INFORMATION UNCERTAINTY AND OTHER INFORMATION AFFECT ANALYSTS' BEHAVIOR?

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ABSTRACT
This study investigates analyst forecast error in different environments of information uncertainty. We use a different approach to the ones commonly used in this literature to analyze analysts' bias dealing with other information in environments under different levels of information uncertainty. Controlling for firms' economic and accounting characteristics, we find that analysts tend to be optimistic when they are dealing with negative other information, while unbiased when dealing with positive other information, this results are more pronounced when evaluating negative news related to mature firms because analysts consider the maturity and past difficult situations held by these firms. We also find that analysts tend to exacerbate their biases when forecasting firms in industries subject to uncertain environments. Our set of results are useful for investors since it offers a way that investors can anticipate the situations in which analysts tend to be more biased, letting them weight better the influence of analysts' suggestions on their portfolios.

Key Words: Forecast Error; Information Uncertainty; Reaction to News; Analyst Bias; Analyst Optimism.

Thematic Area: Mercados Financeiro, de Crédito e de Capitais (MFC).

1 INTRODUCTION

According to several studies in financial and accounting literature, analysts provide new relevant information to the market when they issue reports of equity research and stocks price forecasts. Givoly and Lakonishok (1979), Cheng (2005) and Kothari (2001) document that analysts' forecast capture forward-looking information about fundamentals from different sources than financial statements. In the same direction, Fried and Givoly (1982) and O'Brien (1988) demonstrate the superiority of analysts' forecasts when compared to models such as time-series models for providing surrogates of market expectations. In a recent study Louis, Lys, and Sun (2014) discover that the initial analyst forecast error is negatively associated with conservatism proxies measured before the forecast is published by analyst.

Furthermore studies including Bryan and Tiras (2007) highlights that analysts rely more in other information when environment's information quality is poor. In a practical perspective, suppose that analysts are evaluating the new legalized market, arising discussions about legalization in legislative power of other countries. In this context, established businesses may

decide to switch their attention for this market. Information at this moment would be probably poor, and certainly, analysts would not spend much time evaluating past accounting information in such conditions. Actually, analysts would pay attention to political discussions about the new market and its potential growth, as the findings of Bryan and Tiras (2007) suggests.

Therefore, we already have support that analysts are useful as information intermediaries in financial sector and they rely more on non-accounting information when environment's information quality is poor, but empirical evidence on whether analysts fully reflect other information when forecasting earnings and on how it changes in accordance to the information uncertainty is still necessary.

This paper's goal is to analyze analysts' bias in environments under different levels of information uncertainty by using a different approach to the ones commonly used in the literature. We apply controls like size, maturity, industry and earnings quality to capture bias related to analysts. We bring a variable extensively applied to valuation literature (Dechow, Hutton, & Sloan, 1999; Lo & Lys, 2000) to quantify the impact of new information on earnings and establish a new measure of information uncertainty that just relates to current year earnings and does not relate to accounting information.

We predict that analysts react differently between bad and good news about companies in terms of magnitude or direction of bias. The basis for our prediction is the well-established research in area that document analysts' under react to good news when forecasting earnings and under react even more to bad news. We document that this results are more pronounced when evaluating negative news related to mature firms because analysts consider the maturity and past difficult situations held by these firms.

Our first analysis in this paper corroborate with most of literature that indicates some kind of analysts' bias when they forecast earnings (Zhang, 2006; Amiram, Landsman, Owens, & Stubben, 2014; Francis & Philbrick, 1993; Stickel, 1998; Das, Levine, & Sivaramakrishnan, 1998; Lin & Mcnichols, 1998; Michaely & Womack, 1999; Dechow et al., 1999; Cowen, Groysberg, & Healy, 2006). According with Martinez (2007) most published studies have concluded that the analysts are optimistic. Specifically we find that analysts are generally optimistic when analyzing negative other information and unbiased when analyzing positive other information. The results are prominent for mature firms since we document that analysts are even more optimistic when evaluating very negative news related to mature firms.

The reason may be that analysts are more apprehensive when reacting to very bad news of young firms because these firms still not prove their capacity of overcoming obstacles than when reacting to bad news related to mature firms that already survived in the market for many years and several crisis. This result is in accordance to Michel and Pandes (2015), who present evidence that analysts incorporate on their forecasts valuable information associated to future performance of firms and Pae and Thornton (2003) who find that the last forecast error is more negative for bad news firms than for good news firms.

Our second analysis relates to analysts' behavior in environments with high information uncertainty. We define information uncertainty as the volatility of other information across firms of the same industry in a given year and we find that analysts' optimism is even higher when information uncertainty is high. The main difference between our paper and past studies is that we give special focus on analyst reaction to shocks unrelated to past accounting information and we evaluate it in environments under different levels of information uncertainty about this specific kind of shock.

These results support investors who take into account financial analysts' suggestions. If they base their investments, at least partially, on analysts' forecasts, it is useful for them to

recognize when and in which direction analysts' predictions are biased, so they can better weight analysts' forecasts in their investment decisions.

Also by introducing the variable other information and by establishing a new measure of information uncertainty, we offer a new perspective for future research on analysts' behavior. We recognize that it is not yet a perfect approach for identifying biases since it relies on the assumption that abnormal earnings and other information follow auto-regressive processes, but it offers an alternative for testing robustness of past and future studies.

The paper is organized as follows: in section 2, we present past literature about analyst forecast error and motivate our hypothesis, in section 3, we present the research design including our model, data sample and methodological issues, in section 4, we present evidence corroborating our hypothesis by both descriptive statistics and regression analysis. Finally, in section 5, we provide a brief summary and the conclusion.

2 LITERATURE

2.1 Analysts' bias

Many researchers have developed approaches for improving predictions of future analyst earnings forecast errors (Ali, Klein, & Rosenfeld, 1992; Elgers & Murray, 1992; Lo & Elgers, 1998; Frankel & Lee, 1998; Hughes, Liu, & Su, 2008; Gode & Mohanram, 2009; So, 2013; Larocque, 2013; Mohanram & Gode, 2013). Most of them usually rely on the relation among consensus analyst forecasts, past forecast errors, and firms' characteristics, or on time-series approaches that uses data from past financial statement.

Although these studies make advances in recognizing the relevance of these variables for explaining analyst forecast errors, there is a lack of consideration in other information.

It represents an important gap in literature since, according to Brown, Richardson and Schwager (1987), the observation of new information is exactly what makes analysts' forecasts superior to (or more accurate than) time series forecasting models. Hilary and Hsu (2013) argue that the usefulness of analysts' forecasts should not be based on forecasts' stated accuracy, but rather on forecasts' informativeness.

In fact some studies already considered other information in their analysis in order to comprehend analyst forecast error, but they did it in some implicit way. For example, Stickel (1992), Gleason and Lee (2003) Zhang (2006), Jiang, Lee, and Zhang (2005) and Mendenhall (1991) use post-analyst-revision drift for analyzing the efficiency of analysts/investors absorption of news. We argue that revisions may be caused not by delays in news' absorption, but by occurrence of new value-relevant events. Also, Abarbanell and Lehavy (2003) show a relationship between optimistic analyst forecast error and negative abnormal accruals but as abnormal accruals are accruals that are not predictable by past financial data, we argue that they can be interpreted as one kind of other information.

By the other hand, studies including Basu (1997) explicitly consider other information, but they do it in a noisy way by using stock price return as a proxy for new information. Even though stock price return captures new information that occurred during the current fiscal year, this information may affect any future earnings, not just the current one (the one that is used for analyzing analysts' bias).

For this reason, we bring a variable from valuation literature to analyst forecast error literature: other information. Based on two hypothesis, the Clean Surplus Relation (CSR) and the Linear Information Model (LIM) , and on the definition of abnormal accruals, Ohlson (1995) demonstrates that future earnings may be predicted as a linear function of current earnings, book value and dividends, as follows:

$$x_{t+1} = \omega . R_f . x_t + (1 - \omega) . (R_f - 1) . BV_t - \omega . (R_f - 1) . Div_t + v_{t+1} \quad (1)$$

where x_{t+1} and x_t are next and past fiscal-year earnings, respectively; BV_t is book value; Div_t is dividends, ω and γ are the persistence of abnormal earnings and of the impact of other information on one-year-ahead earnings, respectively; and R_f is one plus the risk free interest rate. The last term, v_{t+1}, is the variable other information. Theoretically, this variable intends to capture exactly what we look for: new information that occurs during a specific fiscal-year that will affect only that specific fiscal-year earnings.

Conflicting results have been found in literature about analyst forecast error. Basu and Markov (2004), for example, fail to reject the hypothesis of unbiasedness, while Zhang (2006), Elliott, Philbrick, and Weidman (1995), and Amiram et al. (2014) find evidence of underreaction and Brown, Foster and Noreen (1985), Stickel (1992), Abarbanell (1991), Francis and Philbrick (1993), Stickel (1998), Das, Levine and Sivaramakrishnan (1998), Lin and McNichols (1998), Michaely and Womack (1999), Dechow, Hutton, and Sloan (1999), and Cowen, Groysberg and Healy (2006) find evidence of optimism in analysts' forecasts. For this reason, we do not have a clear expectation about the relation between other information and forecast error. Therefore, we do not hypothesize the kind of relationship between these variables, but explore the potential bias.

2.2 Asymmetry in analysts' reaction to news

Elliott et al. (1995), Jiang et al. (2005), and Zhang (2006) find that analyst react to good and bad news in different manners. They document that analysts generally underreact to good news when forecasting earnings and under react even more to bad news. As suggested by Zhang (2006), this result may be a consequence of the higher bad news than good news auto correlation or the flow of information to the market (eg, managers fully disclose good news but withhold bad news).

By the other hand, Basu (1997) presents evidence of accounting conservatism or, in other words, presents evidence that bad news is timely recognized in the accounting system while good news is recognized with some delay. Accordingly, if analysts' goal is not to accurately inform reported earnings, but the real firm's performance, then it would be natural that analysts seem optimistic when evaluating good news since they would remove the conservatism present in the accounting system.

Therefore, we develop our first hypothesis in order to test if there are in fact some kind of asymmetric behavior of analysts when dealing with good and bad news:

H1: Analysts' reaction (in terms of magnitude or direction of bias) to bad news is different to analysts' reaction to good news.

2.3 Analysts' reaction under information uncertainty

Past studies document that analysts exacerbate their biases when evaluating firms under higher information uncertainty. For example, Das et al. (1998) find that analysts are biased and even more biased when forecasting firms that have less predictable earnings. Other studies including Zhang (2006) find that if analysts, because of behavioral biases, underreact to new information when their forecasts is revised, then they underreact even more the higher the information uncertainty is. Amiram et al. (2014) document that, during periods of high market uncertainty, analysts underreact to news not only in terms of magnitude (incomplete forecast revisions), but also in terms of time (delay in revising forecasts).

If analysts have some economic incentive for biasing their forecasts and the potential punishment is what mitigates this problem, then it would be expected that analysts intensify their bias when facing high information uncertainty. Consider a hypothetical environment with no information uncertainty. In this context, any forecast error should be strongly punished

because it would make clear that the analyst did a poor job. By the other side, in an environment with high uncertainty, forecast errors are somewhat acceptable. Thus, we make our second hypothesis:

H2: Analysts' reaction (in terms of magnitude or direction of bias) under high information uncertainty is different to analysts' reaction under low information uncertainty.

In order to verify if higher uncertainty according to the impact of other information on earnings would lead to even higher forecast errors, we establish a new measure of information uncertainty based on the volatility of other information across firms of the same industry. Specifically, we are interested to shed some lights on how differently analysts behave in forecasting earnings of firms which belong to industries subject to higher volatile shocks. One of the motivations for this measure is based on Shan, Taylor, and Walter (2014), who show a relationship between other information and systematic/idiosyncratic volatility and suggest that other information contains both firm-specific and market-level information.

We evaluate this potentially increase in analysts bias under high information uncertainty in a different way than past studies. Our work differs to Das et al. (1998) by explicitly considering new information since these authors investigate the relation between the predictive accuracy of past information and the bias of analysts' earnings forecasts. And our work differs to Amiram et al. (2014) and Zhang (2006) by considering the aggregate impact of new information on earnings since these authors use analysts' forecasts revisions, which do not include the whole set of news that occurred during the same fiscal-year.

By establishing our own measure of information uncertainty, we aim to capture only volatility derived from shocks unrelated to past accounting information and that will affect the current fiscal-year earnings. Anyway, we also use in our study abnormal accrual for capturing uncertainty associated to accounting information.

3 RESEARCH DESIGN

3.1 Data sample

The sample in this work relates to the period between 1983 and 2014, in which book value, dividends, and other financial data were obtained from Compustat, consensus analyst forecasts and reported earnings were obtained from I/B/E/S, and stock price from CRSP. We excluded firms with negative book value, as well as firms from regulated financial institutions and utilities. We also excluded firms in which some data were not available. As a matter of comparability with other studies and of caution with computing information derived from data input error, we winsorized all variables yearly at 1% and 99%. By this way, the sample size in our final regression became equal to 34.171 firm-year observations.

3.2 Model

We propose an empirical model that interacts other information, information uncertainty, and firms' maturity in addition to the control variables:

$$\begin{gathered}\mathrm{FE}_{i,t} = \alpha + \beta_1.\mathrm{Neg}_{i,t} + \beta_2.\mathrm{Mat}_{i,t} + \beta_3.\mathrm{High}_{i,t} + \beta_4.|\mathrm{OI}|_{i,t} + \beta_5.\mathrm{Neg}_{i,t}.\mathrm{Mat}_{i,t} + \\ \beta_6.\mathrm{Neg}_{i,t}.\mathrm{High}_{i,t} + \beta_7.\mathrm{Neg}_{i,t}.|\mathrm{OI}|_{i,t} + \beta_8.\mathrm{Mat}_{i,t}.\mathrm{High}_{i,t} + \beta_9.\mathrm{Mat}_{i,t}.|\mathrm{OI}|_{i,t} + \\ \beta_{10}.\mathrm{High}_{i,t}.|\mathrm{OI}|_{i,t} + \beta_{11}.\mathrm{Neg}_{i,t}.\mathrm{Mat}_{i,t}.\mathrm{High}_{i,t} + \beta_{12}.\mathrm{Neg}_{i,t}.\mathrm{Mat}_{i,t}.|\mathrm{OI}|_{i,t} + \\ \beta_{13}.\mathrm{Mat}_{i,t}.\mathrm{High}_{i,t}.|\mathrm{OI}|_{i,t} + \beta_{14}.\mathrm{Neg}_{i,t}.\mathrm{Mat}_{i,t}.\mathrm{High}_{i,t}.|\mathrm{OI}|_{i,t} + \sum_j \delta_j \mathrm{Controls}_{j,i,t} + \varepsilon_{i,t} \qquad (2)\end{gathered}$$

where $Neg_{i,t}$ is a dummy for negative impact of other information on earnings; $Mat_{i,t}$ is a dummy for firms publicly operating for more than 10 years, calculated as the current fiscal-year minus the IPO date; $High_{i,t}$ is a dummy for firms in environments with highest information uncertainty (percentiles 70 or higher); and $|OI|_{i,t}$ is the absolute value of other information's

impact on earnings. The controls refer to analyst coverage, size, time, loss, leverage, book to market, tenure of analysts, and abnormal accruals. Note that, in this regression, positive Betas related to our variables of interest are associated to pessimism while negative Betas are associated to optimism.

According to our empirical model β_2 is associated to effect of maturity on forecast error and allow to verify the impact of firms age on analyst optimism in contact with new information. β_3 is associated to effect of environments with high information uncertainty on forecast error and allow to verify how analysts react when information in more uncertainty. β_7 is associated to effect of negative impact of other information on forecast error and allow to verify the impact of negative news on analyst optimism.

3.2.1 Controls

In our analysis, we control for a large range of firm-specific characteristics: analyst coverage, size, time, loss, leverage, book to market, tenure of analysts, and abnormal accruals.

Kothari (2001) suggests that economic incentives and behavioral cognitive based explanations are the main determinants of analyst optimism. In accordance to the economic incentives-based explanations, while inaccuracy reduces analysts' annual compensation and reputation, biased forecasts may improve analysts' relations with firm's management, what can generate future gains, such as better flow of information and more brokerage businesses. Lim (2001), for example, points that issuing favorable forecast may improve relation with management, while Richardson, Teoh, and Wysocki (2004) points that beatable forecasts would make it. By considering that the higher the number of analysts covering a firm, the lower the analyst capacity of individually influence market expectations about this firm and the higher the punishment for inaccurate predictions, then analysts have lower economic incentives for being intentionally biased when there are more peers covering the same firm. By the other hand, the herd behavior (Trueman, 1994) could affect more heavily analysts' consensus related to firms covered by a higher number of analysts, causing analysts to make bigger errors when more analysts are covering the same firm.

In addition to analyst coverage, we control for size, since Lim (1998) finds that analysts are more optimistic when forecasting quarterly earnings of bigger than smaller firms. Literature also points for the importance of controlling for time; Brown (2001) presents a shift away from analyst optimism toward analyst pessimism in recent years. Loss is another control since Hwang, Jan, and Basu (1996) document more optimistic earnings forecasts for firms whose actual earnings are losses. We also control for leverage and book to market. Industry control is also necessary in this study due to different relative importance that non-accounting information has in different industries; Amir and Lev (1996); for example, find that non-financial information is highly value relevant for wireless communication industry while its financial information has only complementary value. Book to Market is also present; we use it for controlling for accounting conservatism.

Ashbaugh-Skaife, Collins, and LaFond (2006) comment that reliability of financial information depends on the quality and integrity of audit process, while Sengupta (1998) states that a more timely and informative disclosure make the firm be perceived as less likely to hide value-relevant unfavorable information. In this paper, financial transparency or, more specifically, reliability and timeliness of accounting information are used in order to control for potential earnings accounting information uncertainty.

Table 1 shows our control variables, how we calculate them, the reason for using them and the literature that motivates their use.

Table 1 Control Variables

Characteristic and Formula	Reason	Literature
Analyst coverage	Higher coverage reduce economic incentives to improve relation with firm's management and to increase the trading volume;	Kothari (2001)
COV: Number of analysts covering the firm	Herd behavior: the higher the number of analysts covering a firm, the lower their incentives to look for more accurate information and the higher their incentives to follow their peers, what may increase forecast errors	Lim (2001) Richardson et al. (2004) Trueman (1994)
Size (log of market value)	Literature already documented that analysts are more optimistic when forecasting quarterly earnings of bigger than smaller firms	Lim (1998)
Time (fiscal-year)	Shift away from analyst optimism toward analyst optimism in recent years	Brown (2001)
Loss (1 if loss, and 0 otherwise	Literature already documented that analysts are more optimistic when forecasting firms whose actual earnings are losses	Hwang et al. (1996)
Industry – IND'i': 1 if firm pertences to given industry, and 0 otherwise - (48 dummies)	Different relative importance of non-accounting information in different industries. For example, it is highly value relevant for wireless communication industry	Amir and Lev (1996)
Earnings quality - ABNACC: abnormal accrual (following the model of Jones, 1991)	Low earnings quality means that earnings manipulation is more likely and that accounting information uncertainty is higher	Ashbaugh-Skaife et al. (2006) Sengupta (1998) Abarbanell and Lehavy (2003)
Book to Market	Accounting Conservatism: there is evidence that reported earnings react differently to good and bad news; by the same way, it is possible that analysts do not correctly adujst their forecasts to this asymmetric relationship between reported earnings and news; another reason is that analysts' goal may be to accurately inform the firms' real performance, not reported earnings.	Basu (1997)
BTM: book value divided by market value	Book-to-market ratio captures (among other things) conservative characteristics of the accounting systems	Beaver and Ryan (2000)

Source: Elaborated by the author

3.3 Methodological issues

3.3.1 Other information and analyst forecast error

As we are not interested in an ex-post analysis in order to keep the findings usefulness for investors, we follow Bryan and Tiras (2007) and use the residual of the following regression to proxy for other information:

$$\mathrm{AF}_{i,t+1} = \beta_1 . \mathrm{x}_{i,t} + \beta_2 . x^{-}_{i,t} + \beta_3 . \mathrm{BV}_{i,t} + \beta_4 . \mathrm{Div}_{i,t} + \mathrm{v}_{i,t+1} \quad (3)$$

where $AF_{i,t+1}$ is the median analyst forecast of a specific firm. Note that we complement the empirical model of Bryan and Tiras (2007) with the variable $x^{-}_{i,t}$, negative earnings. Using this variable we control our estimative of other information for accounting conservatism. Specifically we let the persistence of positive and negative earnings in our regression be different, in accordance to Basu (1997), that document a higher persistence of positive earnings.

Moreover, note that we do not assume analysts know all public and private information, but that they incorporate timely and unique information not yet reported by the accounting

system in a potentially biased way when making their forecasts. By using the median analyst forecast, the regressions' residuals represent how analysts evaluate the impact of news that occurred during that fiscal-year on that fiscal-year earnings.

Two aspects of the regression that we used for estimating analysts' expectation of other information deserve special attention. First, because analysts do not observe accounting information of future years, the method employed in estimating other information needed to avoid any possible look-ahead bias. For this reason, as in Monte-Mor (2014), a multi-panel procedure was implemented, which means that a panel regression that contains only information of past years was run for each year's regression. Therefore, we ran panel regressions for each given fiscal-year of our sample, where each regression contained only firms of the same industry and only information of past years. The industry was defined in accordance to Fama/French industry classification (48 industries).

Second, because the interest of this paper is to understand the analysts' behavior when they recognize all non-accounting information, we could not use any analyst forecast for calculating analyst consensus, but only forecasts made between the end of the fiscal year and the earnings announcement date. These forecasts' data choice reduces the possibility of collecting forecasts of analysts who still did not know about the realization of some value-relevant event that happened during the evaluated fiscal-year. Our approach, by the other side, let us evaluate whether analysts bias their forecasts when analyzing the impact on earnings of events that already occurred. The timeline in Figure 1 presents an example of this research design by means of a firm with December 31st fiscal-year-end.

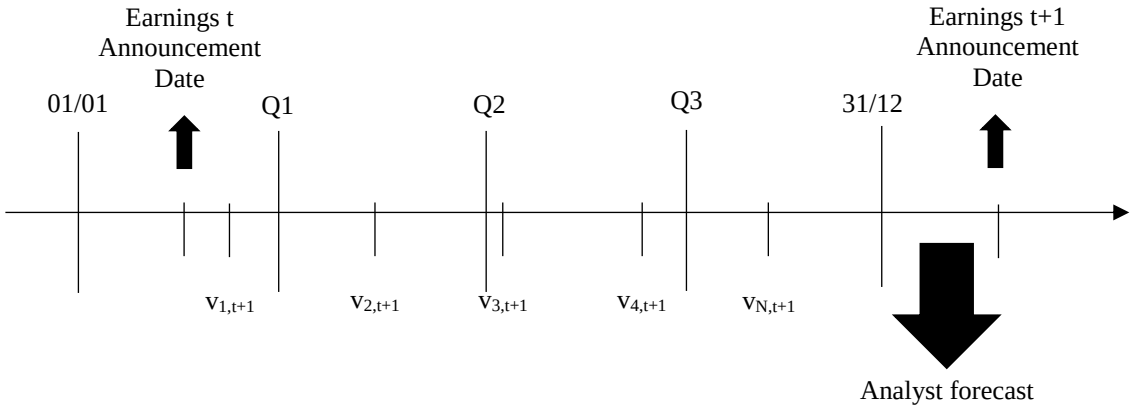

Figure 1. Timeline of a firm-year with December 31st fiscal-year-end
Source: Elaborated by the author

It is important to note that this methodology, while mitigates a potential problem – a measure error related to premature forecasts made by analysts without enough information – it does not alleviate another potential problem: CEOs may observe the consensus close to earnings report and manipulate this report in order, for example, to beat the consensus. Thus, controlling for financial transparency is the way this paper handle this issue. Particularly, we use the model of Jones (1991), one of the most common models on earnings management literature (Dechow, Hutton, & Sloan, 2012).

Using the same analyst consensus presented above, we define analyst forecast error as reported earnings minus analyst consensus.

3.3.2 Information uncertainty

In order to document how analysts adjust their behavior when forecasting other information in environments where this information is more uncertain, we develop a measure with the intention to capture only volatility derived from shocks unrelated to past accounting information and that will affect the current fiscal-year earnings. We use the volatility of other information across the firms of the same industry in a given fiscal-year, what is consistent with Shan et al. (2014) suggestion that other information contains both firm-specific and market-level information. By this way, we intend to isolate the information uncertainty related to other information that will affect the current year earnings to the information uncertainty related to past accounting information or related to any information that will affect future years' earnings.

$$\sigma_i = \sigma_k = EP(v_{t,i}) = \frac{\sqrt[2]{\sum_{i\epsilon k}(v_{t,i}-v)^2}}{n-1}, \forall i\epsilon k \qquad (4)$$

Where the firms i belong to the same industry k.

4 RESULTS

4.1 Descriptive statistics

If analysts are unbiased when predicting other information, then it would be expected that analysts do not make optimistic nor pessimistic forecasts accordingly to the impact of other information on earnings, what would be consistent with the findings of Basu and Markov (2004). Nevertheless conflicting conclusions are present in the literature about analyst bias. As Abarbanell and Lehavy (2003) document, depending on the criteria that researchers use, they may find opposite evidence about analyst behavior. In our sample, we also document this issue: while a mean-based analysis indicates optimism of analysts at 1% significance level, both a median and a positive/negative ratio-based analysis indicate pessimism of analysts (see Table 2).

Table 2 Statistics on Forecast Error Distributions

Number of observations	**62591**
Mean	**-0.0047**
Median	**0.0002**
% Positive	**52.08%**
% Negative	**37.28%**
Zero	**10.64%**

Source: Elaborated by the author

Affirming that analysts react optimistically/pessimistically to news based on the statistics above would be too simplistic. Therefore, we also document that negative other information goes hand in hand with negative forecast errors. Figure 2 shows this relationship, where we associate percentiles of other information and mean forecast errors in intervals of +/- 0.5 percentage points around percentiles of other information. Thus, this figure corroborates hypothesis 1: analysts react differently when forecasting good and bad news.

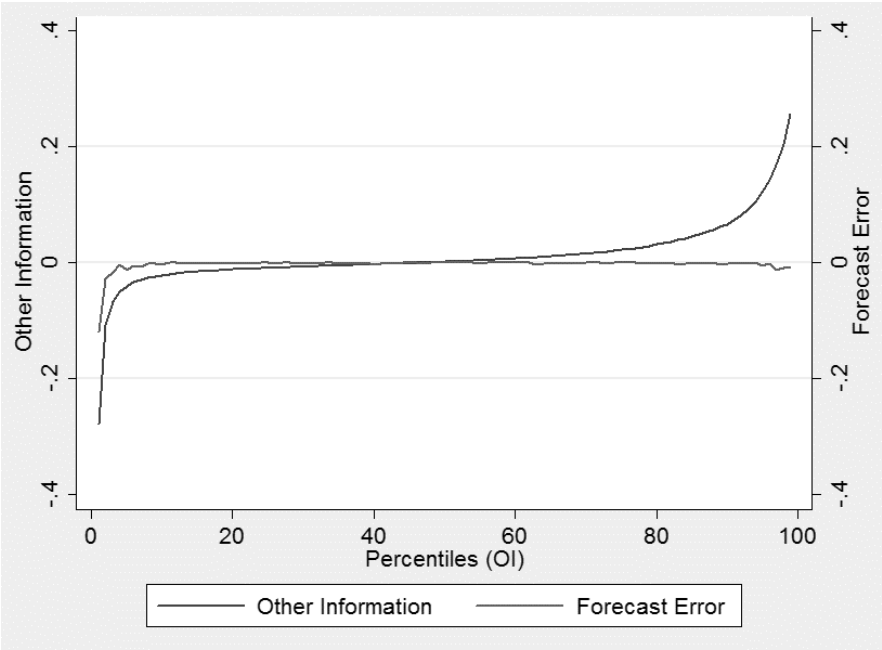

Figure 2. Relationship between other information and forecast errors
Source: Elaborated by the author

Moreover, we show the relationship between new information and analyst forecast error by sign of other information (see Table 3), indicating that hypothesis 1 seems to be correct. Both a mean- and a positive/negative ratio-based analysis corroborate the findings of Zhang (2006) and Elliott et al. (1995) that analysts more heavily underreact to negative news than to good news (in fact, Table 3 suggests that analysts do not even underreact to good news, but overreact to it). A mean comparison t-test indicates at 1% significance level that analysts are on average more optimistic when forecasting bad news than good news. We propose the same explanation made by Zhang (2006): analysts more heavily bias bad news, possibly due to the asymmetric flow of information to the market or to the higher bad than good news autocorrelation.

Table 3 Mean, Median, And Frequency of Forecast Errors by Sign of Other Information

Forecast Error	Sign of Other Information	
	Negative	**Positive**
Number of observations	25170	29155
Mean	-0.0047	-0.0025
Median	0.0001	0.0004
% Positive	51.54%	54.14%
% Negative	38.81%	34.13%
% Zero	9.65%	11.73%

Source: Elaborated by the author

The relationship between forecast error and volatility of other information across firms of the same industry is presented in Table 4. A mean-based analysis suggests that analysts more strongly bias their earnings forecasts when information uncertainty is higher, corroborating with Das et al. (1998), Amiram et al. (2014) and Zhang (2006) and with hypothesis 2.

Table 4 Mean, Median, And Frequency of Forecast Errors by Level of Information Uncertainty

Forecast Error	Information Uncertainty	
	High	**Low**
Number of observations	16236	16252
Mean	-0.0091	-0.0008
Median	0.0004	0.0001
% Positive	53.92%	52.20%
% Negative	33.03%	39.11%
% Zero	13.05%	08.69%

Source: Elaborated by the author

4.2 Regression analysis

Even though our descriptive statistics indicates that our hypothesis 1 and 2 are correct, regression analysis must be considered in order to control for other factors that affect forecast error and to make a more detailed investigation. In fact, the evidence on the descriptive statistics remain somewhat similar on the regression analysis: it still corroborates our two hypothesis. We estimated the model presented in equation 2 using a fixed effect panel regression analysis that controls for a large range of firm-specific attributes.

Table 5 Panel Regression of Forecast Error on Positive/Negative Other Information, Volatility of Other Information across Firms, Firms' Maturity, and Controls

VARIABLES	Model 1		Model 2	
	Coefficient	p-value	Coefficient	p-value
Constant	0.1333	0.26	0.0000	0.99
|OI|	-0.0060	0.27	-0.1679***	0.00
Neg	-0.00147***	0.00	-0.0112***	0.00
Maturity	0.0001	0.25	-0.0001**	0.03
σ^{High}	0.0019	0.25	-0.0063	0.24
Neg .|OI|	0.0908***	0.00	0.2259***	0.00
Neg .Maturity	0.0001***	0.00	0.0003***	0.00
Maturity .|OI|	-0.0005	0.16	0.0062***	0.00
Neg .σ^{High}	0.0006	0.84	0.0763***	0.00
|OI| .σ^{High}	0.0041	0.79	0.1512***	0.00
Maturity .σ^{High}	0.0000	0.78	0.0004	0.13
Neg .Maturity .|OI|	-0.0055***	0.00	-0.0042***	0.00
Neg .σ^{High} .|OI|	-0.2954***	0.00	-0.5445***	0.00
Neg .σ^{High} .Maturity	0.0000	0.85	-0.0022***	0.00
.σ^{High} .Maturity .|OI|	-0.0017	0.14	-0.0118***	0.00
Neg .σ^{High} .Maturity .|OI|	0.0058**	0.01	0.0114	0.00
LOSS	-0.0021***	0.00		
LEV	-0.0002***	0.00		
TIME	-0.0001	0.24		
ABNACC (lagged)	-0.0030***	0.00		
SIZE	0.0004	0.03		
BTM	0.0000	0.63		
TENURE	0.0001	0.21		

Source: Elaborated by the author

Note: |OI| is the absolute value of other information's impact on earnings, Neg is a dummy for negative impacts of other information, Maturity is the number of years since IPO, σ^{High} is the volatility of shocks unrelated to accounting information, and the other variables are controls presented in table 1. The sample size is 34,171 observations.

At 1% significance level, the coefficient of *Neg* indicates that analysts are in general optimistic when the aggregate impact of other information on earnings is adverse. Moreover,

at 1% significance level, the coefficients of *Neg.*|*OI*| indicate that this optimism tend to be smaller for firms that were more strongly and negatively affected by new events. By the other hand, the coefficients of our regression fail to reject the null-hypothesis that analysts bias their forecasts when news are good. Although in accordance to the findings of Elliott, et al. (1995) and Zhang (2006) in the sense that analysts react to good and bad news in different manners, our results are indeed inconsistent with these authors' studies. They suggest that analysts are biased when evaluating new information, mainly if this new information negatively affects earnings, while we find that analysts are biased when evaluating bad news, but unbiased when evaluating good news. Anyway, our results corroborate our hypothesis 1.

We also present evidence corroborating with hypothesis 2. At 1% significance level and corroborating with Das et al. (1998), the coefficient of $Neg.\sigma^{high}.|OI|$ indicates that analysts increase their optimism the more negative the impact of other information is and the more uncertain the environment is.

Looking at the firms' maturity perspective, the older the firm is and the more negative the impact of news are on earnings, the more optimistic analysts tend to be, as the coefficient of *Neg.Maturity.*|*OI*| indicates at 1% significance level. Nevertheless, the coefficient of *Neg.Maturity* indicate that analysts tend to reduce their optimism the older the firm is if the aggregate impact of news on earnings is slightly negative. Furthermore, analysts' optimism is also alleviated when for firms that were negatively impacted by news, when the environment is more uncertain and the firm is older

Besides the results related to our hypothesis, there is another interesting result that deserve attention. We document that more optimistic forecasts are associated to firms in which reported earnings are less reliable, as the coefficient of lagged abnormal accruals suggests at 1% significance level.

5 CONCLUSION

This study investigates analyst forecast error in different environments of information uncertainty. Given the conflicting conclusions about analyst bias, as evidenced by Abarbanell and Lehavy (2003), we include a new variable based on Ohlson (2001) and Bryan and Tiras (2007) in order to capture value-relevant events that occurred in a given fiscal year and still did not affect reported earnings. In past studies these events used to be imperfectly captured by analyst revisions or stock price return (and sometimes just ignored), then we believe that our methodology may assist future research by offering an alternative for the measurement of these events. This is crucial for evaluating analyst behavior and analyst bias since this kind of information is exactly what makes analyst forecasts superior to naïve models with only past information (Brown, Richardson, & Schwager, 1987). More precisely, we move away from the perspective of analyzing the efficiency of analysts' absorption of news via post-analyst-revision drift to the perspective of aggregate news.

We also introduce a new measure of information uncertainty that tries to capture uncertainty related to non-accounting information that will impact only current fiscal-year earnings. The main usefulness of this new measure is to segregate the effects of accounting and non-accounting information uncertainty, which were not segregated in past studies.

We show that analysts tend to be optimistic for bad news, unless the firm is very mature and the negative impact of news on earnings is very low. Specifically about mature firms, we document that analysts are even more optimistic when evaluating very negative news related in comparison with young firms when the set of news has a considerable negative impact on earnings. We offer two insights related to it. First, analysts may trust more on mature firms since they already proved their capacity of overcoming many obstacles, what is in consonance

with Michel and Pandes (2015) who suggest that analysts anticipate future performance of firms in their forecasts. Second, this may just evidence the importance of the research design; if a research design tend to eliminate mature or young firms in a disproportional way, then the results of the work may be associated with the kind of firms that survived in the sample. It may even be an explanation for conflicting conclusions in the literature about analysts' bias.

We agree with Zhang (2006) that the flow of information may be the cause of this asymmetric behavior related to news since bad news tend to be withhold while good news tend to be timely reported.

We also document that, when facing more information uncertainty, analysts have a tendency to increase their optimism the more negative the impact of other information is on earnings and that this optimism intensification is smaller for more mature firms. It is in accordance to the findings of Das et al. (1998) and to the idea that uncertainty reduces the risk and/or weight of punishment for forecast errors.

Our set of results are useful for investors, since it offers a way that investors can anticipate the situations in which analysts tend to be more biased, letting them weight better the influence of analysts' suggestions on their portfolios. One of the reasons why our results may be useful for investors is that we make an ex-ante analysis. We calculate analysts' expectation of other information in place of realized other information exactly for that. Realized other information would turn our analysis an ex-post one. For future research, it would be interesting to assess investment strategies that buy when news has positive or no aggregate impact on earnings (and, so, analysts are not optimistic) and sell when news has negative impact on earnings and information uncertainty is high (analysts are more optimistic).

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