

NEITHER OPTIMISTIC NOR PESSIMISTIC: THE ROLE OF ACCOUNTING FUNDAMENTALS AND OTHER INFORMATION ON ANALYST FORECAST ERRORS

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Abstract: During the last years researchers have produced an array of empirical evidences that have long offered conflicting conclusions according to how biased are the information provided by analysts. One of the reasons for such empirical controversy is that too little is known in the literature about analysts' actual loss functions, and the usual methodologies thus leave unresolved the questions of what cause asymmetries in forecast errors distribution and to what extent analysts fully reflect public available information. In this paper we implement an approach that allow us to disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information, in order to evaluate the extent in which analyst forecast errors are related with information from these two different sources. Our analyses lead to two conclusions: first, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In other words, analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. Second, even when analysts are right, they might be wrong. In these cases, our results suggest that luck trumps skills.

Keywords: Analyst Forecast Errors; Accounting Fundamentals; Other Information.

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1 INTRODUCTION

In a practical perspective, other information can be interpreted as all new information not yet accurate in the financial statement, but that have yet to have an impact on earnings. Among obvious candidates for other information, Myers (1999) posits a discovery of a new petroleum field, new patents, regulatory approval of a new pharmaco, new long-lived contracts, etc. These news are just few examples among an infinite number of other information that may affect firm's future performance and analysts' expectations of firm's future performance.

A study developed by researchers of University of Michigan based on more than 470,000 analyst reports and 18,000 conference call transcripts find that "financial analysts highlight information in reports that aren't mentioned on calls with corporate officers and flesh out issues given just brief mentions on the calls" (University of Michigan, 2014). "... this finding suggests that analysts frequently provide new information by discussing exclusive topics that were not referred to in the CC" (Allen Huang et al., 2014). Whether or not analysts fully reflect other information according to its association with earnings, however, is an issue that still requires empirical verification.

Some studies including Ali, Klein, and Rosenfeld (1992), Elgers and Murray (1992), Lo and Elgers (1998), Frankel and Lee (1998), Hughes, Liu, and Su (2008), Gode and Mohanram (2009), and So (2013) have attempted to develop approaches that intend to present better predictions of future forecast errors by discussing what information is reflected in these errors. The majority of these studies have focused on the relation among consensus analyst forecasts, past forecast errors, and firms's characteristics, or in approaches that shifts the focus toward the time-series prediction of future earnings using historical information contained in the financial statements. Although their results recognize the relevance of analyzing past forecast errors, firms's characteristics, and accounting information in explaining analyst forecast errors, the relation of "other Information² in the assessment of analysts' accuracy have not yet received due attention. The goal of our

paper is implement an approach that allow us to evaluate the extent in which analyst forecast errors are related with accounting information and "other information".

In order to identify and test how accurate analysts are in processing accounting information and other information, we developed a methodology that disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information. We base our analyst error disaggregation approach on the Ohlson's (1995) Linear Information Dynamic that links earnings, book value, dividends, and other information with expectations of future earnings. Our analyst error disaggregation approach fundamentally is based on the assumption that, conditional on a set of available accounting information and other information, in expectation, consensus analyst forecast errors should be zero (Unbiased Forecast Condition - UFC).

By considering the unbiased forecast condition, if analysts on average correctly forecast the persistence of earnings components, book value, and dividends, then the coefficients relating these accounting components to analysts' expectation of next year earnings should be proportional to the coefficients relating these components to next year earnings. But if we reject the null for any of these variables, then it would suggest that analysts do not fully incorporate the persistence of the respective component into their forecast. On the other hand,

² Ohlson (1995) theoretically derived the relation between other information and expectations of future earnings in a valuation context. His contribution comes from the modeling of the linear information dynamic, which allows expectations of future earnings to be expressed as a linear function of earnings, book value, dividends, and other value relevant events (other information), which bear upon future earnings independently of current or past earnings.

if analysts on average correctly forecast the impact of other information on future earnings, then analysts' expectations about the impact of other information on next year earnings and the realized impact of other information on next year earnings should be statistically equal. If we reject this null hypothesis, it would suggest that analysts do not fully forecast the impact of other information on earnings.

When analyzing analyst bias, studies including Abarbanell and Lehavi (2003) find that extreme un- expected accruals go hand in hand with observations in the cross-section that generate the tail asymmetry in analyst forecast errors distribution. Other studies including Zhang (2006) find that "greater information uncertainty predicts more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news" (Zhang, 2006), suggesting that information uncertainty delays the absorption of information into analyst forecasts. Based on these evidences, we predict that as much uncertainty surrounds the firm according to unexpected accruals and the relevance of other information for future earnings, more noisier signals exists about firm's future earnings and more likely are analysts to unintentionally forecast large errors or in acting in their incentives³ to release biased forecasts. Since in both cases analysts may have fewer reputational concerns in release unbiased forecasts, this prediction do not go against the concerns present in the literature about analysts' incentives to bias their forecasts.

In spite of some similarities among our descriptive statistics with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, analyses associated with the distribution of forecast errors of other information raises doubts about this conclusion. In our analyses, far more extreme other information (accounting) forecast errors of greater magnitude are observed in the ex-post "pessimistic" ("optimistic") tail of the distribution rather than in the "optimistic" ("pessimistic") tail. These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information on earnings.

Our analyses lead to two conclusions. First, our results suggest that analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. In summary, our results review that analysts are on average optimistic according to the persistence of accounting information and that book value, normal accruals, and negative abnormal accruals are together the cause of this partial optimism. In the other information dimension, our results suggest that analysts seem to forecast positive other information not with optimism, but with pessimism, and that analysts are even more pessimistic according to good news in poor information environments, where analyst forecast dispersion is high. Second, our analyses present evidences that even when analysts are right, they might be wrong. In other words, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In these cases, it seems that luck trumps skills.

Our study contributes to the analyst literature by documenting the association of analyst forecast errors with information beyond the accounting fundamentals. Our results present evidences that corroborate with analysts being optimistic, but also evidences that suggest pessimism. In particular, when financial accounting reports are less informative, as reflected

³ Some studies including Dugar and Nathan (1995), Das, Levine, and Sivaramakrishnan (1998), Lin and McNichols (1998), Michaely and Womack (1999), and Dechow, Hutton, and Sloan (2000) present concerns about the significant incentive misalignment between analysts and investors. The collective evidence from this literature suggests that analysts have incentives to bias their forecasts, which may originate from agency problems involving the relationship between securities firms and their clients, analysts' dependence on managers for information, among others.

by high abnormal accruals, our results suggest that analysts are more likely to forecast large positive errors, but also generate additional private information that reduces average forecast errors. Since control for other-information related factors and unusual-accruals related factors in the assessment of the relation between analysts' forecast errors and analysts' interpretation of the persistence of accounting information and the impact of other information on earnings, respectively, is a hard task, our disaggregation methodology provides a parsimonious and less biased approach that specify the role of accounting fundamentals and other information on analysts' accuracy.

2 ANALYST ERROR DISAGGREGATION

In order to establish a theoretical link between analyst forecast errors and the respective impact of accounting information and other information on analyst forecasts, we base our analysis on Ohlson (1995), who models a linear information dynamic that links earnings, book value, dividends, and other information with expectation of future earnings. This dynamic is based on two stochastic AR(1) process, as summarized below:

$$\begin{aligned} x_{t+1}^a &= wx_t^a + V_{t+1} + e_{1t+1} \\ V_{t+2} &= \gamma V_{t+1} + e_{2t+2} \end{aligned}$$

Abnormal earnings are defined as earnings above a charge for the use of capital, and are estimated as $x_{t+1}^a = x_{t+1} - r \cdot b_t$, where b_t and r represent book value and the cost of capital at period t , respectively. The persistence of the abnormal earnings and the persistence of the aggregate impact V_{t+1} of new information on one-year-ahead (abnormal) earnings are indicated by the parameters w and γ , respectively. The terms e_{1t+1} and e_{2t+2} represent unpredictable variables with zero mean.

In this information dynamic, all new information must be not correlated with past (abnormal) earnings, since in aggregate its predicted value $E_t[V_{t+1}]$ do not depend on past (abnormal) earnings. The term V_{t+1} , indeed, is theoretically designed to summarize the impact of value relevant events, bearing upon future (abnormal) earnings independently of past (abnormal) earnings.

Using the abnormal earnings definition and considering that all changes in book value must bypass by the difference between earnings and dividends (Clean Surplus Relation), follows directly from the information dynamic that the predicted value of one year-ahead-earnings can be set as a linear function in terms of current earnings, book value, dividends, and other information, as summarized below (Ohlson, 1995):

$$E_t[x_{t+1}] = wRx_t + (1 - w)(R - 1)b_t - w(R - 1)d_t + V_{t+1} \quad (1)$$

where R equals unity plus the cost of capital r . As analyst forecasts not only reflect information about future earnings beyond that conveyed by earnings, book value, and dividends, but also reflect the "stale" information concurrently conveyed by the accounting fundamentals (Brian and Tiras, 2007), we base our analysis considering the theoretical equation 1. Specifically, we are interested in evaluate the extent in which consensus analyst forecast errors are related with other information.

Once V_{t+1} is designed to be not correlated with past accounting data, we proxy the impact of other information on analysts' forecast as the regression residual of analysts' forecast on earnings, book value, and dividends⁴:

$$\hat{V}_{t+1} = E_t[x_{t+1}] - \hat{\beta}_1 x_t - \hat{\beta}_2 b_t - \hat{\beta}_3 d_t \quad (2)$$

where $E_t[x_{t+1}]$ represents analysts' expectation of next year earnings. Note, however, that

⁴ Brian and Tiras (2007) uses the cross section regression residual of consensus analyst forecasts (median of analysts' forecast) on book value and earnings after dividends as proxy for other information.

the residuals of this regression reflect only the aggregate impact of other information expected by analysts, and not the realized impact of other information on next year earnings.

Following Tse and Yaansah (1999), we use realized future earnings as proxy for the perfect earnings forecast. In this case, the residual of realized earnings on past earnings, book value, and dividends must reflect on average the aggregate impact of all new information on earnings:

$$V_{t+1} = x_{t+1} - \hat{\beta}_1^* x_t - \hat{\beta}_2^* b_t - \hat{\beta}_3^* d_t \quad (3)$$

As analysts make their forecasts considering accounting data and other information, the errors ϵ_{t+1} in the formulation of their expectations must result from analysts' failure to fully incorporate accounting information or/and other information into their forecasts. In other words, analyst errors ϵ_{t+1} could be disaggregated into two components: an error $e_{x_{t+1}}$ related to analysts misinterpreting the persistence of accounting data, and an error $e_{V_{t+1}}$ related to analysts misunderstanding the impact of other information on earnings:

$$\epsilon_{t+1} = e_{x_{t+1}} + e_{V_{t+1}} \quad (4)$$

Once V_{t+1} is designed to be not correlated with past accounting data, follow from equations 2 and 3 that analysts' error ϵ_{t+1} and analysts' bias can be written as

$$C_{t+1}^i = E_t[x_{t+1}^i] - x_{t+1}^i = [\hat{\beta}_1 - \hat{\beta}_1^*] x_t^i + (\hat{\beta}_2 - \hat{\beta}_2^*) b_t^i + (\hat{\beta}_3 - \hat{\beta}_3^*) d_t^i + [\hat{V}_{t+1}^i - V_{t+1}^i] = e_{x_{t+1}}^i + e_{V_{t+1}}^i \quad (5)$$

$$Bias_{t+1} = \frac{1}{N} \sum_{i=1}^N C_{t+1}^i = \frac{1}{N} \sum_{i=1}^N (E_t[x_{t+1}^i] - x_{t+1}^i) = \frac{1}{N} \sum_{i=1}^N (e_{x_{t+1}}^i + e_{V_{t+1}}^i) = \bar{e}_{x_{t+1}} + \bar{e}_{V_{t+1}} \quad (6)$$

If analysts correctly forecast the impact of earnings, book value, and dividends on future earnings, then the estimated coefficient $\hat{\beta}_i$ should be proportional to the estimated coefficient $\hat{\beta}_i^*$, $i = 1, 2, 3$, respectively. But if the coefficient β_i relating an accounting component to analysts' expectation of next year earnings is not statistically equal to the coefficient β^* relating this component to next year earnings, then the respective null will be rejected. In other words, it would suggest that analysts would be failing to fully incorporate the persistence of this accounting information into their forecast. On the other hand, if analysts on average correctly forecast the impact of other information on future earnings, then analysts' expectations of the impact of other information on next year earnings and the realized impact of other information on next year earnings should be proportional. If we reject this null hypothesis, it would suggest that analysts could be misunderstanding the impact of other information on earnings.

In terms of persistence of the accounting components and the impact of other information on earnings, the expressions overestimate and underestimate can be related with both positive and negative forecast errors, depending on the sign of the respective accounting component or of the other information. Table 1 illustrates each possible situation by using a variable with a hypothesized persistence that equals one. Note that overestimation (underestimation) is related with an estimated persistence statistically greater (smaller) than one in both types of impacts on earnings (positive and negative), but not with the same sign of analyst forecast errors. In terms of dividends, for example, if analysts overestimate the impact of the dividends distribution policy on earnings, then the effect of analysts' interpretation of the impact of dividends on future earnings would be greater than the realized impact. In this case, even if analyst forecasts are on average greater than realized earnings (positive forecast errors), the contribution of

analysts' interpretation of the impact of the dividends distribution policy on forecast errors would be negative.

Table 1: **The Relation among Persistence Estimation, Earnings, and Analyst Forecast Errors^a**

| <i>Analysts' Estimated Persistence</i> | | |
|--|--|---|
| Impact on Earnings | Persistence > 1 | Persistence < 1 |
| Negative | Overestimate Forecast Errors < 0 Pessimistic | Underestimate Forecast Errors > 0 Optimistic |
| Positive | Overestimate Forecast Errors > 0 Optimistic | Underestimate Forecast Errors < 0 Pessimistic |

^a In terms of persistence of the accounting components, the expressions overestimate and underestimate can be related with both positive and negative forecast errors, depending on the impact of the respective accounting component on future earnings. In this table we illustrate a variable with a hypothesized persistence that equals one. Overestimation (underestimation) is related with a persistence greater (smaller) than one in both types of impact on earnings (positive and negative), but not with the same sign of analyst forecast errors.

Regress analyst forecast errors on earnings, book value, and dividends allow us to test if analysts on average correctly forecast the impact of accounting information on next year earnings:

$$\epsilon_{t+1}^i = \phi_0 + \phi_1 x_t + \phi_2 b_t + \phi_3 d_t + u_{t+1} \quad (7)$$

This implication follows directly from the comparison between equations 5 and 7: test the null hypotheses $H_0^i: \beta_i - \beta_i^* = 0$ is equivalent to test the null hypotheses $H_0^i: \phi_i = 0, i = 1,2,3$, respectively.

In terms of other information, analyze the residual u_{t+1} is not sufficient to test if analysts on average correctly forecast the impact of other information on next year earnings. It follows once the constant ϕ_0 may be capturing both analysts' incentives to bias other information or other analysts' incentives, as bias originated from agency problems involving the relationship between securities firms and their clients, analysts' dependence on managers for information, among others. However, as expected other information and realized other information should be proportional in case of analysts correctly forecasting the impact of other information on earnings, than the coefficient relating expectations and realizations should equal one. The following regression allow us to test if analysts on average correctly forecast the impact of other information on earnings:

$$\hat{V}_{t+1} = p_0 + p_1 V_{t+1} + \epsilon_{t+1} \quad (8)$$

In the following sections we use our analyst error disaggregation approach to investigate to what extent analyst forecast errors are related with accounting information and other information.

Once past-accounting-basis forecast requires analysts to estimate future earnings basing on firm's past performances, earnings with low quality are likely to provide noisier signals about firm's future earnings, leading to information asymmetry among managers, analysts, and the market. If past earnings provide less precise signals about firm's future earnings, we expect that analyst forecast errors related to the predictable time series component of earnings are

likely to increase. Abarbanell and Lehavi (2003) present some evidences consistent with this prediction by identifying an empirical link between the recognition of unexpected accruals and the asymmetries in the distribution of analyst forecast errors. Bradshaw et al. (2001) also show that “analysts’ forecast do not incorporate the predictable future earnings declines associated with high accruals” (Bradshaw et al., 2001).

On the other hand, studies including Zhang (2006) find that “greater information uncertainty predicts more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news” (Zhang, 2006), suggesting that information uncertainty delays the absorption of information into analyst forecasts. In this case, we expect that analyst forecast errors related to other information increase when firms are subject to an uncertain economic environment.

3 SAMPLE SELECTION PROCEDURE AND EMPIRICAL DATA

Our sample was initially identified by merging firms listed on Compustat and I/B/E/S over 1983 to 2012. Book value, dividends, and other financial data were obtained from Compustat. Consensus analyst forecasts and actual earnings were obtained on I/B/E/S. We excluded firms with negative book value and firms from regulated financial institutions and utilities (SIC codes between 6000 and 6999). Observations with missing Compustat data, or missing analyst forecasts and actual earnings were also deleted. As we estimate other information in panel regression by 4-digit SIC code, we restricted our sample for sectors that have firms with all the required data available, with a minimum of 30 observations per sector during the sample period. Observations with consensus forecast errors exceeding in absolute value 100 percent of actual earnings were also excluded, since these observations seem to result from a data input error. After these requirements, we obtained a sample size of 40, 660 firms-year over our 30-years sample period. To enhance comparability with other studies, we also winsorized all variables yearly at 1% and 99% level.

In our analysis, earnings $ACTUAL_t$ are defined as IBES actual earnings, book value BV_t is set as total common equity (Compustat item #60), and DIV_t represents total dividends paid at the end of each fiscal year (sum of Compustat items #19 and #21, plus dividends other than stock dividends declared on other share capital of the company and based on the current year’s net income). CAF_t represents consensus analysts forecast set as the mean⁵ of all forecasts made in the period between the fiscal-year-end and the earnings announcement date.

Following Sloan (1996), total accruals TAC_t are measured by the difference between earnings before extraordinary items $EARN_t$ (Compustat item #18), and cash flow from operating activities CFO_t , reported under SFAS no.95 (Compustat item #308), i.e.,

$$TAC_t = EARN_t - CFO_t$$

For the period before 1988 when Compustat item #308 is not available, we estimate cash flow as the sum of funds from operations FFO_t (Compustat item #110), change in cash and short term investment $\Delta CASH_t$ (Compustat item #1), and change in current liabilities ΔCL_t (Compustat item #5), minus the change in short term debt ΔSTD_t (Compustat item #34), and minus the change in current assets ΔCA_t (Compustat item #4), as follows:

$$CFO_t = FFO_t + \Delta CASH_t + \Delta CL_t - \Delta STD_t - \Delta CA_t$$

⁵ We also used the median of analysts’ forecast in our analyses. All our conclusions follow qualitatively as the same.

As in Xie (2001), we consider normal accruals NAC_t as the predicted value of Jones (1991) model, estimated using a panel regression for each 4-digit SIC code:

$$NAC_t = \widehat{TAC}_t = \widehat{\alpha}_0 + \widehat{\alpha}_1 \Delta REV_t + \widehat{\alpha}_2 PPE_t \quad (9)$$

where ΔREV_t represents changes in sales revenue in fiscal year t (Compustat item #12), and PPE_t is gross property, plant, and equipment (Compustat item #7). All variables were deflated by the beginning-of-fiscal-year total assets TA_{t-1} (Compustat item #6). Abnormal accruals $ABNAC_t$ are given by the residuals of the Jones (1991) model, i.e.,

$$ABNAC_t = TAC_t - NAC_t$$

We estimate analysts' expected impact of other information using a panel for each 4-digit SIC code by regressing consensus analyst forecasts on cash flow, normal accruals, abnormal accruals, book value, and dividends.

$$\widehat{V}_{t+1} = CAF_t - \widehat{\beta}_0 - \widehat{\beta}_1 CFO_t - \widehat{\beta}_2 NAC_t - \widehat{\beta}_3 ABNAC_t - \widehat{\beta}_4 BV_t - \widehat{\beta}_5 DIV_t \quad (10)$$

Analogously, we use the residual of the panel regression of realized next year earnings on cash flow, normal accruals, abnormal accruals, book value, and dividends as proxy for the realized impact of other information on earnings:

$$\widehat{V}_{t+1}^* = ACTUAL_{t+1} - \widehat{\beta}_0^* - \widehat{\beta}_1^* CFO_t - \widehat{\beta}_2^* NAC_t - \widehat{\beta}_3^* ABNAC_t - \widehat{\beta}_4^* BV_t - \widehat{\beta}_5^* DIV_t \quad (11)$$

Table 2: Descriptive Statistics

| Panel A: Descriptive Statistics of Accounting Fundamentals^a | | | | | | | | |
|---|-------------------------|-----------------|---------------|-------------|-----------|-----------|-------------|------------------|
| <u>Variables^b</u> | <u>Mean^c</u> | <u>Std. Dev</u> | <u>Median</u> | <u>Min.</u> | <u>Q1</u> | <u>Q3</u> | <u>Max.</u> | <u>%Positive</u> |
| $EARN_{t+1}$ | 0.032 | 0.143 | 0.051 | -1.214 | 0.011 | 0.096 | 0.412 | 78.63 |
| CFO_t | 0.093 | 0.157 | 0.101 | -3.777 | 0.050 | 0.162 | 0.681 | 86.52 |
| NAC_t | -0.066 | 0.076 | -0.062 | -1.161 | -0.101 | -0.033 | 0.815 | 11.36 |
| $ABNAC_t$ | 0.008 | 0.125 | 0.012 | -4.153 | -0.032 | 0.057 | 1.447 | 57.56 |
| BV_t | 0.626 | 0.399 | 0.562 | 0.000 | 0.376 | 0.790 | 7.131 | 100 |
| DIV_t | 0.013 | 0.022 | 0.000 | 0.000 | 0.000 | 0.019 | 0.245 | 48.49 |

| Panel B: Descriptive Statistics of Returns, Analysts, and Other Information Data | | | | | | | | |
|---|-------------------------|-----------------|---------------|-------------|-----------|-----------|-------------|------------------|
| <u>Variables^b</u> | <u>Mean^c</u> | <u>Std. Dev</u> | <u>Median</u> | <u>Min.</u> | <u>Q1</u> | <u>Q3</u> | <u>Max.</u> | <u>%Positive</u> |
| RET_{t+1} | 0.179 | 0.751 | 0.077 | -0.978 | -0.185 | 0.364 | 26.700 | 48.63 |
| $ABRET_{t+1}$ | 0.050 | 0.683 | -0.035 | -1.737 | -0.267 | 0.211 | 25.962 | 59.80 |
| CAF_t | 0.030 | 0.150 | 0.057 | -1.982 | 0.016 | 0.081 | 0.603 | 85.12 |
| $ACTUAL_{t+1}$ | 0.026 | 0.161 | 0.042 | -1.982 | 0.015 | 0.081 | 0.441 | 84.23 |
| ϵ_t | 0.003 | 0.042 | 0.000 | -0.715 | -0.002 | 0.001 | 1.852 | 37.03 |
| ϵ_{x_t} | 0.009 | 0.035 | 0.004 | -1.132 | -0.001 | 0.015 | 0.921 | 71.10 |
| ϵ_{V_t} | -0.006 | 0.053 | -0.004 | -0.930 | -0.016 | 0.002 | 1.836 | 31.97 |
| \widehat{V}_{t+1} | 0.015 | 0.130 | 0.007 | -1.495 | -0.022 | 0.052 | 0.618 | 56.93 |
| \widehat{V}_{t+1}^* | 0.021 | 0.147 | 0.012 | -1.677 | -0.020 | 0.065 | 0.673 | 60.31 |

^a Our sample was identified by merging firms listed on Compustat and I/B/E/S from 1983 to 2012. Monthly returns data were obtained on CRSP database. In the end, we obtained a sample size of 40, 660 firms-year observations over our 30-year sample period.

^b Variables definitions:

- $EARN_{t+1}$ = income before extraordinary items;
- CFO_t = cash flow from operating activities;
- NAC_t = normal accruals, given by the predicted value of Jones (1991) model, estimated in a panel regression for each 4-digit Sic code;
- $ABNAC_t$ = abnormal accruals, given by the residual of the Jones (1991) model;
- RET_{t+1} = firm's buy-and-hold return for the 12-month period ending three months after the fiscal-year-end;
- $ABRET_{t+1}$ = size-adjusted abnormal return, estimated as the difference between the firm's buy-and-hold return and the buy-and-hold return for the same 12-month period on the market portfolio decile in which the firm belongs;
- CAF_t = consensus analysts' forecast, set as the mean of analysts' forecast;
- $ACTUAL_{t+1}$ = IBES actual earnings;
- \hat{V}_{t+1} = analysts' expectation of other information, estimated for each 4-digit Sic code as the residuals of the panel regression of consensus analyst forecast on past earnings components, book value, and dividends;
- \hat{V}_{t+1}^* = other information, estimated for each 4-digit Sic code as the residuals of the panel regression of actual earnings on past earnings components, book value, and dividends;

In order to avoid any look-ahead-bias in estimating analysts' expected impact of other information, realized other information, and also abnormal accruals, we estimate each of our panel regression using a multi-panel procedure, in which for each year we associate a panel that contain only information of past years. In this case, only the residual of the last year is stored in each panel-year. In terms of other information, for example, if we do not use this multi-panel procedure, than we would require that analysts known at the first years information about future years.

Comparing realizations and expectations in terms of earnings, we find that the mean of analyst forecasts is statistically greater than the mean of actual earnings at 1% significance level over our 30-years sample period. This result is consistent with evidences present in the literature which suggest that analysts are generally optimistic (see, e.g., reviews by Brown, 1993; Das, Levine & Sivaramakrishnan, 1998; Lim, 2001; Kothari, 2001; and Cowen, Groyberg & Healy, 2006). In terms of analyst forecast errors, an untabulated t-test reviews that the mean of analyst forecast errors is greater than zero, which also corroborate with analysts overestimating future earnings.

In spite of the similarities among these descriptive results with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, summary statistics associated with forecast error distributions reported in Panel B of Table 1 raise doubts about this conclusion. It follows because, as in Abarbanell and Lehavy (2003), the only statistical indication that supports analyst optimism is a positive mean forecast error of 0.003. On the other hand, the median error is zero, which suggest unbiased forecasts, while the percentage of positive errors is smaller than the percentage of negative errors, which suggest an apparent analyst pessimism.

This apparent analyst pessimism can also be viewed when we analyse analysts' expectation of other information. As can be seen in Panel B of Table 1, the mean of realized other information is 0.021, while the mean of analysts' expectation of other information is 0.015. An untabulated t-test review that the mean of analysts' expectation of other information is smaller than the realized other information at 1% significance level. At this point, the frequency of negative realized other information is smaller than the frequency of negative expected other information (39.69% vs 43.07%).

In order to better understand the causes of these inconsistencies in the summary statistics, we projected analysts forecast errors in the accounting dimension and in the other information dimension using our disaggregation approach. As can be seen in Panel B of Table 1, the mean of analyst forecast errors according to other information is negative (-0.006), while the mean of

analyst forecast errors according to the accounting components is positive (0.009). Moreover, the frequency of positive analyst forecast errors according to the accounting components is greater than the frequency of positive analyst forecast errors according to other information (71.10% vs 31.97%). Untabulated t-tests also review that the mean of analyst forecast errors according to other information is smaller than zero, while the mean of analyst forecast errors according to the accounting fundamentals is greater than zero. Together, these descriptive results suggest that analysts seem to forecast other information not with optimism, but with pessimism, and that the analysts' optimism widely documented in the literature seem to be associated with accounting information.

4 EMPIRICAL RESULTS

4.1 The Association between Extreme Abnormal Accruals and Analyst Forecast Errors

As in Abarbanell and Lehavy (2003), we are using abnormal accruals to identify ex-post unexpected changes in accruals, in order to assess whether analyst forecast errors are related with these changes. If analysts do not account for the fact that firms may recognize high negative abnormal accruals, then we must have a link between positive analyst forecast errors and extreme negative abnormal accruals.

Table 3 present results for the model 7 when we consider dummies for firms-year with high abnormal accruals and negative abnormal accruals.

$$\epsilon_{t+1} = \phi_0 + \phi_1 \text{CFO}_t + \phi_2 \text{NAC}_t + \phi_3 \text{ABNAC}_t + \phi_4 \text{Neg. ABNAC}_t + \phi_5 \text{High} + \phi_6 \text{High. ABNAC}_t + \phi_7 \text{High. Neg. ABNAC}_t + \phi_8 \text{BV}_t + \phi_9 \text{DIV}_t + u_{t+1}$$

High is a dummy set as 1(0) for firms-year in the up (bottom) 30 percentile of the ranked absolute values of abnormal accruals. Neg is a dummy that indicates firms-year with negative abnormal accruals.

Table 3: The Influence of Abnormal Accruals on Analyst Forecast Errors^a

Panel A: OLS Regression Considering Portfolios Based on Abnormal Accruals

| Variable | Parameter | Estimate ^b | Std. Error | $P > t $ | Estimate | Std. Error | $P > t $ |
|-------------------------------|-----------|-----------------------|------------|-----------|------------|------------|-----------|
| CFO _t | ϕ_1 | -0.0245*** | 0.0014 | 0.000 | -0.0235*** | 0.0014 | 0.000 |
| NAC _t | ϕ_2 | -0.0159*** | 0.0029 | 0.000 | -0.0149*** | 0.0030 | 0.000 |
| ABNAC _t | ϕ_3 | -0.0115*** | 0.0018 | 0.000 | -0.0088 | 0.0289 | 0.765 |
| Neg. ABNAC _t | ϕ_4 | | | | 0.0061 | 0.0291 | 0.835 |
| High | ϕ_5 | | | | 0.0041*** | 0.0005 | 0.000 |
| High. ABNAC _t | ϕ_6 | | | | 0.0572 | 0.0377 | 0.129 |
| High. Neg. ABNAC _t | ϕ_7 | | | | -0.0727** | 0.0378 | 0.055 |
| BV _t | ϕ_8 | 0.0033*** | 0.0005 | 0.000 | 0.0025*** | 0.0005 | 0.000 |
| DIV _t | ϕ_9 | -0.0113 | 0.0098 | 0.230 | -0.0067 | 0.0098 | 0.493 |
| | ϕ_0 | 0.0025*** | 0.0005 | 0.000 | 0.0016 | 0.0005 | 0.001 |

^a Panels A and B present results for the estimation of the following model:

$$\epsilon_{t+1} = \phi_0 + \phi_1 \text{CFO}_t + \phi_2 \text{NAC}_t + \phi_3 \text{ABNAC}_t + \phi_4 \text{Neg. ABNAC}_t + \phi_5 \text{High} + \phi_6 \text{High. ABNAC}_t + \phi_7 \text{High. Neg. ABNAC}_t + \phi_8 \text{BV}_t + \phi_9 \text{DIV}_t + u_{t+1}$$

Variable definitions are present in Table 2. High is a dummy set as 1(0) for firms-year in the up (bottom) 30 percentile of the ranked abnormal accruals (in absolute value). Neg is a dummy that indicates firms-year with negative abnormal accruals.

^b *, ** and *** represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

The coefficient ϕ_7 of high-negative abnormal accruals is negative and significant at 10% significance level, while the coefficients ϕ_3 , ϕ_4 , and ϕ_6 of abnormal accruals, high abnormal accruals, and negative abnormal accruals are not significant. Together, these results suggest that the analysts' underestimated persistence of abnormal accruals documented in the previous subsection seem to be attributed to firms-year with high negative abnormal accruals. This result corroborate with Abarbanell and Lehavy's (2003) findings, in which extreme negative unexpected abnormal accruals go hand in hand with observations that generate the tail asymmetry in the positive domain of forecast errors distribution.

Abarbanell and Lehavy (2003b) argue that one possible reason for the association between extreme negative abnormal accruals and extreme positive forecast errors is that firms may provide an "unforecasted earnings bath", recognizing large nondiscretionary or discretionary negative transitory operating and non- operating items, at the same time as they recognize operating expenses larger than the operational expenses justified by the actual performance of the firm. In these situations, analysts also may have weaker incentives to release uninflated forecasts, since there are less cognitive obstacles that prevent them from revising their forecasts downward. These arguments, combined with the fact that analysts may have to work harder in their task to forecast extreme unusual accruals, could be possible explanations for why analysts do not correctly account for extreme negative abnormal accruals on their forecasts.

4.2 The Influence of Other Information on Inferences Concerning Analysts' Bias

Panel A of Table 4 present results of the model 8 controlling and not controlling for past accounting data. In order to identify the influence of positive and negative other information on analyst forecast errors, we included a dummy variable Neg set as 1 if the realized impact of other information on earnings was negative.

$$V_{t+1} = \beta_0 + \beta_1 \text{Neg} + \beta_2 V_{t+1} + \beta_3 \text{Neg. } V_{t+1} + \beta_4 \text{CFO}_t + \beta_5 \text{NAC}_t + \beta_6 \text{ABNAC}_t + \beta_7 \text{BV}_t + \beta_8 \text{DIV}_t + e_{t+1}$$

The coefficient β_2 is positive, significant, and statistically smaller than one at 1% significance level in both estimations. This result suggest that analysts underestimate positive other information, which in terms of good news are associated with negative forecast errors (pessimism⁶). This result could explain part of the inconsistency documented by Abarbanell and Lehavy (2003) in the upside down U-shape that characterizes mean forecast errors over the range of unexpected accruals. According to Abarbanell and Lehavy (2003), the apparent inconsistency in their results can be attributed to the fact that "if extreme positive unexpected accruals reflect misclassification in the case of firms that experience strong current performance, these would be the same cases in which analysts would tend to underreact to extreme current good news and issue forecasts that fall short of reported earnings", which is exactly the case in which firms experience large positive other information.

⁶ See Table 1 for further details about the interpretations of the impact of good and bad news on analyst forecast errors.

When we consider the estimated coefficient β_3 that account for the incremental effect of bad news over good news on expected other information, we obtain a negative and significant coefficient, which suggest that analysts underestimate even more negative other information over positive other information. Together, β_2 and β_3 suggest that analysts on average are pessimistic according to the impact of positive other information on earnings, but optimistic according to the impact of negative other information on earnings. At this point, negative other information could be a possible explanation for Abarbanaell and Lehavy's (2003) conclusion that "the middle asymmetry also contributes, albeit more subtly than the tail asymmetry, to producing OLS regression coefficients that are consistent with underreaction to bad news" (Abarbanaell and Lehavy, 2003). Figures 1, 2 and 3 present a better overview of the influence of other information on analyst forecast errors distribution. The x-axis includes the percentiles of other information, while the right y-axis presents the value of each percentile. In Figures 1, 2 and 3, the left y-axis presents the mean of forecast errors, other-information forecast errors, and accounting forecast errors, respectively, as described by the solid lines, in intervals of 0.5% around each other information percentile.

According to Figure 1, smallest percentiles of other information are on average associated with larger positive forecast errors. When we decompose analyst forecast errors using our disaggregated approach, Figure 2 shows that the means of forecast errors and other information forecast errors around each of these percentile look as the same. Untabulated mean comparison t-tests do not reject the null hypothesis of equal means at 1% or 5% significance level for the first 14 percentiles of other information. On the other hand, while largest percentiles of positive other information are on average associated with small negative forecast errors, Figure 2 shows that forecast errors are much larger when we consider only the forecast errors according to other information. Untabulated mean comparison t-tests reject the null hypothesis of equal means at 1% significance level for the last 25 percentiles of other information.

Table 4: Testing Analyst Bias according to Other Information^a

Panel A: Analysts' Expected Other Information Regressed on Realized Other Information

| <u>Variable</u> | <u>Parameter</u> | <u>Estimate^b</u> | <u>Std. Error</u> | <u>P > t </u> | <u>Estimate</u> | <u>Std. Error</u> | <u>P > t </u> |
|----------------------|------------------|-----------------------------|-------------------|-------------------|-----------------|-------------------|-------------------|
| Neg | β_1 | -0.0036*** | 0.0009 | 0.000 | -0,0035*** | 0,0009 | 0.000 |
| \hat{V}_{t+1} | β_2 | 0.8513*** | 0.0050 | 0.000 | 0.8637*** | 0,0052 | 0.000 |
| Neg. \hat{V}_{t+1} | β_3 | -0.0630*** | 0.0156 | 0.0000 | -0,0937*** | 0,0167 | 0.000 |
| CFO _t | β_4 | | | | 0,0329*** | 0,0049 | 0.000 |
| NAC _t | β_5 | | | | 0,0383*** | 0,0051 | 0.000 |
| ABNAC _t | β_6 | | | | 0,0045 | 0,0044 | 0.307 |
| BV _t | β_7 | | | | -0,0051*** | 0,0011 | 0.000 |
| DIV _t | β_8 | | | | 0,0121** | 0,0133 | 0.363 |
| | β_0 | -0.0033*** | 0.0003 | 0.000 | -0,0021*** | 0,0008 | 0.009 |
| F Statistic | | 35,305.26 | | | 13,635.46 | | |
| Adj R-squared | | 87.55% | | | 87.73% | | |

Panel B: The Influence of Forecast Dispersion on Other Information Bias

| <u>Variable</u> | <u>Parameter</u> | <u>Estimate^b</u> | <u>Std. Error</u> | <u>P > t </u> | <u>Estimate</u> | <u>Std. Error</u> | <u>P > t </u> |
|----------------------------|------------------|-----------------------------|-------------------|-------------------|-----------------|-------------------|-------------------|
| Neg | β_1 | -0.0002 | 0.0007 | 0.811 | -0.0008 | 0.0007 | 0.215 |
| Neg. High | β_2 | -0.0064*** | 0.0018 | 0.000 | -0.0044** | 0.0018 | 0.013 |
| \hat{V}_{t+1} | β_3 | 0.8513*** | 0.0050 | 0.000 | 0.8629*** | 0.0052 | 0.000 |
| Neg. \hat{V}_{t+1} | β_4 | 0.0444*** | 0.0131 | 0.001 | 0.0125 | 0.0138 | 0.363 |
| Neg. High. \hat{V}_{t+1} | β_5 | -0.1964 | 0.0265 | 0.000 | -0.1887*** | 0.0265 | 0.000 |
| CFO _t | β_6 | | | | 0.0301*** | 0.0046 | 0.000 |
| NAC _t | β_7 | | | | 0.0394*** | 0.0050 | 0.000 |
| ABNAC _t | β_8 | | | | 0.0045 | 0.0042 | 0.0289 |
| BV _t | β_9 | | | | -0.0043 | 0.0011 | 0.000 |
| DIV _t | β_{10} | | | | 0.0208 | 0.0135 | 0.124 |
| | β_0 | -0.0033*** | 0.0003 | 0.000 | -0.0023*** | 0.0008 | 0.003 |
| F Statistic | | 22,983.90 | | | 11,924.19 | | |
| Adj R-squared | | 88.10% | | | 88.26% | | |

^a This table presents results for the estimation of the models described below, estimated using the robust OLS estimator:

$$\hat{V}_{t+1} = \beta_0 + \beta_1 \text{Neg} + \beta_2 V_{t+1} + \beta_3 \text{Neg. } V_{t+1} + \beta_4 \text{CFO}_t + \beta_5 \text{NAC}_t + \beta_6 \text{ABNAC}_t + \beta_7 \text{BV}_t + \beta_8 \text{DIV}_t + e_{t+1}$$

$$\hat{V}_{t+1} = \beta_0 + \beta_1 \text{Neg} + \beta_2 \text{Neg. High} + \beta_3 V_{t+1} + \beta_4 \text{Neg. } V_{t+1} + \beta_5 \text{Neg. High. } V_{t+1} + \beta_6 \text{CFO}_t + \beta_7 \text{NAC}_t + \beta_8 \text{ABNAC}_t + \beta_9 \text{BV}_t + \beta_{10} \text{DIV}_t + e_{t+1}$$

Variable definitions are present in Table 1. Neg is a dummy set as 1 if V_{t+1} is negative, and 0 otherwise. High is a dummy set as 1 for firms-year in the up 30 percentile of ranked analyst forecast dispersion.

^b *, ** and *** represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

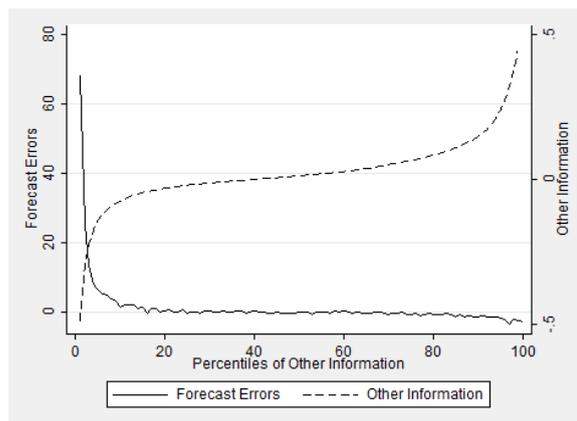


Figure 1: Mean of forecast errors, described by the the solid line, in intervals of 0.5% around each other information percentile.

These analyses lead to two conclusions. First, analysts are neither optimistic nor pessimistic according to other information: it depends on the type, the sign, and the magnitude of the news. At this point, our results confirm prior evidences that analysts are optimistic according to negative other information and pessimistic according to positive other information. Second, Figures 1 and 2 suggest that even when analysts are right, they might be

wrong. In other words, an accurate forecast can be done even when it is associated with large positive (negative) accounting errors and large negative (positive) other information errors.

In order to identify the influence of forecast dispersion on analyst forecast errors according to other information, Panel B of Table 4 present results for the model 8 including a dummy variable High set as 1 for firms-year in the up 30 percentile of ranked analyst forecast dispersion, measured as the standard deviation of analysts' forecast scaled by the mean of analyst forecasts.

$$\hat{V}_{t+1} = \beta_0 + \beta_1 \text{Neg} + \beta_2 \text{Neg. High} + \beta_3 V_{t+1} + \beta_4 \text{Neg. } V_{t+1} + \beta_5 \text{Neg. High. } V_{t+1} + \beta_6 \text{CFO}_t + \beta_7 \text{NAC}_t + \beta_8 \text{ABNAC}_t + \beta_9 \text{BV}_t + \beta_{10} \text{DIV}_t + e_{t+1}$$

As in Panel A, the interpretation of the coefficients β_3 , β_4 , and β_5 suggest that analysts underreact to the impact of both positive and negative other information on earnings, but that the underreaction according to bad news seem to more severe for firms situated in poor information environments where analyst forecast dispersion is high. Untabulated results review that analysts also underreact more to good news when analyst forecast dispersion is high.

5 CONCLUSION

In this paper we implemented an approach that allow us to identify and test how accurate analysts are in processing information from two sources: accounting information and other information. Our methodology disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information. In spite of some similarities among our descriptive statistics with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, analyses associated with the distribution of forecast errors of other information raises doubts about this conclusion.

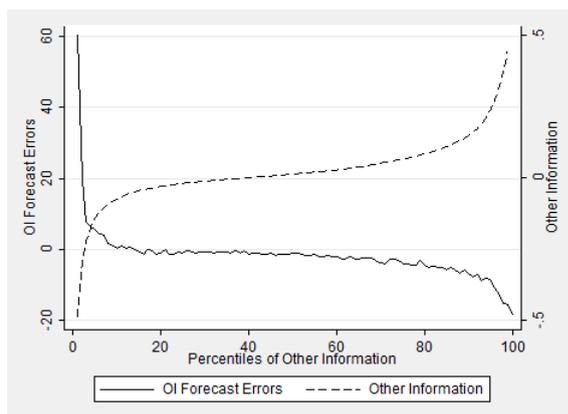


Figure 2: Mean of forecast errors according to other information, described by the solid line, in intervals of 0.5% around each other information percentile.

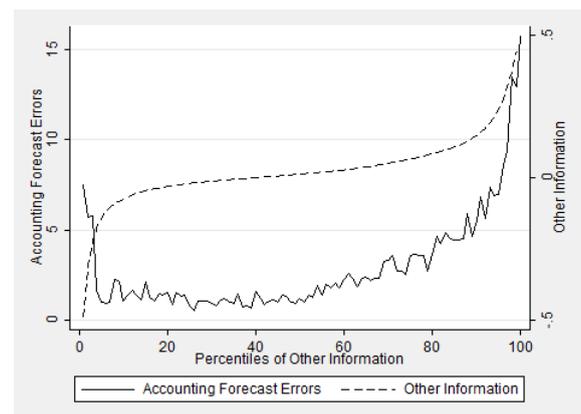


Figure 3: Mean of forecast errors according to the accounting components, described by the solid line, in intervals of 0.5% around each other information percentile.

In our analyses, far more extreme accounting (other information) forecast errors of greater magnitude are observed in the ex-post “optimistic” (“pessimistic”) tail of the distribution than in the “pessimistic” (“optimistic”) tail. These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information on earnings.

Our analyses lead to two conclusions. First, our results suggest that analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. In summary, our results review that analysts are on average optimistic according to the persistence of accounting information and that book value, normal accruals, and negative abnormal accruals are together the cause of this partial optimism. In the other information dimension, our results suggest that analysts seem to forecast positive other information not with optimism, but with pessimism, and that analysts are even more pessimistic according to good news in poor information environments, where analyst forecast dispersion is high. Second, our analyses present evidences that even when analysts are right, they might be wrong. In other words, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In these cases, it seems that luck trumps skills.

Our study contributes to the analyst literature by documenting the association of analyst forecast errors with information beyond the accounting fundamentals. Our results present evidences that corroborate with analysts being optimistic, but also evidences that suggest pessimism. In particular, when financial accounting reports are less informative, as reflected by high abnormal accruals, our results suggest that analysts are more likely to forecast large positive errors, but also generate additional private information that reduces average forecast errors. Since control for other-information related factors and unusual-accruals related factors in the assessment of the relation between analysts’ forecast errors and analysts’ interpretation of the persistence of accounting information and the impact of other information on earnings, respectively, is a hard task, our disaggregation methodology provides a parsimonious and less biased approach that specify the role of accounting fundamentals and other information on analysts’ accuracy.

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