The role of accounting fundamentals and other information in analyst forecast errors

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Abstract
In this paper, we study analyst forecast errors in the United States, and decompose these errors into two different sources: accounting fundamentals and other information. Using data from 1983 to 2012, our results lead to two conclusions. First, using the decomposition approach, we show that on average, the component of analyst forecast errors based on ‘accounting information’ is optimistic; however, the component of analyst forecast errors based on ‘other information’ is pessimistic. Second, although occasionally analysts make forecasts with small errors, the decomposition of such errors provide, on average, larger (positive) accounting errors, and larger (negative) other information errors. In this case, our results suggest that analysts’ luck occasionally surpasses their skills.

1 | INTRODUCTION

The literature has long offered conflicting conclusions on how analysts provide biased information. Although most of the prior literature has documented optimistic bias (see, e.g. Clayman & Schwartz, 1994; Francis & Philbrick, 1993), a few other studies have failed to reject efficiency and unbiasedness in analyst forecasts after implementing approaches that minimize methodological flaws (Basu & Markov, 2004; Abarbanell & Lehavy, 2003; among others).

Most of the studies suggesting that analysts tend to be optimistic in their forecasts show that the mean of analyst forecasts is positive (see, e.g. reviews by Cowen, Groysberg, & Healy, 2006; Das, Levine, & Sivaramakrishnan, 1998; Lim, 2001). However, although the mean forecast error is optimistic, other moments of the distribution (such as the median) are not optimistic. For example, in Abarbanell and Lehavy (2003), the only statistical indication that supports analyst optimism is the mean of forecast error (consensus forecast of quarterly earnings issued prior to earnings announcement...
are, on average, greater than reported earnings). Conversely, the median of forecast error equals zero, which suggests unbiased forecasts, whereas the percentage of forecasts below reported earnings is significantly greater than the percentage of forecasts above reported earnings, suggesting analyst pessimism.

Several studies have analysed skewness in the distribution of forecast errors and possible causes of analysts’ bias by discussing the information that is reflected in forecast errors (Frankel & Lee, 1998; Gode & Mohanram, 2009; Hughes, Liu, & Su, 2008; Lo & Elgers, 1998; So, 2013). Most of these studies have either focused on the interplay of consensus analyst forecasts, past forecast errors, and firm characteristics or have taken approaches that shift the focus towards the time-series prediction of future earnings using historical information contained in the financial statements. Although many of these studies recognize the relevance of analyzing past information in explaining analyst forecast errors, the role of ‘other information’ has not yet been a focus in assessments of analysts’ accuracy.

In the earnings forecasting process, analysts consider not only historical accounting data reflecting firms’ prior performance but also other information not yet contained in the financial statements that has yet to have an impact on future earnings. Examples of other information include, inter alia, the granting of a new patent, the regulatory approval of a new drug, new long-term contracts and sudden CEO death (Myers, 1999). The other information considered by analysts may affect future performance forecasts and thus the asymmetries in forecast error distribution. In such cases, other information that involves analysts' accuracy should be considered in the analysis.

In this paper, we examine the extent to which analyst forecast errors are related to accounting fundamentals and other information. To identify and test analysts’ accuracy in processing information from these two sources, we first disaggregate total analyst forecast errors into one error related to past accounting information and another error related to other information. We define forecast errors as the mean of analyst forecasts minus actual earnings. We base our analyst error disaggregation approach on Ohlson’s (1995) linear information dynamic, which links accounting fundamentals and other information with expectations of future earnings. We also consider the nonlinear relation between accounting fundamentals and valuation functions (Burgstahler & Dichev, 1997; Collins, Pincus & Xie, 1999; Zhang, 2000) to estimate our models.

Our disaggregation tests verify whether analysts efficiently include in their forecast new information (other information) and the persistence of past information (accounting fundamentals). In the usual accounting setting, the Mishkin (1983) test is applied to assess whether the market rationally prices the persistence of accounting components according to its association with the rational forecast of future earnings (see, e.g., Sloan, 1996; Xie, 2001). With modifications in the regression system commonly used in the Mishkin test, we obtain a similar test that allows us to verify whether analysts rationally forecast future earnings.

Despite certain similarities between our descriptive statistics and the widely held belief among accounting and finance academics that analysts generally produce optimistic forecasts, our analyses of the distribution of forecast errors based on other information raises doubts about this conclusion. Our results show that other information (accounting) forecast errors of much greater magnitude are observed in the ‘pessimistic’ (‘optimistic’) tail of the distribution rather than in the ‘optimistic’ (‘pessimistic’) tail. 1 These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviours in forecasting the persistence of accounting data and the impact of new information on earnings. In such cases, we argue that the controversial results in the literature may have been influenced by differences in sample selection procedures that consider firms in which such information plays different roles. Such findings support Abarbanell and Lehavy (2003) and Cohen and Lys’s (2003) main conclusion that certain papers on
analyst bias may be sensitive to the use of the normality assumption in the distribution of forecast errors.

Our efficiency tests show that on average, analysts are optimistic according to the impact of negative other information on earnings but pessimistic according to the impact of positive other information on earnings. Moreover, we present evidence that analysts’ inefficiency increases with the magnitude of other information. This result is aligned with other studies that examine whether analysts efficiently forecast earnings under the assumptions of quadratic and linear loss functions, such as in Chen and Jiang (2005). We also estimate our models considering the convexity relation between equity value and both book value and earnings. The results obtained in these additional tests that consider that equity value is a nonlinear function of accounting variables are basically the same as the linear models.

In general, our results suggest two conclusions. First, the results suggest that analysts forecast other information with pessimism and that the analyst optimism widely documented in the literature appears to be associated with accounting information. Moreover, our results suggest that analysts forecast good news not with optimism but with pessimism and that analysts are more pessimistic according to high levels of other information. Second, our results show that accurate forecasts can be made, including when analysts present large positive accounting forecast errors and large negative other information forecast errors. In this case, we suggest that analysts’ luck occasionally surpasses their skills.

2 | THEORETICAL FRAMEWORK

2.1 | Analyst error disaggregation approach

To establish a theoretical link between analyst forecast errors and the corresponding influence of accounting information and other information on forecasts, we base our analysis on Ohlson (1995) and Zhang (2000). Ohlson (1995) models a linear information dynamic that links earnings ($x_t$), book value ($b_t$), dividends ($d_t$), and other information ($O_{It}$) with expectation of future earnings:

$$E_t[x_{t+1}] = wR_t + (1-w)(R-1)b_t - w(R-1)d_t + O_{It}$$

(1)

where $R$ equals one plus the cost of capital $r$.

In Ohlson’s (1995) information dynamic, all new information must not be correlated with past (abnormal) earnings because in the aggregate, its predicted value $E_t[O_{It}]$ does not depend on past (abnormal) earnings. Indeed, the term $O_{It}$ is theoretically designed to summarize the impact of value-relevant events, bearing upon future (abnormal) earnings independently of past (abnormal) earnings; this is called ‘other information’. Hereafter, we denote other information as $O_{It,t+1}$ to indicate information, that is, known at period $t$ and has an impact on earnings at the end of the year, which is disclosed at period $t + 1$.

Because analyst forecasts not only reflect information about future earnings beyond that conveyed by earnings, book value, and dividends but also reflect ‘stale’ information concurrently conveyed by accounting fundamentals (Bryan & Tiras, 2007), we initially base our analysis on linear Equation 1. Specifically, we are interested in evaluating the extent to which consensus analyst forecasts are related to other information and accounting fundamentals, assuming first that linear valuation functions model the relation between such information and expectations of future earnings.

Once $O_{It,t+1}$ is designed to be uncorrelated with past accounting data, in accordance with Bryan and Tiras (2007), we proxy analysts’ expectation of OI as the regression residual of analyst forecast
of earnings, book value and dividends:

\[
\hat{OI}_{t,t+1} = E_t[x_{t+1}] - \hat{\beta}_1^* x_t - \hat{\beta}_2^* b_t - \hat{\beta}_3^* d_t
\]  \hspace{1cm} (2)

where \(E_t[x_{t+1}]\) represents the average of analysts' expectations of next-year earnings. Note, however, that the residuals \(\hat{OI}_{t,t+1}\) of this regression reflect only the impact of other information as expected by analysts and not the realized impact of other information on next-year earnings.

In accordance with Tse and Yaansah (1999), we use realized future earnings as a proxy for the perfect earnings forecast. In this case, the residual \(c_{OI,t,t+1}\) of realized earnings on past earnings, book value, and dividends must reflect, on average, the impact of all new information on future earnings:

\[
c_{OI,t,t+1} = x_{t+1} - \hat{\beta}_1 x_t - \hat{\beta}_2 b_t - \hat{\beta}_3 d_t
\]  \hspace{1cm} (3)

Since analysts make their forecasts considering accounting fundamentals and other information, the error \(e^i_{t+1}\) of an analyst \(i\) in the formulation of his expectations must result from his failure to fully incorporate accounting information and/or other information plus an unpredictable zero-mean piece of earnings. In other words, analysts' error \(e^i_{t+1}\) can be disaggregated into three components: an error \(e_{ACC}^i\) related to analysts' misinterpreting the persistence of accounting fundamentals, an error \(e_{OIt,t+1}^i\) related to analysts' misunderstanding the influence of other information on future earnings, along with an unpredictable and independent zero-mean error term \(e^i_{t+1}\). In this case, the average error \(e_{t+1}\) can be given, as in Equation 4:

\[
e_{t+1} = e_{ACC} + e_{OIt,t+1}
\]  \hspace{1cm} (4)

Because \(OI_{t,t+1}\) is designed to be uncorrelated with past accounting fundamentals, it follows from Equations 2 and 3 that the analyst forecast error term \(e_{t+1}\) can be written as follows:

\[
e_{t+1} = E_t[x_{t+1}] - x_{t+1}
\]

\[
= \left[ (\hat{\beta}_1^* - \hat{\beta}_1) x_t + (\hat{\beta}_2^* - \hat{\beta}_2) b_t + (\hat{\beta}_3^* - \hat{\beta}_3) d_t \right] + \left[ \hat{OI}_t - OI_t \right] = e_{ACC} + e_{OIt,t+1}
\]  \hspace{1cm} (5)

If analysts correctly forecast the impact of earnings, book value, and dividends on future earnings, \(\hat{\beta}_i^*\) should be proportional to \(\hat{\beta}_i\), \(i = 1, 2, 3\), respectively. However, if the coefficient \(\hat{\beta}_i^*\) relating an accounting component to analysts' expectation of next-year earnings is not statistically equal to the coefficient \(\beta_i\) relating this component to next-year earnings, the corresponding null hypothesis will be rejected. In other words, this finding would suggest that analysts fail to fully incorporate the persistence of this accounting information into their forecasts.

Conversely, if analysts, on average, correctly forecast the influence of other information on future earnings, their 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 misunderstand the influence of other information on earnings.

Regressing analyst forecast errors on earnings, book value, and dividends allows us to test whether analysts, on average, correctly forecast the impact of accounting information on next-year earnings:
\[ \varepsilon_{t+1} = \phi_0 + \phi_1 x_t + \phi_2 b_t + \phi_3 d_t + u_{1t+1} \]  

(6)

This implication follows directly from the comparison between Equations 5 and 6; testing the null hypotheses \( H_0^i : \beta_i^* - \beta_i = 0 \) is equivalent to testing the null hypotheses \( H_0^i : \phi_i = 0, i = 1, 2, 3 \), respectively.

The efficiency test in Equation 6 is closely related to DeBondt and Thaler (1990) and Easterwood and Nutt (1999), who show that analysts do not efficiently use information in past earnings and in extreme past earnings changes, respectively. The idea behind the test is also related to Muth (1961), who argues that expectations are rational if the entire set of information available at the time the forecast is made is uncorrelated with forecast error (Basu & Markov, 2004).

In terms of other information, analyzing the residual \( \hat{u}_{t+1} \) in Equation 6 is not sufficient to test whether analysts forecast other information efficiently. However, if analysts correctly forecast the impact of other information on earnings, their expectation of other information \( \hat{O}l_{t,t+1}^* \) and realized other information \( OI_{t,t+1} \) should be proportional. Thus, the coefficient relating expectations and realizations should equal one. The following third-stage regression allows us to test forecast efficiency according to other information:

\[ \hat{O}l_{t,t+1}^* = p_0 + p_1 \hat{O}l_{t,t+1} + u_{2t+1} \]  

(7)

Regarding the coefficients \( \phi_i = \beta_i^* - \beta_i \) in Equation 6 and \( p_1 \) in Equation 7, the interpretation of the expressions ‘overestimate’ and ‘underestimate’ and how that interpretation relates to optimism and pessimism depends on the magnitude of the coefficient and the signal of the information (positive or negative). Table 1 illustrates each possible situation.

For both types of information (good and bad news), overestimation (underestimation) is generally related to analysts forecasting a component with a value larger (smaller) than the impact of such information on reported earnings. However, the terms ‘optimistic forecasts’ and ‘pessimistic forecasts’ depend on how information affects earnings (positively or negatively).

Another approach that leads to similar conclusions to those obtained in model 6 is to implement the Mishkin (1983) test. With modifications in the regression system commonly used (see Kraft, Leone, & Wasley, 2007; Sloan, 1996; Xie, 2001), we can test whether analysts rationally incorporate past accounting information into their forecasts. The Mishkin test approach begins from the basic implication that conditional on a set of information \( \theta \) available at the end of time \( t \), in expectation,

<table>
<thead>
<tr>
<th>Impact on earnings</th>
<th>Coefficient (Equations 6 and 7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta_i &gt; \beta_i^* ) or ( p_1 &gt; 1 )</td>
</tr>
<tr>
<td>Negative (bad news)</td>
<td>Overestimate</td>
</tr>
<tr>
<td>Forecast errors &lt; 0</td>
<td>Pessimism</td>
</tr>
<tr>
<td>Positive (good news)</td>
<td>Overestimate</td>
</tr>
<tr>
<td>Forecast errors &gt; 0</td>
<td>Optimistic</td>
</tr>
</tbody>
</table>

Table 1  Relating overestimation and underestimation with analysts’ optimism and pessimism
consensus analyst forecast errors should be zero (Unbiased Forecast Condition—UFC):

\[ E[E_t[x_{t+1}] - x_{t+1}|0] = 0 \] (8)

If \( K = \{K_1, K_2, \ldots, K_n\} \) is a set of relevant variables that explain next-year earnings, a model that satisfies the unbiased forecast condition, conditional on the set of information \( \theta \), is

\[ (E_t[x_{t+1}] - x_{t+1}) = \alpha + \delta(x_{t+1} - E^K_t[x_{t+1}|0]) + h_{t+1} \]

where \( \alpha \) is a constant, \( \delta \) is a forecasting multiplier, \( h_{t+1} \) is a disturbance with zero mean conditional on the set of information \( \theta \) and \( E^K_t[x_{t+1}|0] \) is the rational forecast of \( x_{t+1} \) at time \( t \) based on the set of variables \( K \) and conditional on the set of information \( \theta \), which is set as

\[ E^K_t[x_{t+1}|0] = \gamma_0^* + \gamma_1^*K_1 + \gamma_2^*K_2 + \ldots + \gamma_n^*K_n \]

In our analysis, we attempt to split the set of relevant variables \( K \) into two independent sets of information: \( X_i = \{X_{1i}, X_{2i}, \ldots, X_{Mi}\} \), where \( X_{it} \) represents accounting information \( i \) that is relevant to explain future earnings, and \( OI_{t,t+1} \) is other information. Once \( X_i \) and \( OI_{t,t+1} \) are designed to be orthogonal, it follows that

\[ E^K_t[x_{t+1}|0] = E^X_t[x_{t+1}|0] + E^O_{t,t+1}[x_{t+1}|0] \]

\[ = \gamma_0^* + \gamma_1^*X_1 + \gamma_2^*X_2 + \ldots + \gamma_M^*X_M + \gamma_{M+1}^*OI_{t,t+1} \]

As in our setting, we are using past earnings, book value, and dividends to summarize the persistence of past performance on future earnings. We must have

\[ E_t[x_{t+1}|0] = \gamma_0^* + \gamma_1^*x_t + \gamma_2^*b_t + \gamma_3^*d_t + \gamma_4^*OI_{t,t+1} \] (9)

Based on Equation 9, the regression system of the Mishkin test to be estimated is composed of the following equations:

\[ x_{t+1} = \gamma_0 + \gamma_1x_t + \gamma_2b_t + \gamma_3d_t + h_{1t+1} \] (10)

\[ \epsilon_{t+1} = \alpha + \delta(x_{t+1} - \gamma_0^* - \gamma_1^*x_t - \gamma_2^*b_t - \gamma_3^*d_t) + h_{2t+1} \] (11)

where \( \epsilon_{t+1} = E_t[x_{t+1}] - x_{t+1} \) represents consensus analyst forecast errors, and the other variables are defined as previously. In this case, if analysts, on average, correctly forecast the impact of a component \( X_i \) on future earnings, then the analyst forecast coefficient \( \gamma_i^* \) should be proportional to the rational forecast coefficient \( \gamma_i \).

Regarding the Mishkin test, Kraft et al. (2007) show that the exclusion of variables from Equations 10 and 11 may lead to an omitted variables problem that affects inferences about the rational pricing of accounting variables; their exclusion is irrelevant only if the omitted variables are rationally priced or not correlated. Because other information is designed to be orthogonal to accounting fundamentals, excluding other information from Equations 10 and 11 may not affect inferences about the efficiency of specific accounting variables.
Based on equivalent arguments used by Mishkin (1983) and Abel and Mishkin (1983), we can briefly demonstrate that our reformulated Mishkin test and model 6 lead to similar conclusions. Indeed, replacing the forecasting Equation 10 into the analyst Equation 11, we obtain

\[
e_{t+1} = \alpha + \delta(y_0 - y_0^*) + \psi_1 \epsilon_t - \psi_2 h_t - \psi_3 d_t + \delta h_{1t+1} + h_{2t+1}
\]

where \(\psi_i = \delta(y_i - y_i^*)\), with \(i = 1, 2, 3\). Despite the theoretical design, models 6 and 12 are equivalent. Indeed, the coefficients \(\phi_i = \beta_i - \beta_i^*\) of model 6 and the coefficients \(\psi_i = \delta(y_i - y_i^*)\) of model 12 are theoretically the same. Moreover, Mishkin (1983) and Abel and Mishkin (1983) demonstrate an asymptotical equivalence between the Mishkin test (Equations 10 and 11) and an OLS model in Equation 12.

In the next section, we present our empirical design and provide information about how forecast error distribution relates to accounting fundamentals and other information. Next, we present results of efficiency tests that relate forecast errors to accounting fundamentals (Equations 6 and 12) and realized other information to expectations of other information (Equation 7).

3 | SAMPLE SELECTION PROCEDURE AND EMPIRICAL DATA

Our sample was initially identified by merging firms listed on Compustat and I/B/E/S from 1983 to 2012. Financial data were obtained from Compustat. Consensus analyst forecasts and actual earnings were obtained from I/B/E/S. We excluded firms with negative book value, regulated financial institutions and utilities firms (SIC codes between 6000 and 6999). Since we estimate other information in panel regression using the four-digit SIC code, we restricted our sample to industries that have firms with all the required data available, with a minimum of 30 observations per industry during the sample period. Observations with consensus forecast errors exceeding 100 percent in absolute value of actual earnings were also excluded, since these observations may result from a data input error. After these refinements, we obtained a sample size of 40,660 firm-years over our 30-year sample period. To enhance comparability with other studies, we also winsorized all variables yearly at the 1% and 99% levels. All variables are scaled by beginning-of-year total assets.

In our analysis, earnings \(\text{ACTUAL}_t\) are defined as I/B/E/S actual earnings; book value \(\text{BV}_t\) is set as total common equity (Compustat item 60), and \(\text{DIV}_t\) represents total dividends paid at the end of each fiscal year (the 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). \(\text{CAF}_t\) represents consensus analysts forecast, determined as the mean of all forecasts made in the period between fiscal year-end and the earnings announcement date.4

In accordance with Sloan (1996), total accruals \(\text{TAC}_t\) are measured by the difference between earnings before extraordinary items, \(\text{EARN}_t\) (Compustat item 18), and cash flow from operating activities, \(\text{CFO}_t\), reported under SFAS no. 95 (Compustat item 308), that is,

\[
\text{TAC}_t = \text{EARN}_t - \text{CFO}_t
\]

For the period before 1988, for which Compustat item 308 is not available, we estimate cash flow as the sum of funds from operations \(\text{FFO}_t\) (Compustat item 110), change in cash and short-term investment \(\Delta \text{CASH}_t\) (Compustat item 1), and change in current liabilities \(\Delta \text{CL}_t\) (Compustat item 5), minus the change in short-term debt \(\Delta \text{STD}_t\) (Compustat item 34), and minus the change in current...
As in Xie (2001), we consider normal accruals $NAC_t$ as the predicted value of the Jones (1991) model, estimated using a panel regression for each four-digit SIC code.

We estimate analysts’ expectation of other information $\widehat{OI}_{t,t+1}$ (realized other information $\widehat{OI}_{t,t+1}$) using a panel for each four-digit SIC code by regressing consensus analyst forecasts (actual earnings) on cash flow, normal accruals, abnormal accruals, book value, and dividends:

$$\widehat{OI}_{t,t+1} = CAF_{t+1} - \hat{\beta}_0 - \hat{\beta}_1CFO_t - \hat{\beta}_2NAC_t - \hat{\beta}_3ABNAC_t - \hat{\beta}_4BV_t - \hat{\beta}_5DIV_t$$

$$\widehat{OI}_{t,t+1} = ACTUAL_{t+1} - \hat{\beta}_0 - \hat{\beta}_1CFO_t - \hat{\beta}_2NAC_t - \hat{\beta}_3ABNAC_t - \hat{\beta}_4BV_t - \hat{\beta}_5DIV_t$$

In accordance with evidence in the prior literature that linear functions do not fully capture the effects of earnings, book value and dividends on equity value and future earnings (Burgstahler & Dichev, 1997; Collins et al., 1999; Zhang, 2000), we also conduct robustness tests and estimate analysts’ expectation of other information $\widehat{OI}_{t,t+1}$ and realized other information $\widehat{OI}_{t,t+1}$ using non-linear specifications by adding quadratic terms of earnings components, book value and dividends on each panel regression (see Appendix A).

Because other information represents all information beyond accounting fundamentals that has an impact on future earnings, we used only forecasts made between the end of the fiscal year and the earnings announcement date. To avoid any look-ahead bias, we estimate each of our panel regressions using a multi-panel procedure in which for each year, we associate a panel that contains only information about past years. In this case, only the residual of the last year of each panel-window is stored.

### 3.1 Descriptive statistics

Panel A of Table 2 presents descriptive statistics for the accounting fundamentals. The results are comparable to those reported in Xie (2001, Table 2, Panel A), despite the differences in the sample period. Panel B of Table 2 presents descriptive statistics for the variables relating to analyst forecast error. The results show that the mean of the analyst forecasts is greater than the mean of the actual earnings. This result is consistent with evidence presented in the literature, which suggests that analysts tend to be optimistic (see, e.g. reviews by Cowen et al., 2006; Das et al., 1998; Lim, 2001). An untabulated $t$-test also indicates that the mean of analyst forecast errors is greater than zero.

However, summary statistics associated with forecast error distributions reported in Panel B of Table 2 raise doubts about analysts’ optimism. As in Abarbanell and Lehavy (2003), the only statistical indication that supports analyst optimism is a positive mean forecast error of 0.003. Conversely, the median equals zero, which suggests unbiased forecasts, whereas untabulated results show that the percentage of positive errors is smaller than the percentage of negative errors (37.03% vs. 54.25%), suggesting pessimism (forecasts smaller than actual earnings).

The evidence of analyst pessimism can also be viewed when we analyse analysts’ expectation of other information. Panel B shows that the mean of realized other information is 0.021, whereas the mean of analysts’ expectation of other information equals 0.015. An analogous result can be observed
when comparing the percentage of (realized and expected) positive other information (60.66% vs. 57.91%).

Such results provide initial evidence of the existence of an asymmetry in the forecast error distribution, supporting Abarbanell and Lehavy (2003) and Cohen and Lys (2003). Specifically, Cohen and Lys (2003) present tests in addition to those of Abarbanell and Lehavy (2003) and show that analysts' forecast errors are not normally distributed and exhibit a left-tail asymmetry (a high occurrence of actual earnings smaller than consensus forecast). Because we define forecast errors as the mean of analyst forecasts minus actual earnings, our descriptive statistics support their findings. However, Abarbanell and Lehavy (2003) and Cohen and Lys (2003) do not focus on explaining whether such asymmetry is related to other information or analysts misinterpreting the persistence of accounting fundamentals. To better understand the asymmetry in forecast error distribution, we projected analyst forecast errors both in the accounting dimension and in the other information dimension using our disaggregation approach. Panel B of Table 2 shows that the mean of analyst forecast errors according to other information is negative (−0.005), whereas the mean of those errors according to the accounting components is positive (0.009). Untabulated t-tests also indicate that the

### Table 2 Descriptive statistics

#### Panel A: Descriptive statistics of accounting fundamentals

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Min.</th>
<th>Q1</th>
<th>Q3</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>EARN_{t+1}</td>
<td>0.029</td>
<td>0.050</td>
<td>−1.214</td>
<td>0.010</td>
<td>0.097</td>
<td>0.412</td>
</tr>
<tr>
<td>CFO_{t}</td>
<td>0.090</td>
<td>0.101</td>
<td>−3.240</td>
<td>0.048</td>
<td>0.162</td>
<td>0.681</td>
</tr>
<tr>
<td>NAC_{t}</td>
<td>−0.067</td>
<td>−0.062</td>
<td>−1.161</td>
<td>−0.102</td>
<td>−0.034</td>
<td>0.815</td>
</tr>
<tr>
<td>ABNAC_{t}</td>
<td>0.006</td>
<td>0.012</td>
<td>−4.153</td>
<td>−0.033</td>
<td>0.057</td>
<td>1.447</td>
</tr>
<tr>
<td>BV_{t}</td>
<td>0.633</td>
<td>0.565</td>
<td>0.000</td>
<td>0.377</td>
<td>0.795</td>
<td>7.131</td>
</tr>
<tr>
<td>DIV_{t}</td>
<td>0.013</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.018</td>
<td>0.245</td>
</tr>
</tbody>
</table>

#### Panel B: Descriptive statistics of returns, analysts, and other information data

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Min.</th>
<th>Q1</th>
<th>Q3</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAF_{t+1}</td>
<td>0.025</td>
<td>0.043</td>
<td>−3.216</td>
<td>0.015</td>
<td>0.083</td>
<td>1.010</td>
</tr>
<tr>
<td>ACTUAL_{t+1}</td>
<td>0.022</td>
<td>0.043</td>
<td>−3.172</td>
<td>0.015</td>
<td>0.084</td>
<td>0.989</td>
</tr>
<tr>
<td>ε_{t+1}</td>
<td>0.003</td>
<td>0.000</td>
<td>−1.357</td>
<td>−0.002</td>
<td>0.001</td>
<td>2.129</td>
</tr>
<tr>
<td>e_{ACCT_{t+1}}</td>
<td>0.009</td>
<td>0.004</td>
<td>−1.188</td>
<td>−0.001</td>
<td>0.015</td>
<td>1.460</td>
</tr>
<tr>
<td>e_{OIt,t_{t+1}}</td>
<td>−0.005</td>
<td>−0.004</td>
<td>−1.486</td>
<td>−0.016</td>
<td>0.002</td>
<td>2.069</td>
</tr>
<tr>
<td>̂OI_{t+1}</td>
<td>0.015</td>
<td>0.009</td>
<td>−1.486</td>
<td>−0.022</td>
<td>0.056</td>
<td>0.999</td>
</tr>
<tr>
<td>̂OI∗_{t+1}</td>
<td>0.020</td>
<td>0.013</td>
<td>−1.733</td>
<td>−0.020</td>
<td>0.070</td>
<td>0.682</td>
</tr>
</tbody>
</table>

*All Compustat and I/B/E/S variables are scaled by beginning-of-year total assets. Variable 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 the 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; BV_{t}, total common equity; DIV_{t}, total dividends paid at the end of each fiscal year; CAF_{t+1}, consensus analyst forecast, set as the mean of analysts' forecasts; ACTUAL_{t+1}, IBES actual earnings; ε_{t+1}, total analyst forecast errors measured as consensus forecast (CAF_{t+1}) minus actual earnings (ACTUAL_{t+1}); e_{ACCT_{t+1}}, accounting forecast error component measured as the projection of total analyst forecast errors on accounting fundamentals (Equation 5); e_{OIt,t_{t+1}}, other information forecast error component measured as total analyst forecast error (ε_{t+1}) minus the accounting forecast error component; ̂OI_{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; ̂OI∗_{t+1}, realized other information, estimated for each four-digit SIC code as the residuals of the panel regression of actual earnings on past earnings components, book value, and dividends.
mean of analyst forecast errors according to other information is less than zero, whereas the mean of those errors according to the accounting fundamentals is greater than zero. Combined, these descriptive results suggest that analysts appear to forecast other information not with optimism but with pessimism and that the analyst optimism widely documented in the literature appears to be associated with accounting information.

Figures 1 and 2 present more detailed information about analyst forecast errors decomposed into accounting errors and other information errors. Specifically, we rank total forecast errors \( (e_{t+1}) \) and estimate the mean (presented in Figure 1) and median (presented in Figure 2) of accounting errors \( (e_{Acct}) \) and other information errors (\( e_{OI_{t+1}} \)) for each decile of total forecast errors. Moving from left to right, the x-axis ranges from the most negative values of total forecast errors (pessimistic forecasts) to the most positive values (optimistic forecasts). The y-axis indicates the mean and median of accounting and OI forecast errors, respectively.

As can be observed in Figure 1, total forecast errors range, on average, from \(-3.1\%\) of beginning-of-year total assets in the first decile to \(6.8\%\) in the 10th decile of total errors. One distinctive feature of such errors relates to the distributions obtained when total errors are decomposed in accounting errors and other information errors. Although on average, the mean of forecast errors related to accounting fundamentals is positive along all total error deciles, the mean of OI errors is negative in the first nine deciles. These results present evidence that analysts are generally pessimistic according to the impact of new information on future earnings and that other information (and not past accounting data) is the source of pessimism when total errors are, on average, negative. Analyses based on the median of total errors follow the same pattern and are presented on Figure 2.

These findings extend Abarbanell and Lehavy (2003) and Cohen and Lys’s (2003) main conclusion that certain papers on analyst bias may be sensitive to the use of the normality assumption in the distribution of forecast errors. Specifically, these results provide evidence that other information may affect inferences about analyst bias. For example, Das et al. (1998) suggest that mature firms have accounting fundamentals that are more predictable than young and growth firms, whereas young and growth firms are more likely to be other-information intensive. In this case, any selection procedures that force the inclusion or exclusion of young and growth firms in the final sample may unduly affect asymmetry in the forecast error distribution and thus, the following conclusions according to analysts’ bias.

FIGURE 1 Mean accounting error and mean OI error by decile of total error distribution [Colour figure can be viewed at wileyonlinelibrary.com]
Other studies in the literature on forecast inefficiencies also show that certain findings are sensitive to the distributional assumptions (Basu & Markov, 2004; Gu & Wu, 2003). Figures 3 and 4 present a comparison of the histogram of analyst forecast errors with the histogram of each disaggregated error component. The distributions of the decomposed errors are aligned with average results presented by Figure 1 and indicate that analysts are more pessimistic (optimistic) in forecasting the impact of other information (accounting information) on future earnings. These characteristics of the distributions suggest that analysts may have different behaviour in forecasting the persistence of accounting data and the impact of new information.

However, it is not clear whether this apparent pessimism according to other information is driven by analysts' overestimating negative other information (realized other information smaller than analysts' expectation of other information) or underestimating positive other information (analysts' expectation of other information smaller than realized other information). Moreover, such descriptive results do not allow us to access which accounting fundamentals are not efficiently forecasted. In the

**FIGURE 3** Histograms of analyst forecast errors and of the accounting error component
next section, we provide the results of efficiency tests that relate forecast errors to accounting fundamentals and realized other information to expectations of other information.

4 | **EMPIRICAL RESULTS**

4.1 | **The influence of accounting fundamentals on inferences concerning analyst efficiency**

Panels A, B, and C of Table 3 present the results for coefficients of the reformulated Mishkin test (Equations 10 and 11), of model 6 for the entire sample and of portfolios based on positive and negative abnormal accruals. We consider such partitions in accordance with Abarbanell and Lehavy's (2003) findings that extreme negative unexpected accruals included in reported earnings explain part of the tail asymmetry in the forecast errors distribution. The final column of each panel reports the coefficient $MT_i = \delta \gamma_1 - \gamma_i^*$ obtained directly from the coefficients of the Mishkin test. As expected, the coefficients $MT_i$ and $\phi_i$ and the respective $p$-values are identical in all panels, $i = 0, 1, \ldots, 5$, which shows that models 6 and 12 yield empirically equivalent inferences.

Coefficients in Panel A of Table 3 suggest that on average, analysts overestimate the persistence of book value and correctly estimate the persistence of dividends. However, when considering earnings components, analysts generally underestimate the persistence of cash flows, normal accruals and abnormal accruals.

Panels B and C of Table 3 present the results of the Mishkin test and of model 6 for portfolios composed of firm-years with positive and negative abnormal accruals, respectively. The results are qualitatively the same for all variables in both portfolios, except for abnormal accruals. The coefficient $\phi_3$ of Panel B is not significant, whereas the coefficient $\phi_3$ of Panel C is negative and significant at 5%. These results suggest that analysts correctly estimate the persistence of positive abnormal accruals but underestimate the persistence of negative abnormal accruals. In this case, the underestimation of abnormal accruals described in Panel A appears to be attributed to firm-years with negative abnormal accruals, which suggests that optimism based on accounting information is also driven by negative abnormal accruals.

In summary, the results in Table 3 suggest that, on average, analysts are optimistic based on accounting information and that normal accruals and negative abnormal accruals influence the
## TABLE 3  
Mishkin test and OLS comparison for portfolios based on abnormal accruals

<table>
<thead>
<tr>
<th>Forecasting equation</th>
<th>Analyst equation</th>
<th>$H_0: \gamma_1 = \gamma_1$</th>
<th>OLS coefficient</th>
<th>Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>Estimate</td>
<td>$\gamma_1 - \gamma_1$</td>
<td>Parameter</td>
<td>Estimate</td>
</tr>
<tr>
<td>Panel A: OLS and Mishkin test coefficients for the entire sample ($N = 41,117$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>$-0.0211^{***}$</td>
<td>$-0.0005$</td>
<td>$-0.0206^{***}$</td>
<td>$\phi_0$</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>$0.7464^{***}$</td>
<td>$0.4557^{***}$</td>
<td>$0.2907^{***}$</td>
<td>$\phi_1$</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>$0.4774^{***}$</td>
<td>$0.3321^{***}$</td>
<td>$0.1453^{***}$</td>
<td>$\phi_2$</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>$0.3218^{***}$</td>
<td>$0.2555^{***}$</td>
<td>$0.0663^{***}$</td>
<td>$\phi_3$</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>$0.0053^{***}$</td>
<td>$0.0472^{***}$</td>
<td>$-0.0419^{***}$</td>
<td>$\phi_4$</td>
</tr>
<tr>
<td>Panel B: OLS and Mishkin test coefficients for the positive abnormal-accruals portfolio ($N = 23,796$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>$-0.0036$</td>
<td>$-0.0141^*$</td>
<td>$0.0105$</td>
<td>$\phi_0$</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>$0.8610^{***}$</td>
<td>$0.5425^{***}$</td>
<td>$0.1435^{***}$</td>
<td>$\phi_1$</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>$0.6993^{***}$</td>
<td>$0.5558^{***}$</td>
<td>$-0.0189^{***}$</td>
<td>$\phi_2$</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>$0.5312^{***}$</td>
<td>$0.4696^{***}$</td>
<td>$-0.0189^{***}$</td>
<td>$\phi_3$</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>$0.0350$</td>
<td>$0.3581^{**}$</td>
<td>$-0.3231$</td>
<td>$\phi_5$</td>
</tr>
<tr>
<td>Panel C: OLS and Mishkin test coefficients for the negative abnormal-accruals portfolio ($N = 17,321$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>$-0.0402^{***}$</td>
<td>$-0.0220^{**}$</td>
<td>$-0.0182^{***}$</td>
<td>$\phi_0$</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>$0.7198^{***}$</td>
<td>$0.4446^{***}$</td>
<td>$0.2752^{***}$</td>
<td>$\phi_1$</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>$0.4111^{***}$</td>
<td>$0.1750^*$</td>
<td>$0.2361^{***}$</td>
<td>$\phi_2$</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>$0.1962^{***}$</td>
<td>$0.1062^{**}$</td>
<td>$0.0904^{***}$</td>
<td>$\phi_3$</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td></td>
<td></td>
<td>$-0.0577^{***}$</td>
<td>$\phi_4$</td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>$0.2954^{***}$</td>
<td>$0.0554^{***}$</td>
<td>$-0.00216$</td>
<td>$\phi_5$</td>
</tr>
</tbody>
</table>

 Panels A, B, and C present results obtained for Equations 10 and 11 and for the equivalent OLS model described in Equation 6.

 Forecasting equation: \( \text{ACTUAL}_{t+1} = \gamma_0 + \gamma_1 \text{CFO}_t + \gamma_2 \text{NAC}_t + \gamma_3 \text{ABNAC}_t + \gamma_4 \text{BV}_t + \gamma_5 \text{DIV}_t + h_{t+1} \)

 Analyst equation: \( \epsilon_{t+1} = \alpha + \delta (\text{ACTUAL}_{t+1} - \gamma_0 - \gamma_1 \text{CFO}_t - \gamma_2 \text{NAC}_t - \gamma_3 \text{ABNAC}_t - \gamma_4 \text{BV}_t - \gamma_5 \text{DIV}_t) + h_{t+1} \)

 OLS equation: \( \epsilon_{t+1} = \phi_0 - \phi_1 \text{CFO}_t - \phi_2 \text{NAC}_t - \phi_3 \text{ABNAC}_t - \phi_4 \text{BV}_t - \phi_5 \text{DIV}_t + u_{t+1} \)

 * Panels A, B, and C present results obtained for Equations 10 and 11 and for the equivalent OLS model described in Equation 6.

 * The coefficients $\delta$ of the analyst equations of Panels A, B, and C equal $-0.2233$, $-0.1119$, and $-0.1882$, respectively, and are all significant at the 1% level.

 $a$, $b$, $c$, $d$, and $e$ represent significance at 0.10, 0.05, and 0.01 level, respectively.
asymmetry in the positive tail of the distribution of analyst forecast errors based on accounting fundamentals.

Such results are consistent with Abarbanell and Lehavy (2003). Specifically, those researchers 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 that 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 fewer cognitive obstacles that prevent them from revising their forecasts downward. These arguments, combined with the observation that analysts may need to work more diligently in their task to forecast extreme unusual accruals, could explain why analysts do not correctly explain extreme negative abnormal accruals in their forecasts.

4.2 | The influence of other information on inferences concerning analysts' efficiency

Panel A of Table 4 presents the results of Equation 7. The model we estimate is as follows:

$$\text{OI}_{t+1} = \beta_0 + \beta_1 \text{OI}_{t+1}^* + \beta_2 \text{High}_{t+1} + \beta_3 \text{High}_{t+1}^* + e_{t+1}$$

where High is a dummy set as 1(0) for firm-years in the top (bottom) 30th percentile of realized other information (in absolute value). The coefficient $\beta_1$ is positive and smaller than 1 in estimations that consider the full sample and portfolios formed with firm-years with positive and negative other information, respectively. This result suggests that analysts underestimate both positive and negative other information.

In terms of bad news (negative other information portfolio), a coefficient $\beta_1$ positive and smaller than one is associated with consensus forecasts larger than reported earnings, suggesting optimism. However, in terms of good news, a coefficient $\beta_1$ positive and smaller than one is associated with consensus forecasts smaller than reported earnings, suggesting that analysts are pessimistic according to the impact of good news on future earnings.

This result could explain part of the inconsistency documented by Abarbanell and Lehavy (2003) relating to the mean of forecast errors over the range of positive unexpected accruals. According to Abarbanell and Lehavy (2003), the apparent inconsistency in their results relating to extreme positive unexpected accruals can be attributed to the observation 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’. This finding is exactly the case in which firms experience large positive other information.

Regarding coefficient $\beta_3$, which explains the incremental effect of high other information on analysts’ expectation of other information, we obtain negative and significant values in all estimations. Such results suggest that analysts’ optimism and pessimism both increase with the magnitude of information.

5 | CONCLUSION

In this paper, we implemented an approach that allows us to identify and test how accurate analysts are in processing two types of information: accounting information and other
**TABLE 4** Regression of expected other information on realized other information

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full sample (N = 41,117)</th>
<th>Positive other information (N = 29,970)</th>
<th>Negative other information (N = 16,147)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. error</td>
<td>Estimate</td>
</tr>
<tr>
<td>(\widetilde{OI}_{t,t+1})</td>
<td>0.8596***</td>
<td>0.0072</td>
<td>0.9067***</td>
</tr>
<tr>
<td>High(_t)</td>
<td>0.0052***</td>
<td>0.0009</td>
<td>−0.003***</td>
</tr>
<tr>
<td>High(<em>t) * (\widetilde{OI}</em>{t,t+1})</td>
<td>−0.119***</td>
<td>0.0157</td>
<td>−0.0117</td>
</tr>
<tr>
<td>Constant</td>
<td>−0.002***</td>
<td>0.0003</td>
<td>−0.004***</td>
</tr>
<tr>
<td>F-Stat</td>
<td>14,177.94</td>
<td>7,462.51</td>
<td>29,750.71</td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.8777</td>
<td>0.8816</td>
<td>0.8699</td>
</tr>
</tbody>
</table>

*This table presents results of the estimation of the models described below, estimated using the robust OLS estimator. The complete model is:

\[
\widetilde{OI}_{t,t+1} = \beta_0 + \beta_1 \widetilde{OI}_{t,t+1} + \beta_2 \text{High}_{t,t+1} + \beta_3 \text{High}_{t,t+1} * \widetilde{OI}_{t,t+1} + \epsilon_{t,t+1}
\]

Variable definitions are presented in Table 2. High is a dummy set as 1(0) for firms-year in the top (bottom) 30th percentile of realized other information (in absolute value). b *, **, and *** represent significance at 0.10, 0.05, and 0.01 level, respectively.
information. Our analyses lead to two conclusions. First, our results show that the mean of analyst forecast errors according to other information is negative, whereas the mean of these errors according to the accounting components is positive. Combined, these descriptive results suggest that analysts appear to forecast other information with pessimism and that the analyst optimism widely documented in the literature appears to be associated with accounting information. Moreover, our results suggest that analysts forecast good news not with optimism but with pessimism and that analysts are more pessimistic when other information is high (extreme good and bad news). Second, our results show that accurate forecasts can be made when analysts present large positive accounting forecast errors and large negative other information forecast errors. In other words, although occasionally analysts make forecasts with small errors, the decomposition of such errors provides, on average, larger (positive) accounting errors, and larger (negative) other information errors. In this case, we suggest that occasionally, accurate forecasts are more related to luck than to skill.

Our study contributes to the literature by documenting the association of analyst forecast errors with information beyond accounting fundamentals. Since controlling for other-information related factors in the analysis of analysts’ accuracy is a difficult task, our disaggregation method provides a parsimonious approach that specifies the role of accounting fundamentals and other information in analyst forecast errors.

ENDNOTES

1 Because we define forecast errors as the mean of analyst forecasts minus actual earnings, optimism (pessimism) refers to consensus forecasts larger (smaller) than reported earnings.

2 Because information contained in cash flows, normal, and abnormal accruals has different persistence according to future earnings, we consider earnings components instead of total earnings in our empirical analyses. Without loss of interpretation, in this section, we use total earnings instead of earnings components for expositional convenience. Robustness analyses that include quadratic terms for each variable were also considered.

3 Equations 10 and 11 are estimated jointly using a two-stage iterative generalized nonlinear least square estimation procedure, as in Mishkin (1983).

4 We also used the median of analysts' forecast in our analyses. All the conclusions were qualitatively the same.

5 We also estimated other information firm-by-firm in a time series regression, since the impact of new information on next-year earnings must be affected by particular conditions such as firms' economic pressure, production technology, and other firm-specific characteristics (Myers, 1999). All the results were qualitatively the same.

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REFERENCES


APPENDIX A—ROBUSTNESS ANALYSIS

Despite the common use of linear specifications relating to accounting fundamentals and earnings expectations, several studies have documented that linear functions do not fully capture the effects of earnings, book value, and dividends on equity value and future earnings (Burgstahler & Dichev, 1997; Collins et al., 1999; among others). Based on this evidence, Zhang (2000) develops a theoretical model that extends Ohlson (1995) and shows that the equity value of low-efficiency firms and firms that encounter growth opportunities is convex in both earnings and book value. In accordance with such results, we also estimate other information using the nonlinear specifications of Equations 2 and 3 by adding quadratic terms of earnings, book value, and dividends.

\[
\hat{O}_{t,t+1}^* = E_t[x_{t+1}] - \hat{\beta}_1 x_t - \hat{\beta}_2 b_t - \hat{\beta}_3 d_t - \hat{\beta}_4 x_t^2 - \hat{\beta}_5 b_t^2 - \hat{\beta}_6 d_t^2
\]

\[
\hat{O}_{t,t+1} = x_{t+1} - \hat{\beta}_1 x_t - \hat{\beta}_2 b_t - \hat{\beta}_3 d_t - \hat{\beta}_4 x_t^2 - \hat{\beta}_5 b_t^2 - \hat{\beta}_6 d_t^2
\]

Results concerning descriptive statistics, distribution of forecast errors based on accounting fundamentals and other information, along with inferences relating to forecast inefficiency were all qualitatively the same.

Figures A1–A3 present a better overview of the influence of other information on analyst forecast error distribution. The x-axis includes the percentiles of other information, while the right y-axis presents the value of each percentile. In Figures A1–A3, 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 information percentile.
According to Figure A1, the smallest percentiles of other information are generally associated with larger positive forecast errors. When we decompose analyst forecast errors using our disaggregated approach, Figure A2 shows that the means of forecast errors and other information forecast errors around each of these percentiles look the same. Untabulated mean comparison $t$-tests do not reject the null hypothesis of equal means at 1% or 5% significance for the first 14 percentiles of other information Figure A3.

Conversely, although the largest percentiles of positive other information are generally associated with small negative forecast errors, Figure A1 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 for the last 25 percentiles of other information.

In summary, our results suggest that analysts are generally optimistic based on the impact of negative other information on earnings but pessimistic based on the impact of positive other information on earnings. Regardless of the literature findings that linear functions do not fully capture
the effects of earnings, book value, and dividends on equity value and future earnings (Burgstahler & Dichev, 1997; Collins et al., 1999; Zhang, 2000), the equivalence of results based on designers that relate accounting fundamentals to analysts' expectation of future earnings considering either linear and nonlinear specifications suggests that analysts may not formulate their expectations based on nonlinearity. If this basis were the case, analysts’ inefficiency would not increase with the magnitude of earnings. However, our results present evidence that analysts’ inefficiency increases with the magnitude of other information. This result is aligned with other studies that examine whether analysts efficiently forecast earnings under the assumptions of quadratic and linear loss functions, such as in Chen and Jiang (2005).