
	(-0.12)	**(0.45)**	**(0.43)**	**(-0.37)**
Observations	21,287	21,287	21,287	21,287
R-squared	0.047	0.037	0.024	0.016
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	NO	NO	NO	NO

1.11 Figures

Figure 1.1: **Precision around Earnings and Guidance Announcements**
These figures show the evolution of precision around earnings and management guidance announcements. The first figure shows the average precision. The second figure shows the percentage of High and Low precision reports. High (Low) is equal to one if precision is in the top (bottom) sextile. Bars represent 95% confidence intervals.



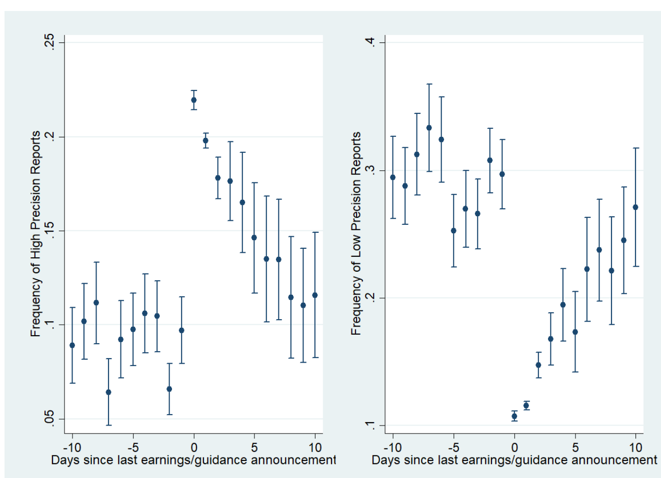
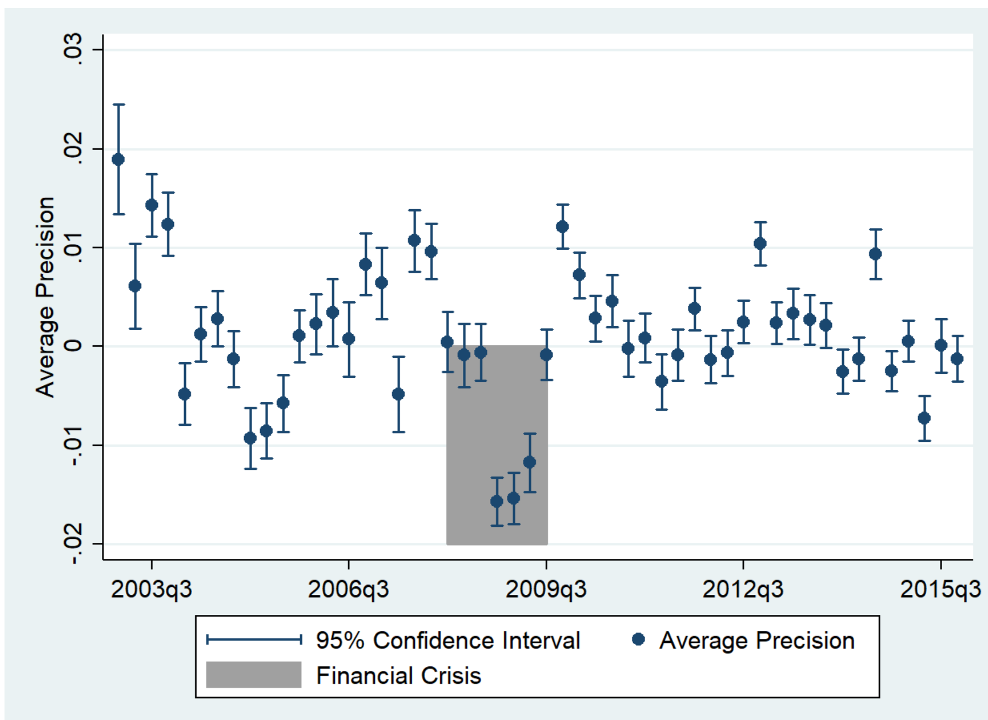


Figure 1.2: **Time Series of Precision**
This figure shows the evolution of average precision across time. Precision measure is de-trended. The period corresponding to the height of the 2008-2009 financial crisis is highlighted.



Chapter 2: Information Asymmetry, Agency Conflicts, and the Cost of Capital

2.1 Introduction

An area that has attracted significant interest by both academia and the popular and business press is how information asymmetry affects the firms' cost of capital. The topic has been a centerpiece of theoretical research for decades (e.g., Leland and Pyle 1977, Myers and Majluf 1984, Diamond 1985, Easley and O'Hara 2004) and has spurred a growing empirical literature on how information asymmetry affects firms' cost of equity (e.g., Welker 1995; Derrien and Kecskés 2013) and cost of debt (e.g., Pittman and Fortin, 2004; Ashbaugh-Skaife et al. 2006; Tang 2009).

The existing literature has focused on the effect of information asymmetry on individual securities (just debt or equity). Conversely, comprehensive empirical investigations of these two phenomena together and variation among them are still very limited, despite the fact that several studies assume or suggest that debt and equity have a different information sensitivity. Indeed, consistent with the pecking order theory of Myers and Majluf (1984), debt is usually considered to be less information sensitive than equity, hence, an information asymmetry shock should be more relevant to the latter. However, this argument underweights the fact that information asymmetry is not only about the firm's performance or management quality, but also about potential wealth transfers from debt to equity (Garleanu and Zwiebel 2009) like risk-shifting (Jensen and Meckling 1976) and strategic default (Hart and Moore 1994, 1998). While information asymmetry about firm value is generally detrimental to shareholders and, generally, to investors, information asymmetry about risk is potentially beneficial for them while being detrimental to debtholders. In other words, an increase in information asymmetry is not necessarily a purely negative shock for shareholders, but it could be beneficial. This also suggests that the different effects on cost of equity and of debt are interrelated and studying the two phenomena together is as much, if not more, important as studying them separately.

This paper studies how information asymmetry differentially affects the cost of debt and of equity as well as how it affects the weighted average cost of capital (WACC). In particular, this study focuses on understanding how managerial agency and debt agency conflicts affect the relation between information asymmetry and cost of capital. An increase in information asymmetry means that it is more difficult for investors to accurately asses the firm's value and performance as well as monitor management.[1] Investors account for this increased uncertainty and increased agency costs by raising the cost of capital, as suggested by existing literature. However, as aforementioned, this also means that it is more difficult or more costly for bond-

[1]For instance, Yu (2008) shows that the presence of strong analysts from top brokers reduce incentives to engage in earnings management. Chen et al. (2015) shows that a decrease in analysts' coverage result in CEOs receiveing excessive compensation and management engaging in earnings management.

holders to assess potential transfers from debt to equity and monitor management, i.e., it is easier for the management to engage in activities like risk-shifting and strategic default that create value for the shareholders but increase the riskiness of debt. As the existing literature suggests (e.g., Garlappi et al. 2008; Favara et al. 2012), incentives to engage in debt-equity transfers are associated with lower equity risk, so the increased ease of engaging in these actions should reasonably result in a lower cost of equity. Consequently, the effect could be reduced, if not reversed, if the latter phenomenon is significant. Noteworthy is that this argument is also consistent with the results of Derrien et al. (2016) that higher information asymmetry results in riskier debt.

Following this argument, I hypothesize that an increase in information asymmetry results in higher cost of equity (debt) when the shock is greater and when incentives to engage in debt-equity transfers are low (high). The shock is large for shareholders of smaller firms (or, similarly, of firms with lower analyst coverage) since these firms usually have less analysts, information about them is usually less available and, generally, information asymmetry is significantly higher. On the other hand, the shock is particularly large for bondholders of less creditworthy firms. These firms have usually a larger amount of debt, proximity to default is often linked to higher agency costs of debt (e.g., Davidenko and Strebulaev 2007; Eisdorfer 2008), default is a bigger determinant of the cost of debt for these firms (Huang and Huang 2003), and, generally, information about firm's performance and management is more relevant for bondholders when the firm is in distress. An increase in information asymmetry is particularly costly for bondholders when management and shareholders have high incentives to engage in risk-shifting/strategic default. Such increase makes it more difficult (or costly) to assess these incentives and monitor their activities.[2] On the other hand, the shock tends to be particularly costly for shareholders when there are low incentives to engage in debt-equity transfers. The reason is that the shock affects the ability of shareholders to accurately value the firm and the management, but it does not yield any benefit in terms of ease to engage in risk-shifting/strategic default. The purpose of this paper is to empirically test these hypotheses.

The common shortcoming of a large part of the existing empirical literature is that the causal link between information asymmetry and the cost of debt or equity is difficult to establish due to the endogenous relation between cost of capital, firm transparency and information asymmetry. To tackle this endogeneity issue, a recent strand of empirical literature on the effects of information asymmetry (e.g., Kelly and Ljungqvist, 2012; Derrien and Kecskés 2013) has employed a quasi-natural experiment related to variation in analyst coverage. Equity analysts are a major source of information about firms and their presence tend to decrease information asymmetry. The idea is to observe an increase in information asymmetry due to the disappearance of analysts resulting from mergers or closures of brokerage firms. These coverage terminations are plausibly exogenous since they are not driven by firms' fundamentals, performance, or stock market behavior. Indeed, they are the results of brokers' business strategies. This literature finds that both the cost of

[2] Li et al. (2018) shows that an information asymmetry increase leads firms to substitute public debt with bank debt, particularly for firms with high risk-shifting risk.

equity and cost of debt increase after the positive shock to information asymmetry. This methodology allows me to study the effect on the cost of equity and the cost of debt in a unified sample and test my hypothesis concerning the effects of debt agency conflicts. To the best of my knowledge, my paper is the first to employ this quasi-natural shock to study how information asymmetry differentially affects equity and debt and how this effect vary across variables that capture incentives to engage in debt-equity transfers.

Using a sample of 595 firms that lost analysts due to 27 broker closures or mergers between 2003 and 2008, I study the effect of an information asymmetry shock on the cost of their equity and the cost of their debt. I identify an equal number of control firms that are comparable ex-ante. Specifically, I match on time, industry, credit rating, analyst coverage, leverage, profitability, and size in order to assure the treated and control firms are similar before the analyst disappearance. I identify the effect of a shock to information generation by comparing the two groups via a difference-in-differences methodology.

Similar to recent literature on the cost of debt and credit markets, I use yield spreads derived from TRACE transactions as a proxy for the cost of debt. However, unlike similar existing literature, I did not use stock market returns alone as a proxy for the change in cost of equity, but also changes in the implied cost of capital (Claus and Thomas 2001; Gebhardt et al. 2001). This methodology allows to better identify the component of stock price change that is due to change in cost of equity, and not change in expected cash flows, and to better assess the magnitude of this change.

Consistent with Derrien et al. (2016), I find that the information asymmetry shock results in a significant increase in the cost of debt of around 23 basis points (bps). Despite using a different sample (time and data source), the magnitude and significance of my results are very close to the ones presented in this previous work. Similarly to previous literature, I also find that the magnitude of the effect tends to be larger for firms with non-investment grade credit. As aforementioned, the loss of an analyst is particularly costly for bondholders of these firms. On the other hand, the effect on the cost of equity appears to be around -4 bps and not significant. However, the effect appears to be larger for small firms. Indeed, information asymmetry between management and shareholders tends to be particularly serious for these firms. The two different results for equity and debt can be ascribed to sample composition, but also to the interplay between managerial and debt agency conflicts.

Consistent with my hypotheses, I observe that the increase in the cost of equity appears to be particularly relevant for firms for which the loss of an analyst is more costly (small firms) and firms where incentives to engage in risk-shifting (higher credit-worthiness and lower risk-taking incentives of CEO) or strategic default (lower liquidity costs and lower bargaining power of equity) are lower. The effect on the cost of equity of these firms is up to over 70 bps and generally significant. On the other hand, the cost of debt tends to increase more significantly when the shock is particularly relevant (non-investment grade firms) and when incentives to engage in risk-shifting and/or strategic default are higher. Cost of debt for these firms tends to increase by around 40 bps. To summarize, my results suggest that the effect of information asymmetry on the cost equity and debt depends on several factors like the relative importance of information and incentives for management and shareholders to act against the bondholders' interests. Therefore, the relative effect on equity and debt depends on the specific characteristics of the firm. Generally speaking, the cost of equity tends to be more sensitive than the cost of debt when firms are smaller, more financially healthy and when incentives to engage in debt-equity transfers are lower. On the other hand, the cost of debt tends to be more sensitive than the cost of equity when firms are larger, more distressed and when incentives to engage in debt-equity transfers are higher.

It is important to underline that my sample is composed mainly of larger companies since an inclusion requirement is having public debt. Moreover, non-investment grade firms represent a significant portion of my sample (around 40%[3]), while very highly rated ones (equal or above A+) only around 7%. Firms in my sample tend also to have a large proportion of intangible assets and high institutional ownership, variables that are linked to higher costs of debt. The accumulated effects of this sample bias, relative to the broaden universe of publicly traded firms, is that I reasonably underestimate the effect on the cost of equity, while I reasonably overestimate the one on the cost of debt.

This also means that, on average, my results are not necessarily inconsistent with the common assumptions about equity and debt sensitivity to information asymmetry suggested by the pecking order theory. Considering all firms and not just my sample, it is reasonable to assume that a large part of the universe would be

[3] In Derrien et al. (2016), they account for around 20%.

represented by smaller firms, with low institutional ownership[4] and where debtholders are highly concentrated (Diamond 1991), i.e., firms whose cost of equity is particularly sensitive, while cost of debt is relatively less sensitive. So, on average, it is reasonable to assume that the cost of equity is more sensitive to information asymmetry than the cost of debt.

I also find that the shock results in an increase in WACC of around 8 (14 bps pre-tax), but it is significant only for the pre-tax measure. Generally speaking, the increase in WACC appears to be around 33 bps (39 bps pre-tax) and particularly significant for smaller firms. This is clearly a direct consequence of the result I obtained for cost of debt and cost of equity. Even if the other parameters play a role regarding the magnitude, cost of equity generally increases for smaller firms. On the other hand, the cost of debt tends to increase or, at most, be close to zero for these firms since they are predominantly non-investment grade. Combining these two results leads to a general increase in WACC for smaller firms.

As a robustness check, I also study the shock effects on a smaller sample that excludes events resulting from merger or closure of smaller brokers or events post-Lehman bankruptcy. The first alternative specification aims to exclude the loss of analysts that are reasonably marginal in terms of information asymmetry and focus on the losses related to the major events in my sample. The results are consistent with the ones obtained using the full sample, but magnitude and significance of the observed phenomena appear to be higher for the cost equity. Instead, the rationale

[4]the Thomson Reuters database median in the 2002-2008 period is less than 50%. The 10th percentile in my sample is around 50%.

of the second specification is to exclude disappearances that may overlap with other events not accounted for in our analysis and that, hence, could hamper the validity of the results. I observe results largely consistent with the ones obtained using the main sample, but the effect on equity appears to be of smaller magnitude and the one on debt of larger. A possible interpretation is that the excluded observations are not necessarily of lower quality, but that during periods of crisis, equity is relatively more sensitive and debt is relatively less sensitive. Following my previous argument, this would suggest that the equity agency conflicts tend to prevail during these periods.

My main contribution is to the growing literature on the cost of debt and the cost of equity. Consistent with existing theoretical and empirical literature, I show that greater information asymmetry results in higher cost of debt and, hence, how the latter is affected by firm disclosure and transparency. This result was obtained using a different sample, based exclusively on TRACE data, than Derrien et al. (2016), suggesting that this result is robust. Furthermore, I show that the effect on both cost of equity and cost of debt vary along different firm characteristics that account for information asymmetry as well as incentives to engage in risk-shifting or strategic default. This suggests that the resulting effect of information asymmetry on cost of capital is also driven by an interplay among different sources of agency conflicts and that the relation between information asymmetry and cost of equity is not necessarily monotonic. Although the argument is different, this is closely related to the result of Rivera (2015) that an increase in shareholder/management moral hazard problem is related to an increase in risk-shifting incentives. I also show that WACC tends to increase for smaller companies, whose debt and, particularly, equity costs tend to be particularly sensitive to information asymmetries. This result also suggests that, at least for smaller firms, the WACC is one of the channels through which information asymmetry influences financial policy decisions given its extensive use by practitioners.

I also contribute to the literature about assets prices and debt agency conflicts. There is a growing literature linking asset prices and incentives to engage in risk-shifting or strategic default (e.g., Davidenko and Strebulaev 2007; Garlappi et al. 2008; Favara et al. 2012). My results show that these incentives tend also to affect the relation between information asymmetry and the cost of debt and cost of equity. In particular, I show that they tend to amplify the effect on the cost of debt of information asymmetry and attenuate the one on the cost of equity.

Moreover, the results highlight furthermore the importance of financial reporting quality and of equity analysts. While their importance for the equity markets is well established, my results suggest that their impact on firms and investors goes well beyond since their presence ,or lack thereof, has an effect on the cost of equity and of debt, hence, wide indirect effects on an array of financial decisions that rely on these parameters. As argued by Derrien et al. (2016), existing academic literature, as well as practitioners, ignore or underestimate this effect.

Finally, I contribute to the growing literature that employs analyst coverage shocks to study the causal effect of information asymmetry. Indeed, existing literature focused on the equity market (Kelly and Ljungqvist 2012), corporate policies (Derrien and Kecskés 2013), earning management (Irani and Oesch 2014), and the debt market (Derrien et al. 2016). My work adds results about the effects on the overall cost of capital and about the different effects on the cost of debt and equity. Moreover, I showed that the quasi-natural experiment is compatible with easily accessible and rich databases like TRACE and, hence, can be employed for a wide range of studies beyond corporate finance ones. Lastly, I highlighted how the selection of events and treated firm is a crucial and important step when using this shock. For instance, not all events are of equal magnitude and the inclusion of losses of analysts working for minor brokers may affect the strength and significance of the results. Furthermore, using events that happened during different periods of the business cycle can be problematic. Other unaccounted events may overlap during periods of crisis, resulting in a less clean identification strategy. Alternatively, the studied effects may vary across the business cycles, hence not separating different events may lead to misleading results. Indeed, I show that the effects appear to be somewhat different in the post-Lehman period.

The rest of the paper is structured as follows. In Section 2, I present my main hypotheses. Section 3 focuses on the construction of the sample and of the measures of the cost of debt and of the cost of equity. Section 4 discusses the main results concerning the sensitivity of the cost of equity and debt to information asymmetry, while Section 5 presents results concerning the variation in this sensitivity. In Section 6, I present some robustness results. Finally, I conclude the paper in Section 7.

2.2 Hypotheses

There is a vast and diverse theoretical literature on cost of capital, particularly the cost of equity, and information asymmetry, e.g., Myers and Majluf (1984), Diamond (1985), Merton (1987), Botosan (1997), and Easley and O'Hara (2004). While the arguments vary, theoretical literature generally supports the idea that information asymmetry increases cost of capital and, particularly, cost of equity. Related literature (e.g., Leland and Pyle 1977, Stiglitz and Weiss 1981, and Diamond 1985), also suggests that information asymmetry increase expected losses to debtholders and, hence, the cost of debt. The relation about information asymmetry, disclosure and cost of capital has been the focus on several empirical studies that, however, cannot clearly establish a causal relation. The reason is that the relation between cost of capital and information asymmetry tend to be endogenous. Consequently, disentangling the causal effect via standard OLS technique is substantially impossible. IV methodologies are also not an optimal choice to use since they require a hard to find valid and strong instrument.

For this reason, recent papers focused on using quasi-natural experiments where a shock to information asymmetry happens. In particular, a growing number of papers used the disappearance of equity analyst coverage due to brokers' mergers or closures as the exogenous shock to information asymmetry. Indeed, the information produced by analysts can be considered mitigatory of the information asymmetries existing between managers and investors. Kelly and Ljungqvist (2012) shows that the loss of an analyst increases the information asymmetry level and the cost of equity. Derrien and Kecskés (2013) shows that the shock of information asymmetry increases the cost of equity as well as impact corporate policies. Derrien et al. (2016) focused on the cost of debt and found that the loss of an analyst results in an increase in the cost of debt and a higher default probability.

H1: The loss of an analyst results in an increase in the cost of equity and in the cost of debt.

The effect should be larger and more significant, greater is the information asymmetry shock. For shareholders, the loss of analyst is particularly costly for smaller firms (and, similarly, for firms with less analysts). Smaller firms usually have less analysts, information about them is usually less available and, generally, information asymmetry is significantly higher. The existing literature has, indeed, found a consistent relation between size and the magnitude of the effects of the loss of an analyst. On the other hand, credit-worthiness is generally considered the best proxy for how relevant is the loss of an analyst for bondholders.[5]

More fragile firms have usually a larger amount of debt, proximity to default is often linked to higher agency costs of debt (e.g., Davidenko and Strebulaev 2007; Eisdorfer 2008) and, generally, information about firm's performance and management is more relevant for bondholders when the firm is in distress.

H2: The increase in the cost of equity is higher for small firms and the increase

[5] I want to underline that I do not exclude the fact that there is a relation between the effect on the cost of debt and size, but I expect that other variables play a more important role. Derrien et al. (2016) find that the effect for smaller firms is indeed higher, but they do not test whether this is simply the result of the fact that smaller firms have lower credit quality. Moreover, size can be seen as a proxy for bondholders concentration, hence monitoring is easier in smaller firms and bondholders bargaining power is higher. In other words, the relation between size and effect on the cost of debt is more ambiguous than what some existing literature suggests.

in the cost of debt is higher for less credit-worthy firms.

However, the loss of an analyst affects not only the information asymmetry existing between investors and management about the firm's performance or management quality, but also the one existing between shareholders and bondholders (Jensen and Meckling 1976; Garleanu and Zwiebel 2009) about potential wealth transfers from bondhodlers to shareholders. While the former, the information asymmetry about firm's value, is detrimental to both shareholders and bondholders, the latter, information asymmetry about risk, could be beneficial to shareholders while being detrimental for bondholders. In other words, the loss of analyst has both a negative and positive effect for shareholders. On one hand, more information asymmetry means that it is harder, or more costly, for shareholders to assess the value of the firm and monitor the management. Shareholders account for this by demanding a higher cost of equity. On the other hand, more information asymmetry means also that it is harder, or more costly, for bondholders to assess potential debt-equity wealth transfers and monitor management that, hence, can make more easily decisions skewed toward the shareholder's interests like risk-shifting (Jensen and Meckling 1976) and strategic default (Hart and Moore 1994, 1998). As existing literature suggests, the possibility to engage in debt-equity transfers could reduce equity risk. It decreases the equity exposition to cash-flow risk by allowing firms to time the default and maximize shareholders payoff in this scenario (Garlappi et al. 2008; Favara et al. 2012), it allows firms to delay bankruptcy (Chen 2011), and it makes easier for firms to engage in projects that have tendentially a low equity risk but have a very high downside risk (Eisdorfer 2010). Hence, reasonably, the increased ease to engage in these actions should translate into a lower cost of equity. So, for shareholders, the net effect of the loss of analyst depends on the relative magnitude of these two opposite phenomena.

Specularly, the loss of an analyst is particularly costly for bondholders if the incentives are high since it is more difficult to assess the risks of the firm and monitor the management. The riskiness of these incentives is also naturally higher when the firm is less financially sound since default is a bigger determinant of the cost of debt (Huang and Huang 2003).

Consistent with existing literature, I use the bargaining power of equity and liquidation costs as measures of incentives to engage in debt-equity transfers, particularly strategic default. Indeed, both these measures represent the amount of assets that bondholders are willing to forgive to avoid a costly liquidation. I also use risk-taking incentives of the management to measure incentives to engage in risk-shifting.

H3: The increase in the cost of equity is higher when the information asymmetry between shareholders and management is higher and incentives to engage in debt-equity wealth transfers (low liquidation costs, low bargaining power of equity, low risk-taking incentives) are lower.

H4: The increase in the cost of debt is higher when incentives to engage in debt-equity wealth transfer are lower and the creditworthiness of the firm is lower.

Existing literature and H1 suggest that both sources of capital are affected. A logical consequence is that also weighted average cost of capital (WACC) is affected. However, the aforementioned double effect on the cost of equity could affect the final result. Generally, WACC should increase when both the cost of equity and the cost of debt are significantly sensitive, i.e., when the cost of the shock is relatively high for both shareholders and bondholders. This is the case for smaller firms, since they also tend to have riskier debt.

H5: The loss of an analyst results in an increase in the weighted average cost of capital (WACC) that is particularly significant for smaller companies.

2.3 Data and Sample Construction

The sample construction largely follows the approach used by existing literature and, particularly, Derrien and Kecskés (2013) and Derrien et al. (2016). The list of brokers mergers and closures was kindly provided by the authors of those papers. The list of events is consistent with ones used in previous literature like Kelly and Ljungqvist (2012) and Hong and Kacperczyk (2010).

Since all the bond transaction data are obtained from TRACE, I had to restrict the time period to 2003-2008. Following Derrien and Kecskés (2013) methodology, I employed I/B/E/S to identify firms whose analysts coverage was affected by the brokers mergers and closures. In brief, an analyst is identified as disappeared for a specific firm if it was covering it at the time the broker closed down or was acquired (i.e., the coverage and, specifically, the earnings estimate was not ”stopped” in I/B/E/S before the official broker closure or acquisition date), but did not cover it afterwards (i.e., the analyst did not issue any new forecast in the following year). In case the disappearance was a product of a merger, I focused on firms who were also covered by the acquiring institution before the merger and did not lose both analysts. This approach ensures that the coverage termination is not due the analyst endogenous decision to not cover it anymore.

The control group, composed of an equal amount of firms, was constructed in order to match the treatment one. Financial firms were excluded and I required that the treated and control firm were in the same industry, i.e., had the same first two digits of the NAICS code. Firms were also matched according to credit rating. The credit rating was constructed based on Mergent FISD that reports several information about each issue as size, maturity and rating. I converted Standard & Poor's and Moody's rating from a letter scale to a number scale (for instance AAA/Aaa = 1) where higher numbers correspond to lower credit rating. The rating for each month of each issue is an average between the two agencies' ratings. The firm rating is an issue size-weighted average of the rating of its different bond issues. I required that the difference between the rating of the control and treated firms is not more than 3 points. I also matched the firms according to the number of analysts. In particular, I required that the difference being not more than five. Finally, I matched the firms based on total assets, profitability (ROA), and leverage (Total Debt / Total Equity) based on Mahalanobis distance. As last step, I dropped matches whose distance was too large (the top 2.5% in terms of Mahalanobis distance) or matches that appeared to be of overall low quality.

The matching procedure results in 595 analyst disappearances. Control firms were, in summary, matched by industry, time, rating, number of analysts, total assets, profitability, and leverage. There are a total of 27 events in the sample, 15 mergers and 12 closures. The matching results are reported in Table 1 where I compare the 25th, 50th and 75th percentile. Additionally, I run tests for the equality of medians and distributions (Kolgomorov-Smirnov test) of both the matching variables and other variables (like yield spread and market capitalization). Overall, the matching process results in a balanced control group. Treated firms appear to have one more analyst than control firms, but I think this is well within reasonable margins. It appears also that the size, as in total assets, right tail for the treated firm to be fatter, but I am comfortable that this is not a major issue. Finally, I checked if my treated firms actually lose more analysts than my control. To no surprise, the treatment effect is equivalent to a loss of 0.88 analysts (t-stat = -4.48), a result fully consistent with the construction of my sample.

All information about the analysts' coverage was obtained, as aforementioned, from I/B/E/S. Firm fundamentals data were obtained from COMPUSTAT and stock information from CRSP. All continuous variables were winsorized at the 2.5th and 97.5th percentile. Differently from Derrien et al. (2016), I relied exclusively on the TRACE (Enhanced) database for bond yield data. The advantage of using TRACE is that it substantially covers all transactions that happens in the corporate credit market, allowing us to have data about bonds that are probably not included in older databases. Hence, it is not surprising that my sample is made of firms that are smaller than the one in Derrien et al. (2016). The downside is that the quality of data is lower and the time period is more restricted.

2.3.1 Cost of Debt

Following the previous literature, I use corporate bond yields from TRACE as proxies of cost of debt. An alternative would be using actual bonds issues, but the amount and frequency of data is significantly lower.

For each bond-issue month, I computed a volume-weighted average yield. To adjust for maturity risk, I matched each issue to a Treasury bond with the same duration. In case no Treasury bond was available, I interpolated the Treasury yield from other bonds. I calculated the difference between the bond yield and the matching Treasury yield as the yield spread. I defined the firm cost of debt (or yield spread) as an issue size-weighted average of issues yield spreads. A further step could be calculating the spread between this and the yield of a portfolio of matching firms, but I avoided this step since it does not really affect the results as pointed out by Derrien et al. (2016). If in one month there were no trades and, hence, no cost of debt was possible to compute, I used the previous month cost of debt. I carried on yield spreads up to 6 months. The change in cost of debt is proxied by the change in yield spread between t-3 and t+3 (a six-month period), where t is the month of the analyst disappearance.

2.3.2 Cost of Equity

As first proxy for the change in cost of equity and following existing literature, I use the stock return[6] in the period between t-2 and t+2 centering on the end of

[6] Similar result are obtained using the excess returns (Daniel et al. 1997)

disappearance month t. The smaller window is consistent with the one used by Derrien and Kecskés (2013)[7]. The implicit assumptions behind using stock returns as a proxy for the change in cost of equity is that the stock price is consistent with a simple dividend discount model and that expected cash flows are not changing around the analysts disappearances. Hence, using returns means implicitly assuming that they reflect exclusively changes in the cost of equity and not change in expected cash flows.

$$P_t = \frac{E[D_{t+1}]}{R}$$

Using stock returns, even if adjusted, carries also other issues. First, stock returns are noisy and, hence, it is difficult to accurately identify the treatment effect. Second, while they can give an idea about the sign of the effect, it is impossible to obtain a reasonable estimate of its magnitude. To overcome these issues, I also used the implied cost of capital (ICC) methods to estimate the cost of equity and its change around the analysts disappearance. ICC methods are largely used in accounting (e.g., Hann et al. 2013) and finance (e.g., Pastor et al. 2008; Lee et al. 2009) literature. ICC models rely on several assumptions, but they are less stringent than the ones behind the stock returns used by previous literature.

A possible issue with using ICC methods is that they employ analysts' forecasts. If, as suggested by Hong and Kacperczyk (2010), the analysts that disappear are the more conservative ones, it could be possible to observe an increase of ex-

[7]The results with a bigger window similar to the one used for bonds are comparable, but generally much noisier.

pected cash flows and cost of equity just because bias is increasing. However, as suggested by the aforementioned paper, this phenomenon appears to be relatively small and restricted to companies with very few analysts that accounts for a tiny fraction (~5%) of my sample. Moreover, they observe the phenomenon in a three-year period and it is sensible to assume that the phenomenon does not unfold over my much shorter period[8]

Particularly, I used the average between two different popular ICC methodologies based on the residual income valuation model; the one suggested by Claus and Thomas (2001) and the one used by Gebhardt et al. (2001).

Claus and Thomas (CT) model is:

$$P_t = B_0 + \sum_{i=1}^{5} \frac{ROE_{t+k} - R}{(1+R)^i} \times B_{t+i-1} + \frac{(ROE_{t+5} - R)(1+g)}{(R-g)(1+R)^5} \times B_{t+4}$$

where P_t is the price at time t, R is the implied cost of capital, B_t is the book equity (per share) and ROE_t is the return on equity. ROE is estimated using analysts' median EPS forecasts ($FEPS_t$). If analysts' forecasts were absent. I estimated the EPS applying the long-term growth rate forecast to previous fiscal year forecast. I required that at least one and two-years ahead forecasts were available. Book equity was determined based on clean surplus accounting, $B_{t+k} = B_{t+k-1} + FEPS_{t+k} - d \times FEPS_{t+k}$. The dividend payout ratio d was estimated using the current ratio if earnings were positive, otherwise it was proxied by the ratio between dividends and 6% of total assets. I required latest book equity to be positive. g is

[8]Even if unreported, I tested if there is an effect on bias in the six-month period around the disappearance of an analyst and I did not observe any.

set equal to the risk free rate.

The Gebhardt et al. model (GLS) is:

$$P_t = B_0 + \sum_{i=1}^{11} \frac{ROE_{t+k} - R}{(1+R)^{11}} \times B_{t+i-1} + \frac{ROE_{t+12} - R}{R(1+R)^{11}} \times B_{t+11}$$

The variables are as previously defined. I assumed that ROE after time $t+3$ converges linearly to the median industry ROE. In calculating the median, I excluded firms with negative earnings. The cost of capital R was found numerically[9]. Due to the requirements, the sample is smaller and consists in 566 disappearances.

2.3.3 Debt-Equity Wealth Transfer Incentives and Loss of an Analyst Relevance

As aforementioned,the main goal of this study is to understand how the loss of an analyst affects differently cost of debt and cost of equity and how it affects the overall cost of capital for different companies. My main argument is that the effect on cost of debt and, particularly, cost of equity depends on both the relative importance of the loss as well as on the incentives that managers have to engage in actions that negative affects shareholders and/or bondholders. As baseline measure of relevance of the loss, I use size for equity and rating for debt. Indeed, previous literature showed that the impact of the loss of an analyst varies significantly across these two dimensions.

[9]The initial value of the cost of equity is set equal to 9% and the results are robust to changing it.

As aforementioned, the loss of an analyst is particularly costly for these smaller firms and particularly for shareholders that lost access to a source of information about the firm. I categorized as "small" the companies in the bottom quartile of total book assets in my sample. I used total assets instead of market capitalization since it is a more stable measure and is less dependent on stock market behavior. Important to underline that firms that I categorize as small are only relatively small since, as aforementioned, I am excluding firms without public debt and, hence, smaller firms.

An alternative measure for the relevance of loss of an analyst is the number of analysts before the shock. Indeed, the loss of an analyst for a firm with several analyst is generally less relevant than for a firm with only few analysts. I classify firms in the bottom quartile as firms with few analysts. However, number of analyst is potentially a less informative measure than size since it ignores other sources of information like buy-side analysts and does not consider the importance of the analysts[10].

On the other hand, proximity to default (here proxied by credit rating) appeared to be especially relevant for the effect on cost of debt. Indeed, information about the firm are more important for bondholders when the company is closer to default, while monitoring is relatively less important if the firm is solid. In few words, regardless of the size of the firm, the loss of an analyst is particularly costly for bondholders holding more risky debt. I divided my sample in investment grade and

[10] Around 75% of my observations is due to the loss of analysts working for major brokers and previous literature has shown that the analysts disappearing are of good quality

non-investment grade, based on the numeric rating scale: >10 for non-investment grade and ≤10 for investment grade.

The other set of measure has the goal of capturing incentives to engage in debt-equity wealth transfers as risk-shifting or strategic default. As aforementioned, credit-worthiness, hereby measured by credit rating, is the first measure I use as a proxy for incentives to engage in these actions, particularly risk-shifting. Other measures aim to measure bargain power of equity, liquidation costs, and incentives to engage in risky projects.

Liquidation costs is one of the most common measure of incentives to engage in debt-equity transfers. Indeed, higher are the liquidation costs, higher is the share of assets that bondholders are willing to concede in order to avoid liquidation. In other words, higher are liquidation costs, larger is the amount of debt that bondholders are willing to forgive. As a proxy for liquidation costs I use two measures: *intangibility* and *non-utility*. Intangibility is measured as one minus the expected liquidation value of tangible assets weighted by total book assets. I use the same values initially suggested by Berger et al. (1996) and largely used in related literature (e.g., Garlappi et al. 2008; Favara et al. 2012). I categorize as "low intangible" the bottom 25th firms in my sample. All data were obtained from Compustat.

$$Intangible = 1 - \frac{0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times PPE}{Total\ Assets}$$

The other measure is a dummy that has value of 0 if the firm is a utility and 1 otherwise. Utility firms have usually a large amount of tangible assets that are very easy to sell in case of bankruptcy (Davidenko and Strebulaev 2007), hence, liquidation costs are usually particularly low. No similar patterns have been observed for other industries.

The other measure I use is a proxy for bargaining power of equity. Indeed, higher is the bargaining power of shareholders, bigger is the share of bargaining surplus they can obtain and, as before, higher is the share of assets that bondholders are willing to concede in order to avoid liquidation. As a proxy for bargaining power I use the percentage of shares held by institutional investors. Institutional investors favor the creation of equity committee that results in deviation from the absolute priority rule (LoPucki and Whitford 1990) and they are usually able to bargain more efficiently. I use data from Thomson Reuters and I categorize as "low institutional shareholding" the bottom 25th percentile of firms in my sample.[11]. Existing literature suggests using also measures related to the percentage of shares held by the management. However, given the size of firms in my sample, management/CEOs generally hold a very small fraction of the shares, hence, firms are relatively similar based on this measure[12].

Last but not the least, I used a proxy for the management's incentives to engage in risky project. Following Davidenko and Strebulaev (2007), I used the numbers of unexpired options held by the CEO normalized by the numbers of shares outstanding. Data were obtained from ExecuComp and I categorized as "low CEO options ownership" the bottom 50th percentile of firms in my sample.

[11]Since, in my sample, the 25th is still a very high percentage, I also used an alternative definition that corresponds to the bottom 10th percentile and obtained comparable if not stronger results

[12]The relation between effect on cost of debt and these measures is however significant and positive.

2.4 Cost of Equity and Cost of Debt Sensitivity to Information Asymmetry

The first analysis consists in verifying in my sample the results observed in previous literature. As aforementioned, my sample is by construction quite different from the ones used in existing studies. While Derrien et al. (2016) relies on TRACE data only for the most recent years in their sample, I rely exclusively on TRACE data. Previous studies that analyzed the stock market had bigger samples encompassing also firms (usually small and, hence, with potential high information asymmetry) that do not have debt traded on the secondary market. Furthermore, I am using a better and more precise methodology to estimate the effect on the cost of equity. The results suggest that cost of debt increases after the loss of an analyst, particularly for firms with lower credit rating. The effect on equity appears to be less significant and generally relevant only for smaller firms.

2.4.1 Sensitivity of Cost of Debt

Table 2 presents the base results for the effects of the loss of an analyst on the bond market. Particularly, Panel A reports the effect observed on the base sample. The result for the bond yield is significant and suggests that it results in an increase in cost of debt of 23 bps. This result is between the 25 bps showed by Derrien et al. (2016) and the 20 bps figure suggested by Tang (2009). Important to notice that this increase of cost of debt translates to over $5 million of additional annual interest expenses for my median firm based on its long-term debt, so it appears to be economically significant. It appears that these results about the cost of debt are quite robust. Indeed the effect is similar in terms of both magnitude and significance even when using a smaller sample (Panel B).

I also tests whether the effect is different for lowly-rated firms (non-investment grade rating) and for smaller firms. To study this phenomenon, I employed a triple diff-in-diff approach. In other words, I tested whether the difference in diff-in-diffs, obtained as in Table 2, between the groups was significant. In the first test, I compared non-investment grade firms to investment-grade ones. In the second, small firms to bigger ones.

Results are reported in Table 3 (Table 4 for restricted sample). The magnitude of the effect of the loss of an analyst appears to be indeed of higher magnitude for low rating firms (even if not significantly), while size appears to not be a relevant discriminant. This seems to suggest that the loss of an analyst matters particularly to firms that are closer to default, regardless what is their size. As aforementioned, this is consistent with the argument that creditworthiness is a better measure of the relevance of information asymmetry for debt than size.

The results for debt presented by Derrien et al. (2016) were definitely stronger, both in terms of magnitude and significance. Firstly, it is important to highlight that I use total assets instead of market capitalization as measure of size and, as aforementioned, the relation between size and cost of debt is ambiguous. Moreover, sample differences could have determined this result. Indeed, for instance, my sample includes a much lower proportion of very highly rated firms than theirs[13].

2.4.2 Sensitivity of Cost of Equity

Table 2 presents the base results for the effects of the loss of an analyst on the cost of equity. Particularly, Panel A reports the effect observed using stock returns as a proxy for the change in cost of equity. On the other hand, Panel B reports results using implied cost of capital estimates.

Concerning the stock market, the shock generates a negative return of around -1%, that however is not significantly different from zero. Non significant result is also obtained by using ICC, that is around -4 bps. This result is different from, for instance, Derrien and Kecskés (2013) that reported a, albeit only marginally, significant negative return in a similar window. The reason of this result can be traced also to the sample construction. As aforementioned, firms in my sample tend to be significantly bigger than the ones used in studies of cost of equity. For instance, my 25th percentile corresponds to around the median in more comprehensive samples that include also firms without public debt.

The conditional analysis reported in Tables 3 and 4, indeed, appears to confirm this idea. Even if not always significantly, the magnitude effect on cost of equity appears to be larger for smaller firms. It is important to underline that these "smaller" firms are not really small. On the other hand, the relation with creditworthiness appears to be less clear.

[13]The treatment effect for these firms in my sample is around 0.

2.4.3 Sensitivity of Weighted Average Cost of Capital (WACC)

Previous results suggest that cost of debt generally increases, while cost of equity is generally not affected. This suggests that the overall cost of capital should increase, but the significance of this increase is not a direct consequence. For simplicity, I assumed that leverage is not affected by the shock, so the results reflect the change in WACC as if the firms did not change their capital structure[14]. I also calculated WACC assuming the there is no taxation or assuming the tax rate is 21%.

The results are reported in Table 2 and suggest that WACC indeed increases by around 11 bps (14 bps pre-tax). However, only the pre-tax effect appears to be significant; this is consistent with the fact that the observed change in WACC is generally driven by the general increase in the cost of debt.

Conditional results are reported in Table 4 and show a clear demarcation between smaller and bigger firms (around 30 bps) and, at a lesser extent, between non-investment grade firms and investment grade firms (around 20 bps). Both these results are driven by what observed when looking at the two securities separately. Cost of equity tends to increase for smaller firms since the shock is bigger for these firms. Similarly, cost of debt tends to increase since these firms are predominately non-investment grade.

To summarize, the loss of an analyst appears to be generally costly for small firms. On the other hand, it appears to be trivial for large companies.

[14] Unreported results suggest this.

2.5 Variation in the Sensitivity to Information Asymmetry

The results in section 4 appear to be puzzling. Equity is generally considered being more sensitive to information asymmetry than debt, starting from the pecking order theory popularized by Myers and Majluf (1984). Nevertheless, my results suggest that while the shock has a significant effect on the cost of debt, the effect on cost of equity is generally not. As aforementioned, this is partially due to the sample construction. The information provided by analyst is particularly relevant for small firms that, however, account for a small fraction of the employed sample. On the other hand, lowly rated debt is the one more sensitive to information asymmetry and it accounts for a significant fraction of the sample. However, as aforementioned, it is also important to highlight that there are two sources of information asymmetry that affect shareholders of firms with public debt; the one between them and the management and the one between them and bondholders. Hence, the effect of a shock on the cost of equity depends on which of these two sources of information asymmetry more significantly increase due to the loss of an analyst. Here I proceed to test under which conditions the cost of debt and/or cost of equity increase significantly. I report only the result on cost of equity obtained using ICC estimates since they better capture the effect and give better magnitude estimates. The results suggest, indeed, that the increase in cost of equity appears to be particularly relevant for firms for which the loss of an analyst is more costly (small firms) and firms where incentives to engage in risk-shifting (higher credit-worthiness and lower risk-taking incentives of CEO) or strategic default (lower liquidity costs and lower bargaining power of equity) are lower. On the other hand, cost of debt tends to increase more significantly for firms when the shock is particularly relevant (non-investment grade firms) and when incentives to engage in risk-shifting and/or strategic default are higher.

As suggested by results in section 4, size is the major discriminant for the relevance of the loss of an analyst for shareholders and creditworthiness for bondholders. However, proximity default is also considered a proxy for risk-shifting incentives and, more generally, debt-equity transfers (e.g., Davidenko and Strebulaev 2007; Eisdorfer 2008). Hence, it is interesting to study how the effect of the cost of equity and debt vary across these two dimensions. The results are reported in Table 5 and are largely consistent with my expectations. The effect on the cost of equity appears to be significant and positive (~50 bps) only for small firms with investment-grade debt, while it appears to be negative, albeit not significantly, for large firms with non-investment grade debt (i.e., firms for which the information asymmetry has potentially high benefits, but low costs). The difference between the two groups of firms is around 77 bps and significant. Reasonable interpretation is, indeed, that for the former firms the increase in information asymmetry is primarily a cost for shareholders since there are no incentives to engage in debt-equity transfers. On the other hand, the increase in information asymmetry for the other set of firms is beneficial given the higher incentives and the low costs. The effect on the cost of debt follows a similar but specular path, i.e., it is non significant only for small investment-grade firms. The low level of incentives to engage in debt-equity transfers and the general higher concentration of debtholders of smaller firms, are reasonably the forces behind this result. I conducted the same analysis using the number of analyst instead of size. The results are reported in Table 6 and are generally similar to the ones observed using size. Effect on cost of equity is positive and significant for firms with few analysts and with investment-grade debt, instead the effect on the cost of debt appears to be more relevant for firms with more analysts[15]

The other set of variables I used are proxies for liquidation costs. Table 7 reports results obtained using "Intangibility" and Table 8 the ones obtained using the "Not utility" dummy variables. Even if not significantly, the effect on the cost of equity appears to be larger for firms with a high proportion of tangible assets compared to firms with a low proportion. As expected, the phenomena appears to be particularly strong for small firms while the effect on large firms with a large percentage of intangible appears to be negative. The difference between small firms with a low proportion of intangible assets and large firms with a high proportion (i.e., that are at the two extremes in terms of size and incentives) is around 60 bps and only marginally insignificant. Results for the cost of debt are similar, but specular. In particular the difference between non-investment grade firms with a high proportion of intangible assets and highly-rated firms with a low proportion is around 44 bps and significant. Similar but stronger result were obtained using the non-utility dummy. Cost of equity tends to increase significantly for utility firms, while tend to decrease (even if not significantly) for other ones. The difference between utilities and non-utilities is around 52 bps and significant. The effect on

[15]Using size or the number of analysts yield similar but less strong results also for the following tests. This is consistent with my argument that size is a more comprehensive measure than number of analysts.

the cost of debt is substantially the opposite, i.e., around -42 bps. The results for equity are even stronger if I analyze only large firms (there are no small utility firms), where the difference between non-utility and utilities is around 63 bps. Noteworthy is that the effect on the cost of equity for large non-utility firms is actually negative and significant. To summarize, the results suggest the existence of a relation between liquidation costs and the effect on the cost of equity and cost of debt of information asymmetry.

Another important variable I used is a proxy for bargaining power of equity, i.e., "institutional ownership". Table 9 reports the results obtained using this variable where low institutional ownership corresponds to the bottom 25th percentile of my sample [16]. The effect on the cost of equity of firm's with low institutional ownership appears to be over 40 bps higher than the ones for firms with high institutional ownership. The difference between small firms with a low institutional ownership and large firms with a high one is more than 65 bps. Oppositely, the effect on the cost of debt of firms with high institutional ownership appears to be nearly 40 bps higher than other firms. In particular, the difference between non-investment grade firms with a high institutional ownership and highly rated firms with a low one is around 60 bps and significant. The results suggest the existence of a relation between bargaining power of equity and the effect on the cost of equity and cost of debt of information asymmetry.

The last variable I looked at is a proxy for risk-taking incentives of the CEO, i.e., options owned by the CEO. The results are reported in Table 10. Even if not

[16] Results obtained with the lower threshold are similar, but more noisy.

significantly, the cost of equity increase appears to be higher for firms with low CEO options ownership. In particular, the effect is significant and positive only for small companies with low CEO options ownership and it is around 66 bps. In particular, the difference between the effect on these firms and larger ones with high CEO option ownership is nearly 80 bps and significant. The results for debt are quite similar, but specular. The difference between non-investment grade firms with high CEO options ownership and investment-grade firms with a low one is around 30 bps and only marginally insignificant.

Generally speaking, the difference in terms of incentives to engage in debt-equity transfers appears to be particularly relevant for shareholders of bigger firms and bondholders holding investment-grade debt, i.e., firms where I assumed the loss of an analyst to be less relevant. This suggests that the debt-equity transfers incentives have a second-order effect and play a role mainly when the increase of information asymmetry is not always very costly. This argument is confirmed by results in Table 11 that present the effects on groups of firms constructed based on size, rating and one of the incentives proxies. Sample sizes if some of these groups could be quite small, so these results should be taken with a grain of salt. However, they suggest that the effect of incentives is generally not significant for the cost of equity of small and financially healthy firms, since the loss of analyst has a very high cost and the potential benefits from equity-debt transfers are trivial.

To summarize, the results suggest that there is a relation between debt agency conflicts and the effect of information asymmetry on the cost of equity and the cost of debt. The relation appears to be similar for the two types of securities, but with opposite sign. Debt agency conflicts appear to amplify the effect of information asymmetry on the cost of debt, but they appear to dampen the effect on the cost of equity. Consequently, the cost of debt and information asymmetry appears to be positively related and the curve is steeper, higher are debt agency conflicts. The cost of equity and information asymmetry appear to be positively related, but the steepness is lower (if not negative), higher are debt agency conflicts. In other words, the relation between cost of debt and information asymmetry is generally monotonic, while the one between the cost of equity and information asymmetry tend to be non-monotonic and convex when debt agency conflicts are significant. This result is consistent with the argument that information asymmetry about risk could be beneficial to shareholders while it is always detrimental to bondholders. Generally speaking, the cost of equity tends to be more sensitive than the cost of debt when firms are smaller, more financially healthy and when incentives to engage in debt-equity transfers are lower. On the other hand, the cost of debt tends to be more sensitive than the cost of equity when firms are larger, more distressed and when incentives to engage in debt-equity transfers are higher. Interesting to point out that the result for large firms (i.e., firms with initial low information asymmetry) is similar to the one obtained by Hackbarth et al. (2015) that show that a shock that made strategic default easier resulted in lower equity risk, but higher credit spreads.

It is important to underline that my results are not necessarily inconsistent with the pecking order theory. As aforementioned, my sample is biased toward larger firms. Furthermore, firms in my sample also tend to have a higher institutional ownership than the average (the 10th percentile in my sample is close to the median in the 2002-2008 period). In other words, it is reasonable to assume the whole universe of publicly traded firms is composed by firms that are smaller, finance themselves mainly through bank debt and have low institutional ownership. Hence, on average is reasonable to expect that the effect on equity dominates the one on debt.

2.5.1 Sensitivity of Weighted Average Cost of Capital (WACC)

The previous results have an interesting consequence, sensitivity of WACC should be generally unrelated to debt agency conflicts. Indeed, as aforementioned, the proxies I used are related to the cost of debt and the cost of equity in a similar but specular way. This means that on average the effect on the overall cost of capital should cancel out. To conserve space, I report in Table 12 only the results for my base specification where I use size and creditworthiness. The effect on the WACC of non-investment grade firms appears to be naturally larger than investment grade firms of comparable size, but the magnitude and significance is trivial compared to the difference between small and big firms. To summarize, WACC tends to increase only for those firms whose equity is sensitive to the information asymmetry shock.

2.6 Robustness

In order to test the robustness of the results, I conducted two further tests using sub-samples of my data. The idea is to have smaller samples where retained events and treated firms offer a cleaner identification. For simplicity, I present the results for my basic specification since other results tend to follow a similar pattern.

The first sub-sample encompasses only firms that lost an analyst due to major events, i.e., closures and mergers of major brokers. Indeed, the loss of an analyst of a minor broker could be considered less relevant and the impact on information asymmetry trivial. In few words, excluding these events means focusing on events that correspond to more significant increases in information asymmetry. The resulting sample consists of 418 firms, or around 75% of the whole sample. The retained firms are similar to the ones in the whole sample. Results are reported in Table 13 and appear to be stronger in terms of magnitude than the main results, suggesting that they are quite robust. In particular, the effects on equity appear to be particularly stronger; the effect on smaller firms is nearly 30 bps higher and the one on larger and closer to default firms is nearly 15 bps lower. These results are consistent with the idea that the information asymmetry shock resulting from the loss of these analysts is indeed more significant.

The second sub-sample excludes any disappearance of analysts happening after Lehman-Brothers bankruptcy. Indeed, in those cases, I cannot exclude that other contemporaneous events are affecting my results. In few words, this sub-sample aims to reduce the possible confounding created by overlapping events that are not considered in the analysis. Furthermore, the results on the full sample could be misleading if the studied phenomena vary across the business cycle. The exclusion procedure results in a sample of 453 firms that lost an analyst between 2003 and May 2008. Results are reported in Table 14. The results for equity are generally quite similar to the one observed in the full sample, but the magnitude appears to be smaller. On the other hand, results for bonds appear to be of significantly larger bigger magnitude and significance. The loss of an analyst appears to increase the cost of debt of over 30 bps and the difference between non-investment and investment grade firms is around 30 bps and significant. As in the previous case, these results support my main results. However, they also suggest that during periods of crisis the relative weight of the studied phenomena is different, i.e., equity agency conflicts tend to prevail, while debt agency conflicts[17] are of secondary importance. This points definitely requires a deeper and more thoughtful analysis.

2.7 Conclusions

In this paper, I study the causal relation between information asymmetry and the cost of capital. Following existing theoretical literature, I hypothesize that an increase in information asymmetry results in a higher cost of equity and cost of debt. However, I argue that an information asymmetry shock is not necessarily costly for shareholders, since it also facilitates debtholders-shareholders wealth transfers like risk-shifting and strategic default. Consistent with existing literature that argue that these strategic actions are related to lower equity risk, I hypothesize that an increase in information asymmetry results in a higher cost of equity (debt) when the shock is greater and when incentives to engage in debt-equity transfers are low (high).

[17] Chen (2011) shows that the benefits of engaging in risk-shifting are lower during economic downturns

Consistent with previous literature, I find that the loss of an analyst leads to an increase in the cost of debt that is statistically and economically significant. On the other hand, the effect on the cost of equity appears to be trivial. I also find that the effect on the cost of equity has generally large magnitude for smaller firms and the one on the cost of debt for firms with non-investment grade debt. These results are similar to what observed in previous literature and reflect the type of firms whose equity or debt is particularly sensitive to information asymmetry.

Consistent with my hypotheses, I observe that the increase in the cost of equity appears to be particularly relevant for firms for which the loss of an analyst is more costly (small firms) and firms where incentives to engage in risk-shifting (higher credit-worthiness and lower risk-taking incentives of CEO) or strategic default (lower liquidity costs and lower bargaining power of equity) are lower. On the other hand, the cost of debt tends to increase more significantly when the shock is particularly relevant (non-investment grade firms) and when incentives to engage in risk-shifting and/or strategic default are higher. Generally speaking, these results suggest that the cost of equity tends to be more sensitive than the cost of debt when firms are smaller, more financially healthy and when incentives to engage in debt-equity transfers are lower. On the other hand, the cost of debt tends to be more sensitive than the cost of equity when firms are larger, more distressed and when incentives to engage in debt-equity transfers are higher. As a result of these forces, I observe that the weighted average cost of capital (WACC) tends to increase only for smaller companies.

I also find that she shock effects appear to be particularly strong when excluding firms who lost analysts working for lesser brokers. The difference is particularly striking for the cost of equity, suggesting that the effect of the loss of a major analyst is particularly costly. The results are also relatively consistent when excluding events that happened after the Lehman bankruptcy. However, the effect on debt appears to be stronger, while the one on equity appears to be weaker. This suggests that the relation between information asymmetry, agency conflicts and cost of capital may vary across the business cycle. These results generally support my findings, but also highlight that attention should be given to the selection of events, particularly when extending the sample beyond 2008.

The paper clearly opens different future research paths. It could be interesting to extend the sample also to firms without public debt. This would allow to better understand how the different phenomena work since my sample is restricted to a specific type of firm. Similarly, it would be interesting to extend the sample beyond 2008, since it would allow us to better understand whether and how the studied phenomena vary across time and, for instance, during periods of crisis. Existing theoretical literature (e.g., Chen 2011), indeed, suggests that the relation between equity risk and debt-equity transfers vary across the business cycle. As previously mentioned, this latter exercise requires particular caution in order to avoid the inclusion of endogenous or noisy events.

It would also be interesting to better understand the relation between information asymmetry, managerial agency conflicts, and debt agency conflicts. Existing literature tends to underweight the role of information asymmetry and the literature about the relation between managerial agency conflicts and debt agency conflicts is relatively limited. For instance, Rivera (2015) shows that an increase in managerial moral hazard tends to result in higher incentives to engage in risk-shifting.

Finally, it would be interesting to improve the exogenous shock employed in this paper and in existing literature. All equity analysts' disappearances are largely treated equally, despite analysts having different characteristics. For instance, in the first essay, I show that analysts' precision is an important variable for investors and that is associated with several market outcomes of the publication of an analyst report. It would be useful to distinguish between analysts who provide precise and informative reports and analysts who provide largely uninformative output.

2.8 Tables

Table 2.1: **Descriptive Statistics**

This table presents descriptive statistics about treated and control firms. The base sample consists in 595 firms that lost an analyst between 2003 and 2008 due to the merger or closure of a broker. Firms are matched by time, industry, profitability, leverage, size, number of analysts and credit rating. Credit rating is expressed in a numeric scale from 1 to 22 (where 1 is the best rating). Profitability is ROA. Leverage is the ratio between total debt and total equity. 1-year EPS forecast is the median EPS analyst forecast. The Kolgomorov-Smirnov test is a test for the equality of distributions

	25th percentile		**Median**		**75th percentile**		**P-value**	
	Treat	**Control**	**Treat**	**Control**	**Treat**	**Control**	**Median**	**K-Smirnov**
Matching variables								
Total assets (log $M)	8.37	8.35	9.25	9.17	10.15	9.86	0.35	0.14
Profitability	2.96%	3.13%	5.45%	5.51%	9.00%	8.73%	0.95	0.23
Leverage	1	1.04	1.52	1.48	2.54	2.31	0.32	0.12
Credit rating (22-point scale)	7	7.3	9	9	12.2	12.1	0.56	0.74
Number of analysts	10	9	15	14	19	18	0.03	0.05
Bond market								
Yield spread (bps)	88	96	172	175	299	280	0.95	0.69
Long-term debt ($M)	943	888	2,250	2,207	5,568	4,754	0.95	0.15
Other								
Market cap ($M)	3,360	3,115	9,016	8,527	23,691	23,404	0.39	0.18
Book-to-market	0.26	0.26	0.41	0.41	0.66	0.62	0.97	0.26
1-year EPS forecast	1.27	1.34	2.25	2.07	3.5	3.32	0.18	0.17
Book value per share	8.91	9.06	14.72	14.54	21.26	21.68	0.97	0.29

Table 2.2: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity**
This table reports the change in the cost of debt and in the cost of equity resulting from the loss of an analyst. Panel A reports results obtained using stock returns as a proxy for change in cost of equity (base sample), panel B ones obtained using implied cost of capital (ICC) models. Stock returns are also calculated after risk adjustment, i.e. as excess return over a matching benchmark portfolio (number of observations in parenthesis). ICC was estimated using the Claus and Thomas (2001) and Gebhardt et al (2001) models. Mean changes for both treated and control firms are presented, as well as the difference between the two groups (difference-in-differences). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	**Treated**	**Control**	**Diff-in-Diffs**	**p-value**
Bond spread change (bps)	89	66	23**	0.02
Stock return	-1.61%	-0.54%	-1.07%	0.31
N	595			

Panel B	**Treated**	**Control**	**Diff-in-Diffs**	**p-value**
Bond spread change (bps)	91	66	25**	0.02
ICC change (bps)	28	32	-4	0.67
WACC	49	41	8	0.17
WACC (pre-tax)	70	56	14*	0.08
N	566			

Table 2.3: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity (Returns) Conditional upon Rating and Size**
This table reports the change in bond yield spread (change in cost of debt) and stock return (change in cost of equity) resulting from the loss of an analyst conditional on credit rating and size. Small firms group includes the bottom quartile. Non-investment grade includes firms whose rating is above 10 according to the used numeric scale. The diff-in-diffs are reported for all four sub-sample changes, as well as the difference between the groups (triple diff-in-diffs). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Non-Investment Grade	**Investment Grade**	**Diff**	**p-value**
Bond diff-in-diffs	31**	17**	13	0.36
Stock diff-in-diffs	-2.42%	-0.25%	-2.17%	0.25
N	225	370		

	Small	**Big**	**Diff**	**p-value**
Bond diff-in-diffs	19	23	-5	0.77
Stock diff-in-diffs	-1.45%	-0.94%	-0.51	0.77
N	151	444		

Table 2.4: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity (ICC) Conditional upon Rating and Size**

This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on credit rating and size. Small firms group includes the bottom quartile. Non-investment grade includes firms whose rating is above 10 according to the used numeric scale. The diff-in-diffs are reported for all four sub-sample changes, as well as the difference between the groups (triple diff-indiffs). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Non-Investment Grade	**Investment Grade**	**Diff**	**p-value**
Bond diff-in-diffs	37**	17**	19	0.23
Stock diff-in-diffs	-10	-1	-9	0.45
WACC	21*	4	17	0.18
WACC (pre-tax)	27**	6	21	0.13
N	214	352		
	Small	**Big**	**Diff**	**p-value**
Bond diff-in-diffs	31*	23***	8	0.65
Stock diff-in-diffs	24	-13	37*	0.08
WACC	33**	3	30**	0.03
WACC (pre-tax)	39***	6	33**	0.04
N	140	426		

Table 2.5: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity Conditional upon Rating, Size, and their Interaction**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on size, rating and their interaction. Small firms group includes the bottom quartile. Non-investment grade includes firms whose rating is above 10 according to the used numeric scale. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Debt
Big × Investment Grade (IG)	-7.98	19.56**
	(0.41)	(0.02)
Big × Non-investment Grade (NIG)	-27.56	31.35*
	(0.24)	(0.09)
Small × Investment Grade (IG)	48.99**	2.95
	(0.02)	(0.89)
Small × Non-investment Grade (NIG)	12.62	43.55*
	(0.64)	(0.05)
Observations	566	566
R-squared	0.01	0.03
Differences		
Small - Big (IG)	56.97**	-16.61
	(0.01)	(0.48)
Small - Big (NIG)	40.18	12.20
	(0.26)	(0.68)
NIG - IG (Big)	-19.58	11.79
	(0.44)	(0.55)
NIG - IG (Small)	-36.37	40.60*
	(0.26)	(0.09)
Small (IG) - Big (NIG)	76.55**	-28.40
	(0.01)	(0.19)

Table 2.6: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity Conditional upon Rating, Number of Analysts, and their Interaction**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on size, rating and their interaction. Small firms group includes the bottom quartile. Non-investment grade includes firms whose rating is above 10 according to the used numeric scale. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Equity	(3) Debt	(4) Debt
Few analysts	6.63		11.76	
	(0.73)		(0.46)	
Many analysts	-5.01		29.86***	
	(0.60)		(0.00)	
Many x Investment Grade (IG)		-7.73		22.66***
		(0.41)		(0.00)
Many x Non-investment Grade (NIG)		0.60		44.68**
		(0.98)		(0.01)
Few x Investment Grade (IG)		47.93**		-2.20
		(0.03)		(0.91)
Few x Non-investment Grade (NIG)		-27.36		23.25
		(0.35)		(0.34)
Observations	566	566	566	566
R-squared	0.00	0.01	0.02	0.03
Differences				
Few - Many	11.64		-18.1	
	(0.59)		(0.31)	
Few - Many (IG)		55.66**		-24.86
		(0.03)		(0.22)
Few - Many (NIG)		-27.96		-21.43
		(0.46)		(0.48)
NIG - IG (Many)		-8.33		22.02
		(0.26)		(0.22)
NIG - IG (Few)		-75.29		25.45
		(0.41)		(0.48)
Few (IG) - Many (NIG)		47.33*		-46.88*
		(0.09)		(0.06)

Table 2.7: **Effect on the Cost of Debt and Cost of Equity Conditional upon Intangibility**

This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on intangibility, size (for equity) and rating (for debt). Low intangibility includes the bottom quartile firms. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Equity	(3) Debt	(4) Debt
Low Intangibility (In)	9.42		10.78	
	(0.65)		(0.35)	
High Intangibility (In)	-11.17		28.47***	
	(0.38)		(0.00)	
Big × Low In		-0.07		
		(1.00)		
Big × High In		-19.71		
		(0.15)		
Small × Low In		42.06		
		(0.30)		
Small × High In		13.96		
		(0.64)		
Investment Grade × Low In				-8.36
				(0.46)
Investment Grade × High In				24.49***
				(0.01)
Non-investment Grade × Low In				31.61
				(0.12)
Non-investment Grade × High In				36.07*
				(0.05)
Observations	564	564	564	564
R-squared	0.00	0.01	0.02	0.03
Differences				
Low In - High In	20.59		-17.69	
	(0.39)		(0.22)	
Low In - High In (Big)		19.64		
		(0.47)		
Low In - High In (Small)		28.10		
		(0.57)		
Low In - High In (IG)				-32.85**
				(0.02)
Low In - High In (NIG)				-4.46
				(0.87)
Low In (Small) - High In (Big)		61.77		
		(0.15)		
Low In (IG) - High In (NIG)				-44.43**
				(0.04)

Table 2.8: **Effect on the Cost of Debt and Cost of Equity Conditional upon Industry (Utilities)**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on industry and rating. Utility group includes utilities. The treatment effect for the different groups is reported, as well as the difference between the groups, for all firms or only big ones. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Equity	Equity	Equity	Equity	Debt	Debt	Debt	Debt
Utility	44.63**		44.63**		-14.44		-14.44	
	(0.03)		(0.03)		(0.49)		(0.49)	
Non-Utility	-7.42		-18.81*		27.41***		26.30***	
	(0.42)		(0.07)		(0.00)		(0.00)	
Utility × Investment Grade		75.86***		75.86***		-4.65		-4.65
		(0.00)		(0.00)		(0.83)		(0.83)
Utility x Non-investment Grade		-26.33		-26.33		-36.68		-36.68
		(0.41)		(0.41)		(0.44)		(0.44)
Non-Utility × Investment Grade		-6.55		-15.41		19.13**		21.71**
		(0.48)		(0.13)		(0.02)		(0.01)
Non-Utility x Non-investment Grade		-8.822		-27.68		40.75***		38.28**
		(0.64)		(0.28)		(0.00)		(0.05)
Observations	566	566	426	426	566	566	426	426
R-squared	0.00	0.01	0.01	0.01	0.02	0.03	0.03	0.03
Differences								
Utility - Non-utility	52.05**		63.44***		-41.85*		-40.74*	
	(0.02)		(0.00)		(0.06)		(0.07)	
Utility - Non-utility (IG)		82.41***		91.27***		-23.78		-22.18
		(0.00)		(0.00)		(0.31)		(0.26)
Utility - Non-utility (NIG)		-17.51		1.35		-77.43		-74.96
		(0.64)		(0.97)		(0.12)		(0.14)
Utility (IG) - Non-utility (NIG)		84.68***		103.54***		-45.4*		-42.93
		(0.00)		(0.00)		(0.08)		(0.14)

Table 2.9: **Effect on the Cost of Debt and Cost of Equity Conditional upon Institutional Ownership**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on institutional ownership, size (for equity) and rating (for debt). Low institutional ownership group includes the bottom quartile firms. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Equity	(3) Debt	(4) Debt
High Institutional Ownership (IO)	-15.38		28.32***	
	(0.13)		(0.00)	
Low Institutional Ownership (IO)	28.31*		-8.80	
	(0.08)		(0.54)	
Big × High IO		-25.50**		
		(0.02)		
Big × Low IO		24.09		
		(0.18)		
Small × High IO		17.20		
		(0.46)		
Small × Low IO		39.75		
		(0.27)		
Investment Grade × High IO				22.19***
				(0.01)
Investment Grade × Low IO				-20.75
				(0.13)
Non-investment Grade × High IO				38.46**
				(0.01)
Non-investment Grade × Low IO				12.38
				(0.69)
Observations	563	563	563	563
R-squared	0.01	0.01	0.02	0.03
Differences				
High IO - Low IO	-43.69**		37.12**	
	(0.02)		(0.02)	
High IO - Low IO (Big)		-49.59**		
		(0.02)		
High IO - Low IO (Small)		-22.55		
		(0.60)		
High IO - Low IO (IG)				42.94***
				(0.00)
High IO - Low IO (NIG)				26.08
				(0.45)
High IO (Big) - Low IO (Small)		-65.25*		
		(0.08)		
High IO (NIG) - Low IO (IG)				59.21***
				(0.00)

Table 2.10: **Effect on the Cost of Debt and Cost of Equity Conditional upon CEO Options Ownership**

This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on CEO options ownership, size (for equity) and rating (for debt). Low CEO options ownership group includes the bottom half firms. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Equity	(3) Debt	(4) Debt
High CEO Options Ownership (OO)	-10.81		33.68***	
	(0.42)		(0.00)	
Low CEO Options Ownership (OO)	-1.07		19.76**	
	(0.92)		(0.05)	
Big × High OO		-11.78		
		(0.45)		
Big × Low OO		-8.78		
		(0.45)		
Small × High OO		-8.73		
		(0.73)		
Small × Low OO		66.33*		
		(0.06)		
Investment Grade × High OO				22.95*
				(0.06)
Investment Grade × Low OO				17.67*
				(0.09)
Non-investment Grade × High OO				48.57**
				(0.02)
Non-investment Grade × Low OO				25.30
				(0.28)
Observations	504	504	504	504
R-squared	0.00	0.01	0.03	0.03
Differences				
High OO - Low OO	-9.74		13.92	
	(0.57)		(0.35)	
High OO - Low OO (Big)		-3.00		
		(0.88)		
High OO - Low OO (Small)		-75.36**		
		(0.04)		
High OO - Low OO (IG)				5.28
				(0.75)
High OO - Low OO (NIG)				23.27
				(0.45)
High OO (Big) - Low OO (Small)		-78.11**		
		(0.04)		
High OO (NIG) - Low OO (IG)				30.90
				(0.18)

Table 2.11: **Effect on the Cost of Debt and Cost of Equity - Multiple Variables Interaction**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst conditional on incentives proxy (Var), size and rating. Variables are as previously defined. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2)	(3)	(4)	(5)	(6)
		Equity			Debt	
VARIABLES	Intangibility	Institutional Ownership	CEO Options Ownership	Intangibility	Institutional Ownership	CEO Options Ownership
Big × Investment Grade × Var High	-1.06	-20.95*	-8.69	27.40***	23.81***	25.61*
	(0.93)	(0.06)	(0.57)	(0.01)	(0.01)	(0.06)
Big × Investment Grade × Var Low	-13.62	25.34	-5.71	-7.98	-14.53	18.10
	(0.57)	(0.16)	(0.63)	(0.51)	(0.32)	(0.10)
Big × Non-investment Grade × Var High	-78.35*	-35.46	-34.81	32.18	35.18*	37.38
	(0.06)	(0.17)	(0.37)	(0.20)	(0.07)	(0.20)
Big × Non-investment Grade × Var Low	21.85	17.73	-1.39	18.96	-19.75	21.38
	(0.65)	(0.76)	(0.96)	(0.39)	(0.53)	(0.34)
Small × Investment Grade × Var High	48.53	57.97**	45.92**	6.23	11.20	-20.19
	(0.30)	(0.02)	(0.05)	(0.81)	(0.64)	(0.27)
Small × Investment Grade × Var Low	56.36**	26.88	65.93	-12.67	-63.05**	69.55
	(0.03)	(0.41)	(0.14)	(0.61)	(0.04)	(0.25)
Small × Non-investment Grade × Var High	-9.39	-1.99	-30.03	40.36	43.13*	47.24
	(0.83)	(0.95)	(0.40)	(0.14)	(0.10)	(0.12)
Small × Non-investment Grade × Var Low	40.56	46.44	48.41	52.04	27.38	89.39
	(0.41)	(0.37)	(0.39)	(0.19)	(0.52)	(0.16)
Observations	564	563	504	564	563	504
R-squared	0.02	0.02	0.01	0.03	0.03	0.04

Table 2.12: **Effect of the Loss of an Analyst on the WACC Conditional upon Rating, Number of Analysts, and their Interaction**

This table reports the change in weighted average cost of capital (WACC) resulting from the loss of an analyst conditional on size, rating and their interaction. Small firms group includes the bottom quartile. Non-investment grade includes firms whose rating is above 10 according to the used numeric scale. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) WACC (Pre-tax)	(2) WACC
Big × Investment Grade	3.50	1.66
	(0.58)	(0.77)
Big × Non-investment Grade	11.57	7.00
	(0.48)	(0.48)
Small × Investment Grade	22.18*	22.34*
	(0.09)	(0.06)
Small × Non-investment Grade	47.19**	38.62**
	(0.02)	(0.03)
Observations	566	566
R-squared	0.02	0.02
Differences		
Small - Big (IG)	18.68	20.67
	(0.20)	(0.12)
Small - Big (NIG)	35.62	31.61
	(0.17)	(0.16)
NIG - IG (Big)	8.07	5.34
	(0.64)	(0.73)
NIG - IG (Small)	25.01	16.28
	(0.30)	(0.44)

Table 2.13: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity Conditional upon Rating, Number of Analysts, and their Interaction - Only Closures/Mergers of Major Brokers**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst of a major broker conditional on size, rating and their interaction. Variables are as previously defined. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Equity	(3) Equity	(4) Debt	(5) Debt	(6) Debt
Small	52.63*			42.21*		
	(0.07)			(0.08)		
Big	-17.03			22.70**		
	(0.14)			(0.01)		
Non-inv. Grade (NIG)		-8.51			46.10**	
		(0.73)			(0.02)	
Inv. Grad (IG)		-0.05			16.99*	
		(1.00)			(0.06)	
Big × Inv. Grad (IG)			-8.83			20.23**
			(0.44)			(0.04)
Big × Non-inv. Grad (NIG)			-39.86			29.57
			(0.18)			(0.17)
Small × Inv. Grad (IG)			63.18**			-6.37
			(0.02)			(0.77)
Small × Non-inv. Grad (NIG)			45.59			74.60**
			(0.31)			(0.04)
Observations	418	418	418	418	418	418
R-squared	0.009	0.001	0.014	0.024	0.028	0.034
Differences						
Small - Big	69.66**			19.51		
	(0.02)			(0.45)		
NIG - IG		-8.46			29.11	
		(0.76)			(0.17)	
Small - Big (IG)			72.01**			-26.60
			(0.01)			(0.27)
Small - Big (NIG)			85.45			45.03
			(0.11)			(0.29)
NIG - IG (Big)			-31.03			9.34
			(0.32)			(0.70)
NIG - IG (Small)			-17.59			80.97*
			(0.73)			(0.06)
Small (IG) - Big (NIG)			103.4***			-35.94
			(0.01)			(0.25)

Table 2.14: **Effect of the Loss of an Analyst on the Cost of Debt and Cost of Equity Conditional upon Rating, Number of Analysts, and their Interaction - Excluding post-Lehman Bankruptcy Events**
This table reports the change in bond yield spread (change in cost of debt) and implied cost of capital (change in cost of equity) resulting from the loss of an analyst before Lehman bankruptcy conditional on size, rating and their interaction. Variables are as previously defined. The treatment effect for the different groups is reported, as well as the difference between the groups. Standard errors were bootstrapped. P-values in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Equity	(2) Equity	(3) Equity	(4) Debt	(5) Debt	(6) Debt
Small	12.12			32.95**		
	(0.51)			(0.04)		
Big	-14.76			30.83***		
	(0.13)			(0.00)		
Non-inv. Grad (NIG)		-10.69			49.97***	
		(0.55)			(0.00)	
Inv. Grad (IG)		-5.22			19.05**	
		(0.53)			(0.01)	
Big × Inv. Grad (IG)			-12.91			21.37***
			(0.16)			(0.01)
Big × Non-inv. Grad (NIG)			-19.12			53.13***
			(0.44)			(0.01)
Small × Inv. Grad (IG)			38.14**			6.04
			(0.05)			(0.78)
Small × Non-inv. Grad (NIG)			-0.73			46.24**
			(0.98)			(0.04)
Observations	453	453	453	453	453	453
R-squared	0.01	0.00	0.01	0.04	0.05	0.05
Differences						
Small - Big	26.88			2.12		
	(0.20)			(0.91)		
NIG - IG		-5.47			30.92*	
		(0.78)			(0.06)	
Small - Big (IG)			51.05**			-15.33
			(0.02)			(0.50)
Small - Big (NIG)			18.39			-6.89
			(0.61)			(0.82)
NIG - IG (Big)			-6.21			31.76
			(0.81)			(0.14)
NIG - IG (Small)			-38.87			40.20
			(0.23)			(0.19)
Small (IG) - Big (NIG)			57.26*			-47.09
			(0.07)			(0.11)

Appendix A: Variables Description

Variable	Description
Size	ln(Total Assets)
Book-to-Market	Book value of common equity / Market cap
Number of Analysts	ln(Number of analysts issuing earning forecasts about a firm)
Report Length	ln(Number of sentences)
Prior-CAR	CAR[-5,-1]
Uncertainty Index	US Economic Policy Uncertainty Index
Deviation from Consensus	EPS - Consensus EPS
Abs(Deviation from Consensus)	| EPS - Consensus EPS |
Absolute Analyst Experience	ln(Number of quarters since first forecast)
Relative Analyst Experience	ln(Number of quarters since first forecast about a firm)
Broker Size	ln(Number of analysts issuing forecasts for a broker)
Change in Earning Forecasts	% Change in EPS forecast, zero if first forecast
Change in Recommendation	Change in recommendation, zero if first or no recommendation

Appendix B: Sample Construction

This Appendix provides more details about how the sample was constructed.

Reports are provided by Thomson One in PDF format. I converted the PDF files to text files, which are easier to manipulate. Not all files can be successfully converted (some are, for instance, only pictures or have an uncommon codification) and, hence, must be excluded. Analysts often publish reports that contain just a few sentences (for instance, a reminder about date and time of a company event). Given the difficulty of using textual analysis techniques on texts that are very short, I excluded all these reports. I also excluded industry reports that cover several firms since it would be hard to identify the firm to which the precision measure refers.

I removed from the text files all disclaimers, disclosures, and analyst certifications sections as well as numerical tables. I also removed other non-content parts of the report, such as contact information and footnotes. I then removed numbers, common stop words (like "the" or "are", from NLTK Python package list) and, for analysis not involving sentences, punctuation. Following the practice in some of the existing finance literature using textual analysis (e.g., Huang et al. 2014), I did not perform "stemming", i.e., using just the root form of a word. Stemming can be problematic in finance applications because, for instance, "market" and "marketing" are equivalent as are "operations" and "operating". Last but not least, I converted each report into an array of words. Following the previous argument, I excluded reports with limited textual data. Specifically, I excluded reports with fewer than 10 sentences or 100 words. I also excluded the capitalized word "May" since it commonly refers to the month and not the verb.[1]

For each report, the Thomson One database provides information that includes the name of the primary analyst, the broker ("Contributor"), and the date the report was published. First, I matched the different Contributors to I/B/E/S estimator IDs. Then, I used the I/B/E/S recommendations database to match I/B/E/S analysts' names and analysts' IDs[2] to the Investext names. Each analyst has a unique name in IBES, but can have different names in Thomson One. I was able to match approximately 4,200 Thomson One analysts' names based on unique date-firm-broker pairs. In a few words, I exploited the fact some brokers have a unique analyst issuing recommendations about a specific firm in a specific period, so I could match the I/B/E/S analyst code to the reports. I also matched about 1,500 names based on the broker and small variations of the analyst name in Investext because an analyst can appear, for instance, as "Smith, John", as "Smith, John et al", or as "Smith, John and team". Further, I manually matched about 420 analysts' names that were not matched in the previous step, but who had issued more than 50 reports. This total of about 6,100 names covers approximately 95 percent of the reports. Remaining reports were issued by unnamed analysts (e.g.,

[1] The results are the same if I do not make this modification

[2] I/B/E/S Academic no longer officially provides a table linking the earning forecasts and the recommendations databases, but it is still possible to match a significant number of observations using the analyst codes.

"Research Department") or by analysts I was not able to reliably match to I/B/E/S.

Appendix C: Examples of Uncertain Sentences

I report here some examples extracted from analysts' reports containing several "uncertainty" words (in bold) according to the list of Loughran and McDonald (2011). Firm names have been redacted.

As we flagged repeatedly recently, the outlook for the thermal coal market is poor in our view. Now, it **appears** the met coal market is also feeling the pain, as the lack of a rebound in global steel production is taking a toll on US met coal demand/exports. While we maintain our view that met coal prices will rebound during the 2nd half of 2012, we **believe** the starting point is getting lower, and we are revising our [. . .] estimates accordingly.

Another factor that **could** cause the stock to rally would be completion of the [...] spin-off faster than we **anticipate**. The stock **may** also perform better than expected if greenhouse gas (GHG) emissions limits are adopted more quickly, or are more accretive to [...] than we project. As with any regulated utility, our rating **could** also be positively or negatively impacted by a significant change, positive or negative, in the regulatory outlook vs. our projection

An increase in aluminum prices is **possible** and can provide further upside. Higher aluminum prices over the forecast period **could** enhance earnings lift from execution. Supply demand characteristics **appear** favorable, and aluminum is currently cheap relative to energy, and competing materials. In addition, we **believe** progress securing long-term power agreements in key operating regions for [...] will allow the company to make attractive incremental investments to expand capacity.

The once-untouchable [. . .] now knows what it is like to compete, in our view. While we **believe** its cost advantage and high margins afford it the most flexibility to price as necessary to defend its turf, we expect the margin impact will be more significant than previously forecast. Although we remain positive longer term, pricing **uncertainty** has been introduced to the [. . .] story, dampening near-term excitement.

Sustained viral responses (SVR) of 6 months after cessation of therapy are required for HCV drug approval, indicating that although early data is extremely impressive, clinical **risk** remains. Moreover, although [. . .] remains the latest-stage PI out of three others known in development, every-8-hour dosing required of this agent keeps the barrier to entry low for a competing drug that **may** be dosed less frequently without compromising efficacy, in our view.

Our recommendations are based on historical trading patterns and our profit expectations, which are subject to a high degree of **risk**. Our profit expectations for [...] hinge on our revenue **assumptions**, which **depend** entirely on **assumptions** we make regarding economic growth, the demand for leisure and business travel, the impact of competition from low-fare carriers, and industry-wide aircraft capacity decisions. Our profit expectations also **depend** on **assumptions** we make about the cost of jet fuel (historically a **volatile** commodity), the impact on revenue and expenses of potential labor disruptions, and the impact of any number of geopolitical events and terrorism **risks** on the demand for air travel, among other things.

Appendix D: Precision and Topics of Reports

The main analysis distinguishes reports based on their tone and, when identifying which reports to exclude, whether they are issued around earnings announcements or guidance publications. However, the analysis ignores any variation in terms of topic. An issue could arise if the observed relation between precision and price reaction, or between tone and price reaction, is driven by the topic(s) covered by the reports. In this appendix, I describe reports according to their topics and then include this new variable in the list of controls in my main specification for price reaction. I also present preliminary results concerning the relation between precision and the topics of reports.

For the topic analysis, I employ Latent Dirichlet Allocation (LDA) introduced by Blei et al. (2003). LDA is a bag-of-words technique that can be employed to discover latent topics in a collection of documents. The approach is similar to the one used by to Huang et al. (2017) to compare topics in conference calls and analyst reports as well as by Fedyk (2018) for Bloomberg news.

D.1 LDA and Data Preparation

The assumption behind the LDA algorithm is that a document can be represented as a random mixture over different topics, where each topic is characterized by its specific distribution over the tokens (words). Specifically, the idea is that each word in a document is generated in two main steps:

1. A topic is randomly drawn from the topic distribution for the document.
2. A word is randomly drawn from the word distribution for the topic obtained in Step 1.

A document is, then, generated by repeating the two steps until the random length of the document is reached. Both topic distribution and word distribution are assumed to follow multinomial distributions whose parameters are randomly drawn from Dirichlet distributions with known parameters. The LDA algorithm relies on this model of documents generation to find the topics and words distributions that best fit the documents used to train it.

To summarize, given a corpus of documents, it is possible to use LDA to identify latent topics and the corresponding distribution of words. An LDA model can be used successively to analyze a new document and obtain the contribution of each latent topic to this document.

Before training the LDA model, in addition to the pre-processing explained in Appendix B, I also remove any word that is not a noun (e.g., verbs). I also exclude words that appear in fewer than two reports or in more than 70 percent of the reports. Of this word list, I keep the 2,000 more frequent ones.

Using this dictionary, I train the LDA model on all the reports sample with different numbers of topics (5 to 30, with steps of 5). The LDA algorithm used is the one available in the Python library "Gensim" (Rehurek and Sojka 2010). I rely on the commonly used perplexity score to identify the optimal model. The idea is to choose a sufficiently diverse set of latent topics; with too few topics each one will tend to capture only very broad concepts, with too many topics several will tend to largely overlap. Figure A1 reports the perplexity scores and suggests that 20 topics is the optimal number, since the goodness-of-fit does not improve with adding more topics.

D.2 Results

Table A1 reports the topics as well as well as their frequency and a list of the 15 most relevant words associated with them. To select the most relevant words I use the measure of Sievert and Shirley (2014), with $\lambda = 0.6$. This metric takes into account the overall frequency of each word and, hence, decreases the relevance of more frequent terms. Based on these most relevant words, I assign a label to each topic. Not surprisingly, a large portion of the reports discuss topics related to valuation, firm performance, management guidance, and management. As aforementioned, the trained LDA model can be used to express each report as a combination of the different topics. I construct 20 different variables containing the proportion of the corresponding topic in each report.

An interesting question is whether there is a relation between topics and precision. I constructed a series of dummy variables for each topic. The dummies take value equal to 1 if the proportion of a topic in a report is greater than 25 percent. Table A2 shows the results of a regression of $PrecisionC$ on these dummies.[1] Unsurprisingly, topics related to forecasts and expectations, such as valuation and management, are associated with lower precision, while reports discussing results or guidance appear to be more precise.

Finally, I use the 20 proportion variables as control variables in the main price reaction specification.[2] The results are reported in Table A2 and are largely consistent with the main results if not somewhat stronger, suggesting that report topics are not driving the results.

As future work, it would be interesting to understand whether the relation between precision and different firm or analyst characteristics as well as the relation between precision and market outcomes vary depending on the topic distribution of a report.

[1] There is no report where topic #20 contributes more than 25 percent.

[2] The results are equivalent, if not stronger, if the dummy variables are used

D.3 Tables

Table D.1: **LDA Topics**
This table reports the 20 topics identified by the LDA algorithm as well as their frequency and a list of 15 most relevant words associated with them. To select the most relevant words I used the measure of Sievert and Shirley (2014), with λ=0.6. I exclude variations of the same word.

#	**Topic Label**	**Most Relevant Words**	**Frequency**
1	Valuation	Target, valuation, stock, earnings, risk, rating, shares, estimates, discount, group, market, p/e, analysis, multiples, value	9.80%
2	Management	Management, years, time, CEO, president, business, strategy, today, opportunity, focus, people, number, meeting, way, investors	9.00%
3	Performance (results)	Quarter, year, sales, income, basis, earnings, increase, expense, tax, results, share, management, operating, points, profit	8.30%
4	Performance (changes and trends)	Margins, cost, volume, pricing, improvement, EBIT, pressure, expansion, cost, savings, leverage, trends, recovery, yoy, headwinds	6.60%
5	Guidance	Guidance, consensus, expectations, street, results, line, estimates, call, range, management, midpoint, conference, outlook, end, forecast	6.20%
6	Retail	Stores, comps, sales, merchandise, apparel, traffic, retailers, inventory, footage, margin, fashion, samestore, fashion, women, department	5.20%
7	Software	Software, storage, product, enterprise, applications, technology, customers, security, market, solutions, platform, products, data, vendors, cloud	5.20%
8	Oil/Energy	Production, oil, gas, rig, drilling, wells, exploration, reserves, crude, activity, prices, Gulf, play, resource, shale	4.90%

#	Topic Label	Most Relevant Words	Frequency
9	Strategy & International Business	Sales, China, food, brand, customers, markets, currency, products, Japan, Europe, category, countries, consumers, innovation, categories	4.90%
10	Accounting	Revenues, yoy, bookings, qoq, services, days, business, margin, GAAP, strength, estimates, seasonality, revs, nonGAAP, segment	4.80%
11	Balance Sheet	Cash, flow, dividend, capital, share, debt, sheet, balance, yield, shareholders, buyback, CAPEX, value, repurchase, return	4.70%
12	Technology / Electronics	Semiconductor, equipment, orders, communication, products, systems, markets, segment, wireless, revenues, order, backlog, technology, contracts, electronics	4.10%
13	Power Utility	Fuel, prices, capacity, coal, costs, energy, yield, earnings, power, utility, fleet, plant, gas, contracts, weather	4.00%
14	Real Estate	Property, credit, assets, land, debt, estate, interest, value, housing, sale, portfolio, equity, development, rate, construction	3.70%
15	Supply and Demand	Demand, industry, inventory, markets, units, supply, shipments, capacity, pricing, share, levels, utilization, product, days, production	3.60%
16	Healthcare	Patients, drug, phase, study, data, treatment, trial, approval, patent, pipeline, safety, processing, FDA, reimbursement, disease	3.50%
17	Periodical Data	Week, year, month, trends, checks, March, June, day, period, season, occupancy, July, data, September, December	3.30%
18	Media	Advertising, media, network, wireless, cable, internet, video, content, access, entertainment, subscribers, service, online, users, revenues	2.90%
19	M&A	Acquisition, deal, transaction, synergies, care, merger, integration, agreement, business, accretion, stake, dilution, purchase, EBITDA, assets	2.60%
20	Analyst Notes	Report, research, services, information, investment, companies, securities, views, firm, acreage, ratings, section, analyst, spread, metrics, stock	2.60%

Table D.2: **Precision and Report Topics**

This table reports the results of different regressions of Precision (in percentage points) on a set of dummies for each LDA topic. Each dummy is equal to 1 if the topic contributes more than 25% to the report. Earnings is a dummy equal to one if the report is published within two days from an earnings or management guidance announcement. Standard errors are double clustered at analyst and firm level. t-stats in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)		(1)
Topic Label	PrecisionC	Topic Label	PrecisionC
Valuation	-4.684***	Power Utility	-0.010
	(-20.22)		(-0.03)
Management	-1.209***	Real Estate	0.693
	(-4.18)		(1.27)
Performance (results)	3.270***	Suppy & Demand	-1.622***
	(16.85)		(-4.59)
Performance (trends)	0.815***	Healthcare	-1.901***
	(3.71)		(-3.42)
Guidance	3.171***	Periodical Data	0.659
	(14.92)		(0.84)
Retail	2.206***	Media	1.188*
	(6.97)		(1.74)
Software	-0.246	M&A	-2.099***
	(-0.77)		(-3.40)
Oil/Energy	-0.036	Litigation	-0.557
	(-0.07)		(-1.06)
Strategy & International Business	1.542***		
	(4.85)	Observations	99,499
Accounting	4.041***	Adjusted R-squared	0.442
	(21.59)	Earnings	YES
Balance Sheet	-0.101	Month FE	YES
	(-0.20)	Analyst-Firm FE	YES
Technology	2.129***		
	(7.73)		

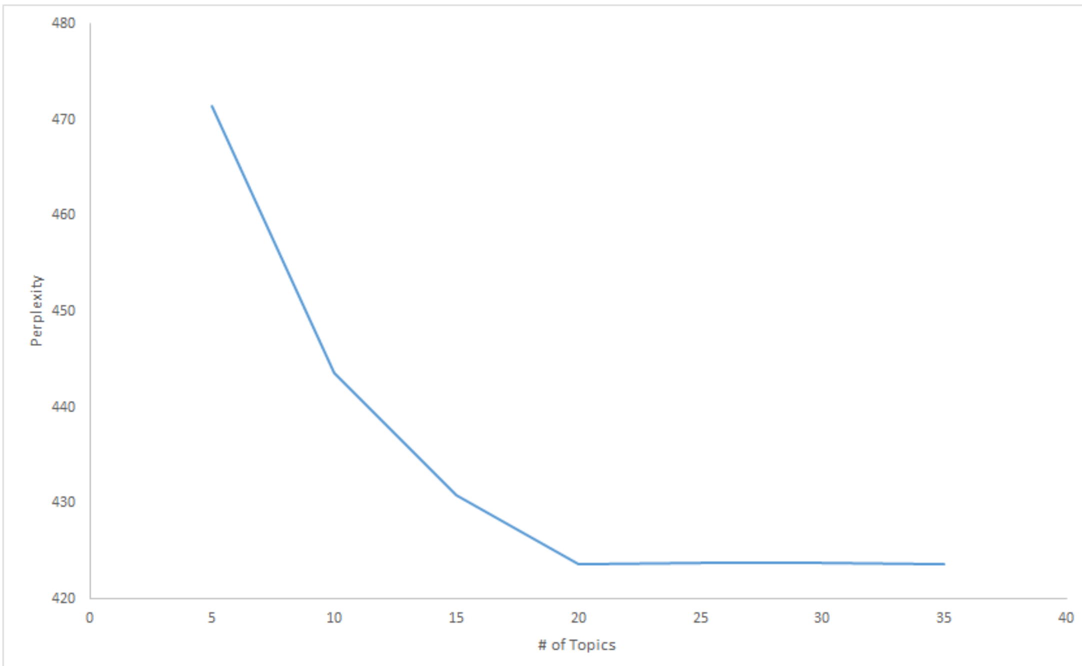
Table D.3: **Price reaction to analyst report precision – Controlling for topic**

This table reports the relation price reaction (Cumulative Abnormal Return, multiplied by 100) to the publication of an analyst report and its precision. Reports are double sorted into Tone and Precision groups. Tone sorting is based on quartiles, Precision sorting is based on monthly sextiles. Controls include size, B/M, number of analysts, uncertainty index, prior-CAR, absolute and relative analyst experience, deviation from consensus, broker size, report length, and report topics distribution. Rev Controls include change in recommendation and change in EPS forecast. Standard errors are double clustered at analyst and industry-week level. t-stats in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) CAR[0,1]	(2) CAR[0,2]	(3) CAR[0,4]	(4) CAR[0,6]
Tone = 1, Pessimistic	-0.248	-0.078	-0.037	0.298
	(-1.52)	(-0.41)	(-0.17)	-1.12
Tone = 2, Optimistic	0.251	0.243	0.075	0.022
	-1.31	-1.12	-0.28	-0.07
Precision = 1, Medium	-0.125	-0.052	-0.11	-0.045
	(-1.10)	(-0.40)	(-0.74)	(-0.25)
Precision = 2, High	-0.262*	-0.145	-0.263	-0.127
	(-1.73)	(-0.85)	(-1.27)	(-0.54)
Pessimistic×Medium	**-0.193**	**-0.285**	**-0.139**	**-0.346**
	(-1.07)	**(-1.37)**	**(-0.56)**	**(-1.19)**
Pessimistic×High	**-0.489****	**-0.723*****	**-0.691****	**-0.912****
	(-2.01)	**(-2.62)**	**(-2.04)**	**(-2.35)**
Optimistic×Medium	**0.028**	**-0.035**	**0.162**	**0.076**
	-0.14	**(-0.16)**	**-0.58**	**-0.25**
Optimistic×High	**-0.183**	**-0.221**	**-0.045**	**-0.094**
	(-0.83)	**(-0.89)**	**(-0.14)**	**(-0.26)**
Observations	21,361	21,361	21,361	21,361
R-squared	0.245	0.229	0.217	0.21
Controls	YES	YES	YES	YES
Rev Controls	YES	YES	YES	YES
Analyst-Firm FE	YES	YES	YES	YES

D.4 Figures

Figure D.1: **Perplexity Score**
This plot depicts the perplexity score of LDA models with different numbers of topics.



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