# When Do Analysts Use Accruals in Their Forecasting? Evidence from Loss Firms[1]

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**Abstract**
Are analysts' forecasts driven by cash flows or earnings? When and how do analysts incorporate accruals in their forecast? This study finds that the first analysts' forecasts for the future quarter are associated more with cash-driven prediction, which is future earnings prediction based on only current cash flows. The result implies that analysts use cash flows more in their first forecasts. Future earnings prediction based on current cash flows and current accruals or current earnings is associated more with the last analysts' forecast before future earnings are announced, suggesting that over time, analysts incorporate accruals information into their forecasts. Then, I hypothesize that analysts have fixated on cash-driven prediction because the accruals information among firms reporting losses in the current quarter is less useful to analysts in making future forecasts. The results show that the stronger association documented between the first analyst forecast and cash-driven prediction exists only for the sample of firms reporting losses.

Keywords: Accruals, Cash flows, analysts' forecast
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## 1. Introduction

Researchers have widely examined analyst forecasts in accounting and finance, with a focus largely on the impact of forecast errors. For example, see on Ramnath et al. (2008) and Bradshaw (2011). However, little is known about how analysts actually make their earnings forecasts and what information is included. Further, while reason would dictate that analysts would incorporate the information in financial statements such as earnings, cash flows, and accruals, the degree to which this information is incorporated (and how) remains a black box. Of greater concern is whether value-relevant information is ignored. For example, analysts may rely on only cash flows to forecast future earnings and ignore the information content of accruals. This study explores the importance of using accruals in analysts' forecasts and their usage.

When financial statements are released, analysts can choose to predict future earnings with either: *a*. earnings (which is sum of cash flows from operations and accruals), *b*. cash flows and accruals separately, or *c*. cash flows only. Sloan (1996) show current earnings are better explained by both past cash flows and accrual than past earnings. Further, Sloan (1996) show that the persistence on past accruals is lower than that of past cash flows. Thus, in theory, informative analyst forecasts should incorporate the information in both, to make the most informative forecasts. In other words, the optimal choice would be *b*. Choosing *a* means that analysts perceive the persistence of accruals is same as cash flows, which implies that, while accruals are used as a predictor, analysts put too much weight on persistence of accruals. Finally, choosing *c* means that analysts ignore information in accruals, and accruals have no predictive power. This study uses this framework to find out whether and how analysts use accruals information in their forecasts.

To address this research question, I first construct future earnings' prediction based on financial statements, using *a*. current earnings (earnings-driven prediction), *b*. current cash flows and accruals (accruals-driven prediction) and *c*. current cash flows only (cash-driven prediction).[3] Then, the associations between analysts forecasts and cash-driven, accruals-driven and earnings driven prediction are compared. If analysts use cash flows and accruals with separate persistence, as empirically documented in Sloan (1996), the association between analysts' forecasts and accruals-driven prediction would be the strongest, compared to the association with cash-driven and earnings-driven prediction

Both cash-driven and earnings-driven predictions are misspecified because it is shown that past cash flows and accruals explain current earnings, and accruals' persistence is lower than that of cash flows. Cash-driven prediction, which uses only cash flows and its persistence to predict future earnings, does not use accruals information, and earnings-driven prediction uses earnings and its persistence but restricts the persistence of accruals same as cash. However, it is plausible that analysts are fixated on cash flows or earnings. For example, analysts could place more importance on cash flows if the environment surrounding firms is more uncertain and they believe that cash flows alone are a more robust predictor than earnings. This view is consistent with what Sloan (1996) cites as motivating his paper based on Berstein (1993): Cash flow from operations is a less

[3] Cash-driven, accruals-driven, and earnings-driven predictions are made in the following method. First, current earnings are regressed on 1. past cash flows only, 2. past cash flows and past accruals and 3. past earnings. Then, using corresponding regression parameters, future earnings are predicted using 1. current cash flows only (cash driven), 2. current cash flows and current accruals (accruals driven), and 3. current earnings (earnings driven) for each firm and quarter. More details are shown on page 10.

subjective measure of performance. Berstein (1993) further argues that "analysts prefer to relate to CFO to reported net income as a check on quality of earnings." On the other hand, analysts could fixate on earnings and its trend (Sloan 1996), believing that accruals are equally as persistent as cash flows, just as investors do. If such fixations prevail, the empirical result will show that analysts' forecasts are more associated with cash-driven or earnings-driven prediction. In particular, if analysts' forecasts are more associated with cash-driven prediction than with accruals-driven or earnings-driven prediction, then the usefulness of accruals among sophisticated users of financial data may be questioned.

I found that analysts' first forecasts are associated with cash-driven prediction more than with accruals-driven or earnings-driven prediction.[4] This result suggests that analysts' forecasts use cash flows more than accruals or earnings at first. However, the associations of their last forecast are not significantly different across cash-driven, accruals-driven and earnings-driven prediction methods, suggesting that analysts gradually come to understand the role of current accruals in predicting future earnings and incorporate them into their forecast.

An intriguing result is that analysts' first forecasts are more cash flow driven. Even analysts' last forecasts are still strongly associated with cash-driven prediction. These results suggest that there may be some firm characteristics for which analysts do not use current accruals in their forecast. To further investigate when analysts find cash flows more useful in their forecasts, I explore the information asymmetry that loss can create and managerial incentives to avoid losses using accruals. Hayn (1995) argues that loss firms are less informative than profitable firms due to liquidation options and that earnings response coefficients are very low for loss firms. A loss that affects investors' information can affect analysts' forecasts such that they may discount information in earnings or accruals in earnings and become fixated on cash flows. Additionally, previous research shows that firms rely on accruals to avoid losses (Beaver, McNichols and Nelson 2003). Given that firms cannot avoid losses, accruals in loss firms have little information value to analysts, and this view is supported in other research. Burgstahler and Eames (2003) find that analysts anticipate earnings management to avoid loss. In loss firms, accruals are not useful to avoid loss, and analysts may find accruals in loss firms to be less useful in their forecasts. Thus, I hypothesize that analysts are biased toward cash flows in their forecasting and ignore accruals or earnings for firm reporting losses. If this hypothesis is supported, then analysts' forecasts are associated with cash flow-driven prediction more (less) for loss (non-loss) firms.

The results in Tables 4 and 5 show that the documented stronger association between analysts' forecasts and cash-driven prediction is much more pronounced for firms reporting losses. In fact, in the sample of loss firms, analysts' forecasts are not significantly associated with accruals-driven or earnings-driven prediction but are significantly associated only with cash-driven prediction. When firm reports losses, analysts tend to use cash flows, not accruals or earnings, in their forecasts.

For the sample of non-loss firms, a different empirical result is shown: analysts' forecasts are associated more with earnings-driven than with cash-driven prediction. This result indicates that analysts use earnings-driven prediction more when firms do not report losses. The association between analysts' forecast and earnings-driven prediction is

[4] The first (last) forecast is defined as the first median analysts' forecast for the t+1 quarter after (before) quarter t's earnings result is announced.

significantly higher than the association with cash-driven or accruals-driven prediction. Accruals-driven prediction is still more associated with analysts' forecasts than cash-driven prediction is, but its association is lower than that with earnings-driven prediction. Therefore, while accruals are used in analysts' forecasts, overall, the result implies that analysts do not use lower persistence of accruals in their forecast. Nam (2019) shows that among the three prediction methods, earnings-driven prediction is the most precise. Analysts may be aware that current earnings are a better predictor of future earnings.

Furthermore, I investigate whether analysts understand the contribution of current accruals to predicting future earnings. The contribution of accruals is defined as the difference between the prediction error of the accruals-driven and cash-driven prediction. It measures the extent to which current accruals reduce prediction error beyond the cash-driven model in predicting future earnings. The contribution of accruals is unknown to analysts at the time they make their forecasts, as it will be revealed when future earnings are realized. If including current accruals to predict future earnings can reduce prediction errors and analysts' forecasts incorporate the contribution of accruals, then their forecast error will be negatively associated with this contribution. For this research question, I regress analysts' forecast error on the contribution of accruals. A negative association with analysts' forecast error would imply that analysts' forecasts already incorporate this contribution; therefore, they are able to reduce their forecast error using the contribution of accruals.

The results show that analysts' forecast error based on analysts' first forecast is not associated with the contribution of accruals, indicating that analysts do not know how to reduce forecast error by using accruals at first. This result would not be surprising, as analysts' first forecast was associated more with cash-driven prediction. However, analysts' forecast error based on their last forecast is negatively associated with the contribution of accruals. Combined with the result that analysts' forecasts gradually incorporate accruals, this result indicates by the time they forecast last before future earnings is announced, analysts understand how much accruals can contribute to their forecast.

For loss firms, analysts' forecast error, either based on their first or last forecasts, is not associated with the contribution of accruals, whereas their forecast error based on their last forecast is negatively associated with the contribution of accruals for non-loss firms. The empirical results further confirm that analysts' forecasts are cash driven for loss firms. If accruals are not useful as predictors for loss firms, the contribution of accruals would not be needed for analysts' forecasts.

This study contributes to analysts' forecast literature by showing which accounting information is more useful to analysts and identify the conditions under which such accounting information is useful. There is an extensive body of literature on analysts' forecasts, but such studies rarely examine analysts' forecasts themselves. This research infers analysts' behavior by linking what current financial statements predict to be future earnings with analysts' forecasts. The results show that analysts find cash flows more useful than accruals or earnings at first but that they seem to incorporate current accruals in their last forecast. By focusing on loss firms, I show that analysts' fixation on cash could be due to firms reporting losses, possibly due to information asymmetry that loss firms create and the fact that losses may signal to analysts that accruals are not useful. Without losses, analysts find earnings, the sum of cash flows and accruals, more useful than cash flows and accruals separately. While accruals have lower persistence, what analysts use for prediction is earnings when firms are profitable.

The remainder of this paper is organized as follows. Section 2 discusses the literature review and motivation. Section 3 develops the research design and hypothesis. Section 4 demonstrates the methodology and sample. Section 5 discusses the results, and Section 6 concludes the paper.

## 2. Literature review and motivation

Determining how analysts model their forecasts is a difficult task since the information set of analysts can be beyond a firm's financial reports. For example, Ramnath et al. (2008) list earnings, other information from SEC filings, industry information, macroeconomic information and management communication and other information as analysts' reporting input environment. Financial statements supply only information about earnings, cash flows and accruals. Analysts' forecasts are superior to the times series prediction of earnings based on a trend due to the more extensive information environment and timing advantages (Brown et al. 1987). Also unknown is how they model their forecasts.

Prior literature examined the roles of earnings components in analysts' decision processes in the aspects of sales forecasts (Chandra et al. 1999), transitory components in earnings (Mest and Plummer 1999), the usefulness of actual earnings reported in I/B/E/S (Brown and Sivakumar 2003) and nonrecurring items (Gu and Chen 2004).

With respect to accruals, prior studies examined them in the context of the inefficiency of stock prices and the inefficiency of analysts' forecasts. Teoh and Wong (2002) show that analysts do not fully adjust earnings forecasts for past abnormal accruals. Bradshaw et al. (2002) investigates whether sell-side analysts can identify low-quality earnings induced by high accruals and convey information to investors and show that their forecasts do not incorporate the predictable declines in future earnings associated with high accruals. Ahmed et al. (2005) extend the work of Bradshaw et al. (2002) and show that analysts' forecasts do not distinguish discretionary accruals from nondiscretionary accruals. Barth and Hutton (2004) examine analysts' forecast revision and its association with the future year's change in accruals and earnings. Since they found that analysts' forecast revisions are positively associated with current accruals, they conclude that high accruals are associated with over-optimism in analysts' forecasts. Finally, Liu (2005) examines analysts' forecasts as a response to earning management, indicating that analysts make forecasts below the optimal level if firms engage in accruals activities in downward earnings management, such as a big bath. Overall, in prior literature, there is evidence that accruals are misused by analysts in that they cause bias in their forecasts, but no study has examined the relative importance of accruals over cash flows in analysts' forecasts.

What this study attempts to achieve is to determine whether analysts use current earnings and its components, cash and accruals along with their history to make forecasts when they receive financial reports. However, it is difficult to penetrate the black box of analysts' modeling or information processing. I do not address how the decision processes of analysts' forecasts occur. Instead, I attempt to infer the decision processes of how analysts use accruals information by examining the association between their forecasts and future earnings' predictions based on financial statements.

On the other hand, there is also a large body of literature that investigates the properties of earnings, mainly centered on the role of accruals, starting with Sloan (1996). In regressing current earnings on past cash flows and past accruals, the coefficient on past accruals is lower than that on past cash flows, and the prior literature refers to it as the lower persistence of accruals. This is also interpreted as the tendency for high accruals to lead to lower profitability. Prior literature focuses on the distortion of accruals (Sloan 1996; Xie 2001; Dechow and Dichev 2002) or accruals reflecting the economic condition of firms or earnings quality (Fairfield et al. 2003; Zhang 2007). However, the prior literature also suggests that current earnings are explained by past cash flows and past accruals with different persistence as follows.

$$\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha + \beta_1 \frac{CFO_{t-1}}{Total\ assets_{t-1}} + \beta_2 \frac{ACC_{t-1}}{Total\ assets_{t-1}} + \varepsilon \qquad (1)$$

where CFO is the cash flows from operations and ACC is accruals (earnings – CFO). In turn, future earnings at t+1, $Earnings_{t+1}$, can be predicted by $CFO_t$, and $ACC_t$ from $\hat{\alpha} + \hat{\beta}_1 \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2 \frac{ACC_t}{Total\ assets_t}$. I denote this as accruals-driven prediction (PREDICT $_{\text{CFO ACC}}$).

## 3. Research design and hypothesis

In addition to accruals-driven prediction, the following two models are considered.

$$\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha_1 + \beta_{11} \frac{CFO_{t-1}}{Total\ assets_{t-1}} + \theta \qquad (2)$$

$$\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha_2 + \beta_{21} \frac{Earnings_{t-1}}{Total\ assets_{t-1}} + \gamma \qquad (3)$$

Future earnings prediction based on model (2) is $\hat{\alpha}_1 + \hat{\beta}_{11} \frac{CFO_t}{Total\ assets_t}$ (cash-driven prediction, PREDICT $_{\text{CFO}}$), and that for (3) is $\hat{\alpha}_2 + \hat{\beta}_{21} \frac{Earning_t}{Total\ assets_t}$ (earnings-driven prediction, PREDICT $_{\text{EARN}}$). [5]

Both (2) and (3) are misspecified. With (2), accruals are omitted, or the coefficients on accruals are set to zero. A future earnings prediction based on only current cash flows would not incorporate the role of accruals in predicting future earnings. When accruals have lower persistence, current accruals can contribute to the prediction of future earnings. Nam (2019) shows that accruals-driven prediction based on model (2) is more precise than cash-driven prediction in model (1). Model (3) is also misspecified. Accruals' persistence, $\beta_2$ in (1), is lower than cash flows, $\beta_1$ in (1). Model (3) ignores the lower persistence in past accruals and makes it equally persistent as past cash flows. While it is misspecified, Nam

[5] Liu (2005) is similar to this study in the sense that that study links analysts' forecasts with the ARIMA model's earnings prediction (Brown and Rozeff 1979). The ARIMA model predicts future earnings with only past earnings, whereas this study's method can predict future earnings with only current cash flows, with current cash flows and accruals, or with earnings, therefore allowing me to examine which prediction method is more associated with analysts' forecasts.

(2019) shows that earning-driven prediction based on model (3) is more accurate in terms of lower prediction error than the prediction in model (2) is.

The basic premise of the research is that analysts' forecasts are associated with these three future earnings prediction methods. While analysts' forecasts embody predictors from all the other information, as long as these predictions are effective in predicting future earnings, their forecasts would be associated with them. The question is which type of prediction – cash-driven, accruals-driven or earnings-driven prediction – is more associated with analysts' forecasts. The seemingly correct answer to this question is that analysts' forecasts are associated with accruals-driven prediction, as it is well known that accruals have lower persistence than cash flows. The empirical results documented in prior research, such as Sloan (1996), suggest that analysts incorporate lower persistence of accruals in their forecasts to reduce their forecast error; therefore, analysts' forecasts are most positively associated with accruals-driven prediction. However, it is also possible that analysts use cash-driven or earnings-driven prediction in their forecasting.

By examining the association between analysts' forecast error and the level of accruals, Bradshaw et al. (2001) show that analysts do not fully incorporate the different levels of persistence in accruals in their forecasts. Ahmed et al. (2005) show that the association between analysts' forecasts and past accruals is smaller than the association between current earnings and past accruals. Therefore, the two papers show that analysts underweight the accrual information. The results from the papers are not directly related to my study, since their research questions aim to address the role of past accruals in analysts' current forecasts or forecast error. In contrast, this study addresses the association between analysts' forecasts for the future period and future earnings prediction based on current financial report information in an attempt to determine which type of prediction is useful to analysts.

Analysts may find cash-driven prediction to be more useful than the other types if accruals are not informative. Accruals are known to be noisy or to have measurement error (Sloan 1996). Cash flows may be less subjective than accruals, and high current accruals may lead to lower future profitability (Lewellen and Restek 2018). The usefulness of cash-driven prediction may also be due to the information environment in a given firm, industry, or time. One particular firm-specific characteristic of earnings is losses. When a firm announces losses in the current period, t, the prediction based on models (1), (2) and (3) suffers significantly in terms of precision because the dependent variable in the regressions, current earnings, is negative and negative current earnings are used to predict future earnings. This result is empirically supported in my study since untabulated results show that when models (1), (2) and (3) are compared, cash-driven prediction is more accurate than accruals-driven or earnings-driven prediction when firms report losses.[6] When losses occur suddenly, persistence is revised downward. Analysts could react more negatively such that they could use cash flows exclusively if accruals are considered unreliable or not useful. Analysts may already be aware of the usefulness of accruals as a predictor of future earnings in loss firms and may rationally use cash flows as the only predictor of future earnings.

[6] For a loss firm, the mean prediction error from cash-driven prediction, based on model (1), is 0.0265, whereas the mean prediction error from accruals-driven prediction, based on model (2), is 0.0315 and the mean prediction error from earnings-driven prediction, based on model (3), is 0.0310. The difference between the means of 0.0265 and 0.0315 and between 0.0265 and 0.0310 are significant at the 0.1% level.

It is also well known that firms reporting losses exhibit higher information asymmetry. Hayn (1995) shows that firms reporting losses have a lower earning response coefficient (ERC) than profitable firms. Ertimur (2004) shows that loss firms have higher information asymmetry in terms of higher bid and ask spreads. These two studies suggest that when firms report losses, investors do not know how to interpret the information in earnings. I argue that this is more related to accruals than cash flows, since accruals tend to be transitory. In this case, analysts rely on cash-driven prediction rather than accruals-driven or earnings-driven prediction. The other explanation for why accruals are less informative in loss firms is that analysts anticipate that firms would engage in earnings management using accruals to avoid losses (Burgstahler and Eames 2003). Reporting losses can signal to analysts that accruals would not be useful in their forecasts.

It is also possible that analysts are optimistic in that they overweight the persistence of accruals. Then analysts forecast would be more associated with earnings-driven prediction. If earnings are smoothed, then firms would report smooth growth over time. In this case, both cash flows and accruals could be managed to smooth earnings. Analysts may view the transitory components in earnings as small and find earnings-driven prediction to work best for their forecasts. Optimistic analysts' forecasts have been documented in numerous studies, especially in short-term forecasts such as quarterly earnings per share (Richardson et al. 2004) as well as selection biases. Analysts cover firms of which they have optimistic views (McNichols and O'Brien 1997). In the case of profitable firms, earnings-driven prediction may then be incorporated more into analysts' forecasts. Analysts may be aware that earnings-driven prediction is most accurate for profitable firms, which I found as well. [7]

Regarding which prediction model is more associated with analysts' forecasts, I do not have a hypothesis because of the competing arguments. While the conjecture is that analysts' forecasts are based on an accruals-driven model, cash- or earnings-driven prediction may be more embedded in analysts' forecasts. For loss firms, I hypothesize as follows:

H1: Analysts' forecasts are more associated with cash-driven prediction in their forecast at t+1 when a firm reports a loss at t.

Then, I turn to a question of whether analysts' forecasts include the contribution of accruals in predicting future earnings. Specifically, the contribution of accruals is defined as the difference between the absolute prediction error from cash-driven prediction in (2) and the absolute prediction error from accruals-driven prediction in (1).

$$ABSE_{CFO} = \left|\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO}\right|$$

$$ABSE_{CFO\ ACC} = \left|\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO\ ACC}\right|$$

[7] For a non-loss firm, the mean prediction error from earnings-driven prediction, based on model (3), is 0.0103, whereas the mean prediction error from accruals-driven prediction, based on model (2), is 0.0106 and the mean prediction error from cash-driven prediction, based on model (1), is 0.0122. The difference in the means of 0.0103 and 0.0106 and between 0.0103 and 0.0122 are significant at the 0.1% level.

The contribution of accruals, ACCCONTRIB, is $ABSE_{CFO} - ABSE_{CFO\ ACC}$. This captures the extent to which current accruals in (1) contribute to reducing the error in predicting future earnings. The question is whether analysts know that accruals can contribute to the prediction of future earnings and incorporate them into their forecasts. I regress analysts' forecast error on the contribution of accruals. [8] Analysts can determine the contribution of accruals gradually over time. This information could be incorporated in ways other than predictions based on financial reports if analysts acquire information beyond financial reports to confirm this contribution. I conjecture that if analysts' forecasts include this contribution, their forecast error would be negatively associated with the contribution of accruals.

Considering the implication of a firm's reporting loss, analysts may find that the contribution of accruals is weak for the loss firm. When information asymmetry affects analysts such that accruals are a less useful predictor, analysts may ignore this contribution, particularly when they do not use accruals in their forecasts. This is a rational response from analysts if loss firms' financial reporting creates enough uncertainty about accruals as predictors.

Overall, I predict that analysts' forecast error based on their last forecast is negatively associated with the contribution of accruals. Additionally, I predict that analysts' forecast error has a more negative association among firms reporting profits than among those reporting losses.

## 4. Methodology and sample

The research design of this study uses firm-specific prediction of future earnings, based on the estimated regression of current earnings on past cash flows, past accruals, and past earnings. For cash flows, I use cash flows from operations (CFO), and accruals are defined as the difference between earnings and CFO. I use quarterly data rather than annual data. Annual estimation of parameters usually employs 20-40 years of observations (Francis and Smith 2005). In addition to the smaller sample size due to long time series data requirements, using annual data presents problems in that the estimated parameters may be outdated. Accruals or earnings are based on manager inputs, and different managers may use different accounting policies for financial reporting. Additionally, accounting rules tend to change over time, for example, noncontrolling interest versus minority interest, or different pension expenses based on accumulated benefit obligations or projected benefit obligations. While annual data are preferred in equity valuation or credit analysis, the research questions in this paper do not address such applications. Therefore, I use quarterly data. The sample requirement for estimating regression in this study is 32 quarters.

Quarterly data, however, exhibit seasonality. Similar to Brochet et al. (2008) and Nam (2019), I use the X11 procedure to deseasonalize the quarterly cash flows and earnings and adjust the quarterly time series for seasonality. [9] For example, if time series

[8] I was not able to find an association between analysts' forecasts and the contribution of accruals (ACCCONTRIB),

[9] Prior research suggests future earnings can be predicted in various time series methods, such as 1. random walk, $E(Earnings_t) = Earnings_{t-1} + \delta$; 2. seasonal random walk, $E(Earnings_t) = Earnings_{t-4} + \delta$; and 3. Foster's (1977) ARIMA model, $E(Earnings_t) = Earnings_{t-4} + \beta\,(Earnings_{t-1} - Earnings_{t-5}) + \delta$, where $\beta$ is the autoregressive parameter, and Brown and Rozeff's ARIMA model, $E(Earnings_t) = Earnings_{t-4} + \beta_1\,(Earnings_{t-1} - Earnings_{t-5}) - \beta_2 a_{t-4} + \delta$, where $\beta_1$ is the autoregressive parameter, $\beta_1$ is the seasonal moving-average parameter and $a_{t-4}$ is the disturbance term at time t-4. Brochet et al. (2008) and Nam (2019) use a

data are presented as $O_t$, t=1,…n, then X11 breaks down the data into four components: $S_t + C_t + D_t + I_t$. $S_t$ represents the seasonal components; $C_t$ is known as trend cycle components that can be explained by the long-term trend, business cycle and other long-term cyclical factors; $D_t$ is the variation that can be attributed to calendar composition; and $I_t$ is the irregular component, which is residual variation. Seasonally adjusted or deseasonalized series would be $C_t + I_t$. Both cash flows and earnings are deseasonalized in this way. To estimate parameters in estimations (1), (2) and (3) and make predictions, both Earnings and CFO are seasonally adjusted. Accruals, ACC, is the difference between deseasonalized Earnings and CFO. Using 32 past observations, the parameters in (1), (2), and (3) are estimated for each firm-quarter. Then, based on the estimated parameters, the predicted values of earnings for quarter t+1, PREDICT $_{CFO}$, PREDICT $_{CFO\ ACC}$, and PREDICT $_{EARN}$ are obtained. [10]

For the dependent variables, the median value of analysts' forecasts is from I/B/E/S. I use two I/B/E/S for median analysts' forecasts; FORECAST $_{FIRST}$ is the first consensus (median) forecasts by analysts for quarter t+1, made after the earnings announcement date of quarter t, divided by the share price at the measurement date. FORECAST $_{LAST}$ is the last consensus (median) forecasts by analysts for quarter t+1, made before the earnings announcement date of quarter t+1, divided by the share price at the measurement date.

To determine how analysts' forecast for earnings $_{t+1}$ is associated with cash-, accruals- and earnings-driven prediction, I run the following regression.

$$FORECAST_{i,t+1} = \alpha + \beta_1 PREDICT_{i,t} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 LOSS_{i,t} + \beta_5 SIZE_{i,t} + \beta_6 NUMEST_{i,t} + \beta_7 STDEV_{i,t} + \beta_8 \Delta ACTUAL_{i,t} + \epsilon_{i,t}, \quad (4)$$

If analysts use future earnings prediction based on financial reports, I expect their forecasts to be positively associated with PREDICT $_{CFO}$, PREDICT $_{CFO\ ACC,}$ and PREDICT $_{EARN}$. The question is which of PREDICT $_{CFO}$, PREDICT $_{CFO\ ACC,}$ and PREDICT $_{EARN}$ is

deseasonalized process of earnings and cash flows. Brochet et al. (2008) predict future cash flows, and Nam (2019) predicts future earnings. Nam (2019) finds that the prediction of future earnings based on coefficients from regressing seasonally adjusted current earnings on seasonally adjusted past earnings has lower prediction error than the previous methods in predicting future earnings. In my sample, untabulated results show that prediction methods based on (1), (2) and (3) have lower prediction error than a random walk, the seasonal random walk method, or Foster's (1977) or Brown and Rozeff's (1979) prediction of future earnings (untabulated). For example, the mean absolute prediction error of earnings-driven prediction, based on model (3), is 0.0224 of total assets, and a seasonal random walk, which predicts future earnings using the last 4 quarters' earnings ($E_{t+1} = E(E_{t-4})$), has a mean prediction error of 0.0334 of total assets. The difference between 0.0224 and 0.0334 is significant at the 0.1% level.

[10] Alternatively, past literature used the estimation using on four quarter prior data. For example, (1) is estimated as in $\frac{Earnings_t}{Total\ Assets_{t-4}} = \alpha + \beta_1 \frac{CFO_{t-4}}{Total\ Assets_{t-4}} + \beta_2 \frac{ACC_{t-4}}{Total\ Assets_{t-4}} + \theta$. Then, the prediction of earnings$_{t+1}$ would be $\hat{\alpha} + \hat{\beta}_1 \frac{CFO_{t-3}}{Total\ Assets_{t-3}} + \hat{\beta}_2 \frac{ACC_{t-3}}{Total\ Assets_{t-3}}$. In this case, the concern for seasonality is not strong since the regression of earnings at t is run on cash flows and accruals at t-4 assuming that the seasonal component is the same across years. Nam (2019) documents that while similar results are observed using this approach, the prediction from an estimation using seasonally adjusted quarterly data using the X11 procedure produces lower prediction error. Therefore, the result is presented based on seasonally adjusted data. In addition, I repeat the analysis in Table 3-6 with the approach that use four quarter prior data, and obtained qualitatively similar result. The result is available upon request.

more strongly associated with analysts' forecasts. If analysts predict earnings based on cash flows only (cash-driven prediction, PREDICT $_{CFO}$), then the association will be more positive than the association with PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$. When the sample is divided into loss firms and non-loss firms, based on the hypothesis, I expect the association of PREDICT $_{CFO}$ with analysts' forecasts to be stronger in loss firms than in non-loss firms.

A limitation of these measures is that I do not know how analysts form predictions based on financial reports. For example, the sample requirement of 32 observations to estimate (1), (2) and (3) may not coincide with what analysts use. Additionally, they may use a more sophisticated model to employ cash flows, accruals, and earnings as predictors. Therefore, the implicit assumption that I make is that cash-driven, accruals-driven, and earnings-driven prediction are proxies for what analysts regard as a significant predictions using these measures.

The prior literature contains few studies examining the determinants of analysts' forecasts; rather, the studies focus on analysts' forecast bias. Very few papers examine analysts' forecasts as the dependent variable. Bradshaw (2011) points out that "none provide direct evidence on how analysts go about generating forecasts" and notes that they "typically regress forecast errors on different independent variables to explain forecast errors".[11] The independent variables are chosen from two literature review papers: Ramnath et al. (2008) and Bradshaw (2011), and more recent papers. First, growth in a firm is measured as the book-to-market ratio (BTM). BTM is measured at quarter t as book value (equity) divided by market capitalization. BTM is also a measure of uncertainty, and Zhang (2006) shows that analysts exhibit more behavioral biases in cases of greater information uncertainty. RET is buy-and-hold size-adjusted returns, accumulated from 2 days after the earnings announcement date of quarter t-1 to 1 day before the earnings announcement date of quarter t. This variable is used to control for the information environment. Stock returns capture information about firms; positive (negative) past stock returns imply that there may be good (bad) news about firms, and analysts incorporate such information in their forecasts. Abarbenell (1991) finds that analysts' forecasts do not fully reflect the information in prior stock price changes. Additionally, Lys and Sohn (1990) show that analysts' forecasts underreact to information in prior stock price changes. Therefore, it is possible that the RET would have a spurious association. SIZE is measured as the log of market capitalization (quarterly close price, PRCCQ times the common share outstanding at the end of quarter t, CSHOQ), measured at fiscal quarter end t. SIZE captures the information environment of a firm, but Brown (1997) finds that analysts' forecasts are less optimistic. Thus, SIZE is predicted to have a negative coefficient. LOSS is an indicator variable that equals one if Earnings at quarter t <0 and is otherwise equal to zero. This is the main variable in my study; therefore, in the subsequent test, the sample is divided into loss firms and non-loss firms. Given that firms report losses in quarter t, analysts will have difficulty adjusting their forecast for quarter t+1. Easterwood and Nutt (1999) show that analysts underreact to negative information. Basu et al. (2005) document larger forecast

[11] The two papers related to this study either use analysts' forecasts errors as dependent variables or do not provide the determinants of analysts' forecasts. Bradshaw et al. (2002), in addressing whether analysts use accrual information, uses a research design with ordinary least square regressions of analysts' forecast errors on a working capital accruals portfolio. Ahmed et al.'s (2005) research design involves regressing current analysts' forecasts on past discretionary accruals, non-discretionary accruals and cash flows.

errors for loss firms. Compared to profitable firms, loss firms present a challenge to analysts because of the uncertainty about future profitability. Therefore, I predict the coefficient on LOSS to be negative. NUMEST is the number of analysts in the forecast, and STDEV is the standard deviation of analysts' forecasts. Since the dependent variable in the regression is either analysts' first or last forecasts, the variables are adjusted for the respective forecasts. NUMEST is used to control for forecast bias as documented in Lim (2001) and Gu and Wu (2003). While Lim (2001) documents the effect of a firm's rich information environment in reducing optimistic bias in forecasts, Gu and Wu (2003) find that optimistic bias is positively associated with the information environment. VOLEARN is the volatility of seasonally adjusted earnings in the last sixteen quarters. STDEV and VOLEARN are variables that control for information uncertainty. Finally, ΔACTUAL is the difference between I/B/E/S reported earnings at t and t-4. Prior literature examined this variable in the context of analysts' forecast errors. In my study, ΔACTUAL could be a key variable to explain analysts' forecasts. If actual earnings increase over that in the last year's same quarter, t-4, then analysts would issue stronger forecasts for t+1. Therefore, the coefficient on ΔACTUAL is expected to be positive.

In prior research, these control variables are not enough to control for the information environment of analysts and firms. An industry-specific and macroeconomic level of information and regulatory environment will affect analysts' forecasts. Analysts generally specialize in an industry to reduce their forecast errors (Dunn and Nathan 2005). And their forecasts may depend on certain time period. For example, Bailey et al. (2003) and Heflin et al. (2003) examine regulation FD as a new information environment. Therefore, prior studies use industry and time fixed effects in their regression. I also include firm fixed effects to control for specific firms' information environment.

For analysts' forecast errors, the following regression is estimated.

$$AFE_{i,t+1} = \alpha + \beta_1 ACCCONTRIB_{i,t+1} + \beta_2 STDEV_{i,t+1} + \beta_3 NUMEST_{i,t+1} + \beta_4 SIZE_{i,t} + \beta_5 ABSDISCACC_{i,t} + \beta_6 ABSRMPROXY_{i,t} + \beta_7 ROA_{i,t} + \beta_8 VOLEARN_{i,t} + +\beta_9 \mathrm{LOSS}_{i,t} + \beta_{10} \Delta ACTUAL_{i,t} \epsilon_{i,t} \quad , \tag{5}$$

The contribution of accruals, ACCONTRIB, is defined early as the difference between the absolute prediction error from model (2) and model (1). Analysts' forecast error (AFE) is used as the dependent variable for regression (5) below. AFE $_{\text{FIRST}}$ is the absolute value of analysts' forecast error based on the first consensus forecast for quarter t+1, made after the earnings announcement date of quarter t, |Actual EPS $_{t+1}$ – FORECAST $_{\text{FIRST, }t+1}$|, divided by the share price measured at the forecast date. AFE $_{\text{LAST}}$ is the absolute value of analysts' forecast error based on the last consensus forecast for quarter t+1, made before earnings announcement date of quarter t+1, |Actual EPS $_{t+1}$ – FORECAST $_{\text{LAST, }t+1}$| divided by the share price measured at the forecast date.

$\beta_1$ in (5) is used to test whether analysts' forecast error is associated with the contribution of accruals in predicting future earnings. If analysts use accrual information to reduce their forecast error, then $\beta_1$ would be negative. On the other hand, if analysts do not use the contribution of accruals and their other information does not complement it, then $\beta_1$ could be positive when accruals can reduce analysts' forecast error. $\beta_1$ can be nonsignificant when accruals are not useful in the prediction of future earnings. For a loss firm, cash-driven prediction is expected to be more useful to analysts and thus have a more positive association with analysts' forecasts. I conjecture that for loss firms, $\beta_1$ could be nonsignificant if the hypothesis is supported. A nonsignificant value for $\beta_1$ in (5) among loss firms would further support the argument that analysts find cash to be a more useful predictor of future earnings. For non-loss firms, I expect $\beta_1$ in (5) to be negative, since accruals contribute to the prediction of future earnings.

The control variables included are the number of analysts, the standard deviation of analysts' forecasts, size, accrual management, real earnings management, ROA, and volatility of earnings, and the change in reported I/B/E/S earnings, in addition to firm, industry and time fixed effects. STDEV is the standard deviation of analysts' forecasts ($STDEV_{FIRST}$ when the dependent variable is $AFE_{FIRST}$ and $STDEV_{LAST}$ when it is $AFE_{LAST}$). NUMEST is the number of analysts who made forecasts ($NUMEST_{FIRST}$ when the dependent variable is $AFE_{FIRST}$ and $NUMEST_{LAST}$ when it is $AFE_{LAST}$). SIZE is the log of market capitalization at the end of quarter t, defined the same as the SIZE variable in (4). STDEV is expected to have a positive association with AFE, and SIZE and NUMEST are expected to have a negative association. These three variables are used to control for the information environment of firms.

I also include current discretionary accruals and a proxy for real earnings management (RMProxy). ABSDISCACC is the absolute value of discretionary accruals based on the modified Jones (1992) model. ABSRMPROXY is the absolute value of the RM proxy (Cohen et al. 2008). Eiler et al. (2016) examine the impact of real earnings management on analysts' forecast errors and show that the real earnings management proxy has a negative association with analysts' forecast errors. Real earnings management typically involves shifting operating activities to meet financial reporting objectives, but such objectives are often dictated by an incentive to meet analysts' forecasts. Analysts would find it challenging to incorporate real earnings management into their forecasts. However, when firms report losses, reaching the objectives is impossible; therefore, I conjecture that the association of analysts' forecast errors and RMProxy is more positive for firms reporting profits.

Accrual management through discretionary accruals to meet the financial reporting objective is also possible. However, given that accrual management is monitored closely after the Sarbanes-Oxley Act (Bartov and Cohen 2009), earnings management may have shifted to real earnings management; therefore, finding a significant association between discretionary accruals and analysts' forecast error could be difficult.

VOLEARN is the volatility of past 16 quarters' earnings. VOLEARN is expected to be positively associated with AFE. ROA is the return on assets, defined as earnings divided by average total assets at t-1 and total assets at t. For the type of earnings documented in prior literature (Dowen 1996; Ciccone 2005), I include LOSS and $\Delta$ACTUAL. LOSS is an indicator variable that equals 1 when the firm reports losses at t and is 0 otherwise. Loss firms create information asymmetry, under which analysts may find forecasting more difficult. LOSS is expected to have a positive association. $\Delta$ACTUAL is the difference between I/B/E/S reported earnings at t and t-4. Bradshaw et al. (2009) show that analysts have difficulty forecasting when earnings increase or decrease. Additionally, as with estimation (4), firm, industry and time fixed effects are included in the estimation. The industry factor is documented in Sinha et al. (1997), and time factors such as Reg FD and the 2008 financial crisis are documented in prior literature (see Bailey et al. 2003 and Heflin et al. 2003).

The sample of 40,452 firm-quarters is constructed using the following criteria. 1. The time period is between 2003 and 2017 (56 quarters), and the data to estimate the (1), (2) and (3) prediction models and calculate BTM, SIZE, ROA and VOLEARN should be available in CompuStat. The estimation requires 33 quarterly time series of earnings (NIQ - XIDOQ) and cash flows (32 for estimation and 1 more for the earnings $_{t+1}$ prediction). [12] Cash flows are from the quarterly cash flows statement (OANCFY - XIDOCY).[13] The sample starts in 2003 because cash flow data are available since 1995. I exclude firms in the financial industry (SIC code 6000-6999) and regulated industries such as energy and utilities (SIC code 4900-4999). This approach results in 61,228 firm-quarter observations. 2. The data to calculate the accrual management proxy (ABSDISCACC) and real earnings management proxy (RMProxy) are available in CompuStat. There are 51,119 firms-quarter observations remaining. 3. Analysts' first and last forecasts and actual reported earnings are available in I/B/E/S. The difference between analysts' last and first forecasts should be at least a month (46,183 firm-quarter observations remain). 4. The data to calculate past stock returns (RET) are available in CRSP. The final sample includes 40,452 firm-quarter observations, and 2,505 firms appear in this sample. The independent variables in the estimation of (4) and (5) are winsorized at the top 1% and bottom 1%.

Table 1 describes the sample. On average, total assets are \$6.2 billion, and market capitalization is \$8.5 billion. Seasonally adjusted cash flows and earnings are \$201 million and \$112 million, respectively. A total of 14.6% of the firms report losses. FORECAST $_{\text{FIRST}}$ is \$1.21 per share, and FORECAST $_{\text{LAST}}$ is \$1.14 per share. Thus, over the period, analysts revised downward for quarter t+1. In doing so, they reduce their forecast errors. Analysts' forecasts error based on first forecast, AFE $_{\text{FIRST}}$ is 0.0043 relative to share price, and, based on last forecast, AFE $_{\text{LAST}}$ is 0.0037. Cash-driven prediction (PREDICT $_{\text{CFO}}$), accruals-driven prediction (PREDICT $_{\text{CFO ACC}}$) and earnings-driven prediction (PREDICT $_{\text{EARN}}$) produces a different prediction for quarter t+1 earnings, 0.0147, 0.0135 and 0.0133, respectively, relative to total assets at quarter t. Accruals contribute to the prediction of future earnings; ACCCONTRIB is 0.0006 on average, relative to the total assets at quarter t.

Moving on to the correlation, Table 2 shows the correlation between variables in (4) and (5) separately. In Table 2a, Pearson correlation shows that FORECAST $_{\text{FIRST}}$ is correlated with PREDICT $_{\text{CFO,}}$ and its coefficient is 0.212. With PREDICT $_{\text{CFO ACC}}$ and PREDICT $_{\text{EARN}}$, its correlation is 0.154 and 0.154. FORECAST $_{\text{LAST}}$ shows a similar pattern; correlation with PREDICT $_{\text{CFO}}$ is 0.219, with PREDICT $_{\text{CFO ACC}}$, it is 0.171, and with PREDICT $_{\text{EARN}}$, it is 0.173. Therefore, the first analysts' forecast is more strongly correlated with cash-driven prediction (PREDICT $_{\text{CFO}}$) than accruals-driven prediction (PREDICT $_{\text{CFO ACC}}$) or earnings-driven prediction (PREDICT $_{\text{EARN}}$). The correlation with cash-driven prediction becomes weaker with analysts' last forecasts (0.219), while PREDICT $_{\text{CFO ACC}}$ and PREDICT $_{\text{EARN}}$ become more positively associated with analysts' last forecasts (0.171 and 0.173, respectively). Spearman's correlation, which is based on the ranked relationship, shows different results. In this case, FORECAST $_{\text{FIRST}}$ and FORECAST $_{\text{LAST}}$ are more strongly correlated with PREDICT $_{\text{EARN}}$. (0.213 and 0.243, respectively). Since this study is more focused on the linear relationship that Pearson's

[12] NIQ is net income (loss), and XIDOQ is extraordinary items and discontinued operations in CompuStat quarterly.
[13] OANCFY is operating activities – net cash flows and XIDOCY is extraordinary items and discontinued operations in Statement of Cash Flows in CompuStat quarterly.

## Glossary: Variable definition

| |
|---|
| FORECAST $_{\text{FIRST}}$ is the first consensus forecast for quarter t+1, made after the earnings announcement date of quarter t, divided by the price at the time of the measurement date. |
| FORECAST $_{\text{LAST}}$ is the last consensus forecast for quarter t+1, made before the earnings announcement date of quarter t+1, divided by the price at the time of the measurement date. |
| CFO is operating activities – net cash flows (data item, OANCFY) less Extraordinary Items and Discontinued Operations in Statement of Cash Flows (data item, XIDOCY) in fiscal quarter end t, and it is treated for seasonality using the X11 procedure. |
| EARN is earnings (data item, NIQ) – extraordinary items and discontinued operations in income statement (data item, XIDOQ) in fiscal quarter end t, and it is adjusted for seasonality using the X11 procedure. |
| ACC is the difference between EARN and CFO. |
| TA is total assets, measured at fiscal quarter end t. |
| MKTCAP is market capitalization, measured at fiscal quarter end t (quarterly close price, PRCCQ times the common share outstanding at the end of quarter t, CSHOQ). |
| BTM is the book-to-market ratio: book value (equity) divided by market capitalization at fiscal quarter end t. |
| RET is buy-and-hold size-adjusted return, accumulated from 2 days after the earnings announcement date of quarter t-1 to 1 day before the earnings announcement date of quarter t. |
| LOSS is an indicator variable that equals one if Earnings in quarter t <0 and 0 otherwise. |
| PREDICT $_{\text{CFO}}$ is $\hat{\alpha}_1 + \hat{\beta}_{11}\frac{CFO_t}{Total\ assets_t}$,where $\hat{\alpha}_1$ and $\hat{\beta}_{11}$are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on constant and $\frac{CFO_{t-1}}{Total\ assets_{t-1}}$ using past 32 observations. Variables in the regression and $CFO_t$ are treated for seasonality using the X11 procedure. |
| PREDICT $_{\text{CFO ACC}}$ is $\hat{\alpha} + \hat{\beta}_1\frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2\frac{ACC_t}{Total\ assets_t}$, where $\hat{\alpha}$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on constant, $\frac{CFO_{t-1}}{Total\ assets_{t-1}}$ and $\frac{ACC_{t-1}}{Total\ assets_{t-1}}$ using past 32 observations.. Variables in the regression and $CFO_t$ are treated for seasonality using the X11 procedure. Accruals, the difference between $EARN_t$ and $CFO_t$. |
| PREDICT $_{\text{EARN}}$ is $\hat{\alpha}_2 + \hat{\beta}_{21}\frac{Earning_t}{Total\ assets_t}$, where α$\hat{\alpha}_2$ and $\hat{\beta}_{21}$are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on $\frac{Earnings_{t-1}}{Total\ assets_{t-1}}$ using past 32 observations. Variables in the regression and $Earnings_t$ are treated for seasonality using the X11 procedure. |
| AFE $_{\text{FIRST}}$ is the absolute value of analysts' forecast error, based on the first consensus forecast for quarter t+1, made after the earnings announcement date of quarter t-1, $\lvert$Actual EPS $_{t+1}$ – FORECAST $_{\text{FIRST}, t+1}\rvert$, divided by the share price at the time of the measurement date. |
| AFE $_{\text{LAST}}$ is the absolute value of analysts' forecast error, based on the last consensus forecast for quarter t+1, made before the earnings announcement date of quarter t, $\lvert$Actual EPS $_{t+1}$ – FORECAST $_{\text{LAST}, t+1}\rvert$ divided by the share price at the time of the measurement date. |
| STDEV $_{\text{FIRST}}$ is the standard deviation of the analysts' first forecast. |
| NUMEST $_{\text{FIRST}}$ is the number of analysts who made the analysts' first forecast. |
| STDEV $_{\text{LAST}}$ is the standard deviation of the analysts' last forecast. |
| NUMEST $_{\text{LAST}}$ is the number of analysts who made the analysts' last forecast. |
| ABSDISCACC is the absolute value of discretionary accruals at fiscal end t, based on the modified Jones (1991) model. |
| ABSRMPROXY is the absolute value of the RM proxy at fiscal end t, as suggested in Cohen et al. (2008) |
| ROA is the return on assets, defined as $Earnings_t$ divided by the average of Total $assets_{t-1}$ and Total $assets_t$. Earnings is adjusted for seasonality using the X11 procedure. |
| VOLEARN is the standard deviation of Earnings divided by the average of Total $assets_{t-1}$ and Total $assets_t$ in the past 16 quarters. Earnings is adjusted for seasonality using the X11 procedure. |
| ACCCONTRIB is the difference between $ABSE_{CFO}$ and $ABSE_{CFO\ ACC}$. $ABSE_{CFO}$ is the absolute value of the prediction error of cash-driven prediction, $\left\lvert\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO}\right\rvert$, and $ABSE_{CFO\ ACC}$ is the absolute value of the prediction error of accruals-driven prediction, $\left\lvert\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO\ ACC}\right\rvert$. |
| ΔACTUAL is the difference between I/B/E/S reported earnings at t and t-4. |

**Table 1. Descriptive statistics (N = 40,452)**

| | Mean | Standard Deviation | 1st Percentile | 10th Percentile | Median | 90th Percentile | 99th Percentile |
|---|---|---|---|---|---|---|---|
| **$FORECAST_{FIRST}$** | 0.0121 | 0.0219 | -0.0426 | 0.0019 | 0.0129 | 0.0241 | 0.0467 |
| **$FORECAST_{LAST}$** | 0.0114 | 0.0221 | -0.0478 | 0.0009 | 0.0124 | 0.0237 | 0.0474 |
| **CFO** | 201.31 | 792.85 | -73.48 | -0.34 | 33.28 | 382.86 | 3243.27 |
| **ACC** | -89.16 | 444.62 | -1537.87 | -191.77 | -13.42 | 13.10 | 199.70 |
| **EARN** | 112.14 | 570.27 | -232.54 | -4.17 | 16.69 | 212.50 | 2003.42 |
| **TA** | 6,287.63 | 19,622.80 | 66.95 | 209.11 | 1,390.62 | 12,982.00 | 91,327.00 |
| **MKTCAP** | 8,507.91 | 28,738.74 | 114.98 | 241.69 | 1,519.78 | 16,026.23 | 137,193.28 |
| **BTM** | 0.4740 | 0.3864 | -0.1599 | 0.1515 | 0.4062 | 0.8905 | 1.6454 |
| **RET** | 0.0166 | 1.5462 | -0.4167 | -0.1908 | 0.0021 | 0.2120 | 0.5855 |
| **LOSS** | 0.1461 | 0.3532 | 0 | 0 | 0 | 1 | 1 |
| **$PREDICT_{CFO}$** | 0.0147 | 0.0221 | -0.0537 | -0.0031 | 0.0150 | 0.0345 | 0.0649 |
| **$PREDICT_{CFO\ ACC}$** | 0.0136 | 0.0371 | -0.0721 | -0.0049 | 0.0148 | 0.0357 | 0.0697 |
| **$PREDICT_{EARN}$** | 0.0133 | 0.0355 | -0.0667 | -0.0041 | 0.0144 | 0.0348 | 0.0652 |
| **$AFE_{FIRST}$** | 0.0043 | 0.0159 | 0.0000 | 0.0001 | 0.0015 | 0.0089 | 0.0435 |
| **$AFE_{LAST}$** | 0.0037 | 0.0218 | 0.0000 | 0.0000 | 0.0012 | 0.0072 | 0.0366 |
| **$STDEV_{FIRST}$** | 0.0363 | 0.0535 | 0 | 0.01 | 0.02 | 0.08 | 0.26 |
| **$NUMEST_{FIRST}$** | 9.6959 | 6.9977 | 2 | 3 | 8 | 20 | 31 |
| **$STDEV_{LAST}$** | 0.0324 | 0.0492 | 0 | 0 | 0.02 | 0.07 | 0.23 |
| **$NUMEST_{LAST}$** | 10.0215 | 7.1545 | 2 | 3 | 8 | 20 | 32 |
| **ABSDISCACC** | 0.0159 | 0.0166 | 0.0002 | 0.0018 | 0.0108 | 0.0363 | 0.0812 |
| **ABSRMPROXY** | 0.0252 | 0.0290 | 0.0003 | 0.0029 | 0.0168 | 0.0557 | 0.1363 |
| **ROA** | 0.0140 | 0.0327 | -0.0956 | -0.0063 | 0.0151 | 0.0388 | 0.0760 |
| **VOLEARN** | 0.0173 | 0.0192 | 0.0020 | 0.0040 | 0.0104 | 0.0393 | 0.1124 |
| **ACCCONTRIB** | 0.0006 | 0.0281 | -0.0294 | -0.0032 | 0.0006 | 0.0081 | 0.0284 |
| **ΔACTUAL** | 0.02361 | 0.34532 | -1.0400 | -0.1900 | 0.0300 | 0.2400 | 0.8800 |

Variables are defined in the glossary.

correlation estimates, further examination and confirmation in multivariate regression in (4) is needed.

The correlation of $PREDICT_{CFO}$ correlation with $PREDICT_{CFO\ ACC}$ is 0.597, and that with $PREDICT_{CFO}$ is 0.517. The correlation between $PREDICT_{CFO\ ACC}$ and $PREDICT_{CFO}$ is 0.944. While cash-driven prediction is relatively different from accruals-driven or earnings-driven prediction, accruals-driven and earnings-driven prediction are quite similar to each other. Among the control variables, LOSS and ΔACTUAL are significantly correlated with $FORECAST_{FIRST}$ and $FORECAST_{LAST}$. For example, LOSS and $FORECAST_{LAST}$ are negatively correlated (-0.327), and ΔACTUAL and $FORECAST_{LAST}$ are positively correlated (0.155). Analysts reduce their forecasts for future earnings significantly when firms report losses in the current quarter. By contrast, they revise their

**Table 2a. Correlation table for analysts' forecasts (N = 40,452; Pearson's correlations in the lower triangle and Spearman's correlations in the upper triangle)**

| | $FORECAST_{FIRST}$ | $FORECAST_{LAST}$ | $PREDICT_{CFO}$ | $PREDICT_{CFO\ ACC}$ | $PREDICT_{EARN}$ | EARN/TA | CFO/TA | ACC/TA | BTM | RET | LOSS | SIZE | $NUMEST_{FIRST}$ | $NUMEST_{FIRST}$ | $STDEV_{FIRST}$ | $STDEV_{LAST}$ | ΔACTUAL | VOLEARN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **$FORECAST_{FIRST}$** | 1 | 0.947 | 0.159 | 0.209 | 0.213 | 0.241 | 0.133 | 0.070 | 0.162 | -0.014 | -0.354 | 0.125 | 0.063 | 0.062 | 0.122 | 0.116 | 0.146 | -0.168 |
| **$FORECAST_{LAST}$** | 0.906 | 1 | 0.177 | 0.239 | 0.243 | 0.279 | 0.148 | 0.082 | 0.139 | -0.066 | -0.382 | 0.145 | 0.076 | 0.074 | 0.095 | 0.101 | 0.195 | -0.178 |
| **$PREDICT_{CFO}$** | 0.212 | 0.219 | 1 | 0.879 | 0.818 | 0.648 | 0.554 | -0.052 | -0.370 | 0.030 | -0.374 | 0.326 | 0.214 | 0.215 | -0.158 | -0.162 | 0.105 | -0.188 |
| **$PREDICT_{CFO\ ACC}$** | 0.154 | 0.171 | 0.597 | 1 | 0.937 | 0.823 | 0.529 | 0.096 | -0.435 | 0.064 | -0.485 | 0.339 | 0.195 | 0.199 | -0.178 | -0.176 | 0.243 | -0.195 |
| **$PREDICT_{EARN}$** | 0.154 | 0.173 | 0.517 | 0.944 | 1 | 0.839 | 0.463 | 0.171 | -0.433 | 0.058 | -0.500 | 0.358 | 0.204 | 0.208 | -0.175 | -0.175 | 0.236 | -0.233 |
| **EARN/TA** | 0.213 | 0.255 | 0.518 | 0.705 | 0.734 | 1 | 0.489 | 0.251 | -0.467 | 0.096 | -0.559 | 0.313 | 0.161 | 0.167 | -0.191 | -0.186 | 0.365 | -0.134 |
| **CFO/TA** | 0.156 | 0.164 | 0.586 | 0.360 | 0.313 | 0.379 | 1 | -0.628 | -0.298 | 0.076 | -0.267 | 0.211 | 0.169 | 0.172 | -0.092 | -0.096 | 0.153 | -0.025 |
| **ACC/TA** | 0.072 | 0.104 | -0.001 | 0.366 | 0.433 | 0.630 | -0.480 | 1 | -0.033 | -0.002 | -0.228 | 0.040 | -0.050 | -0.049 | -0.054 | -0.048 | 0.133 | -0.118 |
| **BTM** | 0.000 | -0.016 | -0.161 | -0.156 | -0.153 | -0.203 | -0.171 | -0.049 | 1 | -0.136 | 0.165 | -0.400 | -0.232 | -0.239 | 0.195 | 0.194 | -0.213 | 0.016 |
| **RET** | -0.002 | 0.000 | 0.001 | 0.006 | 0.005 | 0.008 | 0.007 | 0.002 | -0.014 | 1 | -0.068 | 0.061 | -0.005 | -0.001 | -0.042 | -0.043 | 0.144 | -0.008 |
| **LOSS** | -0.290 | -0.327 | -0.373 | -0.354 | -0.365 | -0.511 | -0.264 | -0.263 | 0.180 | -0.008 | 1 | -0.234 | -0.101 | -0.106 | 0.152 | 0.158 | -0.261 | 0.299 |
| **SIZE** | 0.098 | 0.117 | 0.279 | 0.194 | 0.204 | 0.216 | 0.187 | 0.048 | -0.305 | 0.004 | -0.226 | 1 | 0.732 | 0.743 | 0.094 | 0.081 | 0.177 | -0.206 |
| **$NUMEST_{FIRST}$** | 0.036 | 0.042 | 0.185 | 0.107 | 0.112 | 0.104 | 0.165 | -0.040 | -0.149 | -0.006 | -0.095 | 0.709 | 1 | 0.976 | 0.102 | 0.086 | 0.079 | -0.062 |
| **$NUMEST_{FIRST}$** | 0.035 | 0.042 | 0.185 | 0.109 | 0.114 | 0.106 | 0.167 | -0.040 | -0.152 | -0.006 | -0.097 | 0.720 | 0.981 | 1 | 0.103 | 0.091 | 0.083 | -0.063 |
| **$STDEV_{FIRST}$** | -0.005 | -0.029 | -0.071 | -0.066 | -0.067 | -0.098 | -0.039 | -0.060 | 0.133 | -0.005 | 0.156 | 0.080 | 0.050 | 0.058 | 1 | 0.849 | -0.011 | 0.116 |
| **$STDEV_{FIRST}$** | -0.019 | -0.036 | -0.085 | -0.073 | -0.072 | -0.108 | -0.058 | -0.053 | 0.133 | -0.005 | 0.166 | 0.057 | 0.033 | 0.039 | 0.807 | 1 | -0.001 | 0.112 |
| **ΔACTUAL** | 0.111 | 0.155 | 0.075 | 0.136 | 0.135 | 0.229 | 0.111 | 0.124 | -0.150 | 0.010 | -0.229 | 0.084 | 0.030 | 0.030 | -0.092 | -0.087 | 1 | -0.057 |
| **VOLEARN** | -0.139 | -0.146 | -0.294 | -0.231 | -0.266 | -0.237 | -0.095 | -0.145 | 0.004 | 0.001 | 0.246 | -0.178 | -0.064 | -0.064 | 0.059 | 0.050 | -0.029 | 1 |

Variables are defined in the glossary.

**Table 2b. Correlation table for analysts' forecast error (N = 40,452; Pearson's correlations in the lower triangle and Spearman's correlations in the upper triangle)**

| | $AFE_{FIRST}$ | $AFE_{LAST}$ | $STDEV_{FIRST}$ | $STDEV_{LAST}$ | $NUMEST_{FIRST}$ | $NUMEST_{LAST}$ | SIZE | ABSDISCACC | ABSRMPROXY | ACCCONTRIB | ROA | LOSS | ΔACTUAL | VOLEARN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **$AFE_{FIRST}$** | 1 | 0.838 | 0.316 | 0.319 | -0.213 | -0.217 | -0.329 | 0.126 | 0.158 | -0.010 | -0.285 | 0.294 | -0.101 | 0.279 |
| **$AFE_{LAST}$** | 0.822 | 1 | 0.297 | 0.334 | -0.218 | -0.224 | -0.318 | 0.116 | 0.143 | -0.019 | -0.256 | 0.267 | -0.046 | 0.267 |
| **$STDEV_{FIRST}$** | 0.216 | 0.144 | 1 | 0.849 | 0.102 | 0.103 | 0.094 | 0.000 | 0.023 | -0.030 | -0.178 | 0.152 | -0.011 | 0.116 |
| **$STDEV_{LAST}$** | 0.247 | 0.182 | 0.807 | 1 | 0.086 | 0.091 | 0.081 | 0.004 | 0.026 | -0.031 | -0.175 | 0.158 | -0.001 | 0.112 |
| **$NUMEST_{FIRST}$** | -0.078 | -0.054 | 0.050 | 0.033 | 1 | 0.976 | 0.732 | -0.132 | -0.104 | -0.015 | 0.157 | -0.101 | 0.079 | -0.062 |
| **$NUMEST_{LAST}$** | -0.081 | -0.056 | 0.058 | 0.039 | 0.981 | 1 | 0.743 | -0.134 | -0.105 | -0.017 | 0.162 | -0.106 | 0.083 | -0.063 |
| **SIZE** | -0.150 | -0.100 | 0.080 | 0.057 | 0.709 | 0.720 | 1 | -0.207 | -0.183 | -0.021 | 0.305 | -0.234 | 0.177 | -0.206 |
| **ABSDISCACC** | 0.085 | 0.050 | 0.034 | 0.043 | -0.127 | -0.129 | -0.206 | 1 | 0.353 | 0.028 | -0.042 | 0.106 | -0.027 | 0.165 |
| **ABSRMPROXY** | 0.124 | 0.096 | 0.066 | 0.069 | -0.084 | -0.084 | -0.174 | 0.399 | 1 | 0.006 | -0.058 | 0.151 | -0.013 | 0.235 |
| **ACCCONTRIB** | -0.063 | -0.060 | -0.017 | -0.019 | -0.001 | -0.001 | 0.008 | -0.024 | -0.186 | 1 | 0.100 | -0.057 | 0.008 | -0.012 |
| **ROA** | -0.213 | -0.170 | -0.095 | -0.106 | 0.108 | 0.109 | 0.218 | -0.074 | -0.256 | 0.316 | 1 | -0.611 | 0.356 | -0.138 |
| **LOSS** | 0.226 | 0.147 | 0.156 | 0.166 | -0.095 | -0.097 | -0.226 | 0.123 | 0.200 | -0.083 | -0.559 | 1 | -0.261 | 0.299 |
| **ΔACTUAL** | -0.232 | -0.181 | -0.092 | -0.087 | 0.030 | 0.030 | 0.084 | -0.025 | -0.037 | 0.029 | 0.229 | -0.229 | 1 | -0.057 |
| **VOLEARN** | 0.121 | 0.082 | 0.059 | 0.050 | -0.064 | -0.064 | -0.178 | 0.172 | 0.270 | -0.105 | -0.216 | 0.246 | -0.029 | 1 |

Variables are defined in the glossary.

forecasts upward when firms improve their earnings in the current quarter, compared to the same quarter last year.

In Table 2b, the correlation for the variable in estimation (5) is shown. In particular, AFE $_{\text{FIRST}}$ and AFE $_{\text{LAST}}$ are negatively associated with ACCCONTRIB. Pearson's correlation is -0.063 between AFE $_{\text{FIRST}}$ and ACCCONTRIB and is -0.060 between ACCCONTRIB and AFE $_{\text{LAST}}$. I expected that the negative correlation with AFE $_{\text{LAST}}$ would be stronger, but since the difference is small, again, this will have to be examined further in multivariate analysis in (5).

Except for a strong negative correlation with the standard deviation of analysts' forecasts (STDEV $_{\text{FIRST}}$ and STDEV $_{\text{LAST}}$), the control variables that are significantly correlated with AFE $_{\text{FIRST}}$ and AFE $_{\text{LAST}}$ are, again, LOSS and ΔACTUAL. Pearson's correlation between LOSS and AFE $_{\text{FIRST}}$ (AFE $_{\text{LAST}}$) is 0.226 (0.147). After firms report losses in the current quarter, analysts struggle to make their forecasts correctly. This could occur either because analysts make forecasts that are too pessimistic after the quarter with losses or because earnings are volatile after the quarter with losses. Pearson's correlation between ΔACTUAL and AFE $_{\text{FIRST}}$ (AFE $_{\text{LAST}}$) is -0.232 (-0.181), indicating that analysts' future forecasts are more accurate after firms improve their earnings in the current quarter.

## 5. Multivariate results

First, to determine whether analysts' forecasts are associated with cash flows and accruals differently, as documented in Ahmed et al. (2005), I estimate the following.

$$FORECAST_{i,t+1} = \alpha + \beta_1 \frac{CFO_{i,t}}{TA_{i,t}} + \beta_2 \frac{ACC_{i,t}}{TA_{i,t}} + \beta_3 BTM_{i,t} + \beta_4 RET_{i,t} + \beta_5 LOSS_{i,t} + \beta_6 SIZE_{i,t} + \epsilon_{i,t}, \quad (6)$$

The estimation in (6) seeks to replicate the results in Ahmed et al. (2005), showing that cash flow persistence in analysts' forecasts is higher than persistence in accruals, and their empirical test is based on annual data. This study's data are quarterly and based on seasonally adjusted cash flows (CFO), and accruals (ACC) are the difference between seasonally adjusted earnings and cash flows. Confirming results that are similar to those of past studies would enhance the validity of the seasonal adjustment of the data. In Table 3 Panel A, the first column shows the result; the coefficient on ACC/TA is 0.078 (p-value < 0.001), whereas the coefficient on CFO/TA is 0.135 (p-value < 0.001) when the dependent variable is AFE $_{\text{FIRST}}$. A similar pattern is observed when the dependent variable is AFE $_{\text{LAST}}$. Therefore, the result confirms what Ahmed et al. (2005) report: accruals are underweighted in analysts' forecasts.

Next, I estimate (4) using PREDICT $_{\text{CFO}}$, PREDICT $_{\text{CFO ACC}}$ and PREDICT $_{\text{EARN}}$ separately as an explanatory variable in analysts' forecasts. The result is reported in Table 3 Panel A. When the dependent variable is FORECAST $_{\text{FIRST}}$, PREDICT $_{\text{CFO}}$ has a more positive association than PREDICT $_{\text{CFO ACC}}$ and PREDICT $_{\text{EARN}}$. The coefficient on PREDICT $_{\text{CFO}}$ is 0.162 (p-value < 0.001), whereas the coefficient on PREDICT $_{\text{CFO ACC}}$ is 0.111 (p-value < 0.001) and that on PREDICT $_{\text{EARN}}$ is 0.115 (p-value < 0.001). This result suggests that in analysts' first forecasts, cash-driven prediction of future earnings is more embedded than accruals- or earnings-driven prediction. The test of the difference between the coefficients on PREDICT $_{\text{CFO}}$ and PREDICT $_{\text{CFO}}$

$_{ACC}$ and those on PREDICT $_{CFO}$ and PREDICT $_{EARN}$ shows that the coefficient on PREDICT $_{CFO}$ is significantly larger than that on PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$.

**Table 3. Regression of analysts' forecasts at t+1 on cash-driven, accruals-driven and earnings-driven predictions (N obs. = 40,452)**

$$FORECAST_{i,t+1} = \alpha + \beta_{1a}\frac{CFO_{i,t}}{TA_{i,t}} + \beta_{1b}\frac{ACC_{i,t}}{TA_{i,t}} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 LOSS_{i,t} + \beta_5 SIZE_{i,t-} + \beta_6 NUMEST_{i,t} + \beta_7 STDEV_{i,t} + \beta_8 \Delta ACTUAL_{i,t} + \beta_9 VOLEARN_{i,t} + \epsilon_{i,t}$$

$$FORECAST_{i,t+1} = \alpha + \beta_1 PREDICT_{i,t} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 LOSS_{i,t} + \beta_5 SIZE_{i,t} + \beta_6 NUMEST_{i,t} + \beta_7 STDEV_{i,t} + \beta_8 \Delta ACTUAL_{i,t} + \beta_9 VOLEARN_{i,t} + \epsilon_{i,t}$$

## Panel A. Estimation of regression

| Dependent variable | | FORECAST$_{FIRST}$ | | | | FORECAST$_{LAST}$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| **CONSTANT** | α | -0.027 | -0.025 | -0.026 | -0.026 | -0.037 | -0.036 | -0.036 | -0.036 |
| | | (2.71)** | (2.58)** | (2.64)** | (2.64)** | (3.57)*** | (3.50)*** | (3.53)*** | (3.49)*** |
| **CFO/TA** | $\beta_{1a}$ | 0.135 | | | | 0.149 | | | |
| | | (8.41)*** | | | | (9.05)*** | | | |
| **ACC/TA** | $\beta_{1b}$ | 0.078 | | | | 0.097 | | | |
| | | (6.49)*** | | | | (7.62)*** | | | |
| **PREDICT $_{CFO}$** | $\beta_1$ | | 0.162 | | | | 0.152 | | |
| | | | (9.99)*** | | | | (10.09)*** | | |
| **PREDICT $_{CFO\ ACC}$** | $\beta_1$ | | | 0.111 | | | | 0.117 | |
| | | | | (6.99)*** | | | | (7.62)*** | |
| **PREDICT $_{EARN}$** | $\beta_1$ | | | | 0.115 | | | | 0.136 |
| | | | | | (7.26)*** | | | | (7.88)*** |
| **BTM** | $\beta_2$ | 0.015 | 0.014 | 0.015 | 0.015 | 0.017 | 0.016 | 0.017 | 0.017 |
| | | (5.59)*** | (5.27)*** | (5.47)*** | (5.45)*** | (5.79)*** | (5.49)*** | (5.67)*** | (5.64)*** |
| **RET** | $\beta_3$ | -0.002 | -0.002 | -0.002 | -0.002 | -0.003 | -0.002 | -0.002 | -0.002 |
| | | (1.48) | (1.06) | (1.20) | (1.17) | (2.05)* | (1.58) | (1.73)$ | (1.69)$ |
| **LOSS** | $\beta_4$ | -0.010 | -0.012 | -0.011 | -0.011 | -0.011 | -0.013 | -0.012 | -0.012 |
| | | (17.88)*** | (24.94)*** | (22.44)*** | (22.51)*** | (18.68)*** | (27.30)*** | (23.89)*** | (23.60)*** |
| **SIZE** | $\beta_5$ | 0.004 | 0.004 | 0.004 | 0.004 | 0.006 | 0.006 | 0.006 | 0.006 |
| | | (4.04)*** | (3.77)*** | (4.14)*** | (4.02)*** | (5.34)*** | (5.20)*** | (5.51)*** | (5.27)*** |
| **NUMEST$_{FIRST}$** | $\beta_6$ | 0.000 | 0.000 | 0.000 | 0.000 | | | | |
| | | (0.68) | (1.66)$ | (0.88) | (0.91) | | | | |
| **STDEV$_{FIRST}$** | $\beta_7$ | 0.002 | 0.000 | 0.001 | 0.000 | | | | |
| | | (0.15) | (0.03) | (0.05) | (0.02) | | | | |
| **NUMEST$_{LAST}$** | $\beta_6$ | | | | | -0.000 | -0.000 | -0.000 | -0.000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | (2.43)* | (3.53)*** | (2.73)** | (2.73)** |
| **$STDEV_{LAST}$** | $\beta_7$ | | | | | -0.013 | -0.016 | -0.015 | -0.015 |
| | | | | | | (1.43) | (1.68)$ | (1.60) | (1.63) |
| **ΔACTUAL** | $\beta_8$ | 0.003 | 0.005 | 0.004 | 0.004 | 0.007 | 0.008 | 0.008 | 0.008 |
| | | (3.48)*** | (5.07)*** | (4.30)*** | (4.32)*** | (8.37)*** | (10.48)*** | (9.55)*** | (9.42)*** |
| **VOLEARN** | $\beta_9$ | -0.032 | -0.026 | -0.027 | -0.024 | -0.033 | -0.028 | -0.028 | -0.024 |
| | | (3.53)*** | (2.74)*** | (2.90)*** | (2.59)** | (3.66)*** | (3.12)** | (3.11)** | (2.61)** |
| **Fixed effects** | | Firm, industry (two-digit SICs) and time effects | | | | | | | |
| **Adjusted R-squared** | | 0.237 | 0.235 | 0.233 | 0.233 | 0.314 | 0.311 | 0.31 | 0.31 |

$ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%.
The table reports the coefficient and t-stat in parentheses.
Variables are defined in the glossary.

**Panel B. Results of testing the equality of coefficients**

| | **$FORECAST_{FIRST}$ regression** | | | **$FORECAST_{LAST}$ regression** | | |
|---|---|---|---|---|---|---|
| | **PREDICT CFO** | **PREDICT CFO ACC** | **PREDICT EARN** | **PREDICT CFO** | **PREDICT CFO ACC** | **PREDICT EARN** |
| **Coefficient** | 0.162 | 0.111 | 0.115 | 0.152 | 0.117 | 0.136 |
| **$\chi^2$ statistics and p-value to test coefficients on $PREDICT_{CFO}$ and $PREDICT_{CFO\ ACC}$** | 7.91<br>0.005 | | | 0.15<br>0.696 | | |
| **$\chi^2$ statistics and p-value to test coefficients on $PREDICT_{CFO\ ACC}$ and $PREDICT_{EARN}$** | | 0.24<br>0.626 | | | 0.30<br>0.581 | |
| **$\chi^2$ statistics and p-value to test coefficients on $PREDICT_{CFO}$ and $PREDICT_{EARN}$** | | | 5.69<br>0.017 | | | 0.01<br>0.920 |

The $\chi^2$ statistic to test the equality of the coefficient on PREDICT $_{CFO}$ and that on PREDICT $_{CFO\ ACC}$ is 7.91 (p-value = 0.005), and to test the equality of the coefficient on PREDICT $_{CFO}$ and that on PREDICT $_{EARN}$ is 5.69 (p-value =0.017).

When the dependent variable is FORECAST $_{LAST}$, the associations of the analysts' forecast error with PREDICT $_{CFO}$, PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$ are similar. The coefficient on PREDICT $_{CFO}$ is 0.152 (p-value < 0.001), whereas the coefficient on PREDICT $_{CFO\ ACC}$ is 0.117 (p-value < 0.001) and that on PREDICT $_{EARN}$ is 0.136 (p-value < 0.001). The results of the test of the equality between the coefficients are all nonsignificant, indicating that analysts' forecasts incorporate all predictions equally.

Another interesting pattern is that the coefficient on PREDICT $_{CFO}$ decreased, whereas that on PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$ increased from the FORECAST $_{FIRST}$ regression and FORECAST $_{LAST}$ regression. This result can be interpreted as the tendency of analysts to incorporate accrual information into their forecasts gradually over time. Analysts may include accruals in their forecasts by referring to other firms, industry trends and macroeconomic factors even if they do not fully understand how accruals can contribute. However, it is still interesting that cash-driven prediction can be as positively associated as accruals-driven or earnings-driven prediction in analysts' last forecast. Cash-driven prediction ignores all accrual information that can be useful in predicting future earnings. Thus, I consider losses as an explanation.

H1 hypothesizes that loss can create information asymmetry, a situation in which analysts consider accrual information to be irrelevant. To test this hypothesis, I partition the sample into loss firms and non-loss firms and re-estimate (4) without the LOSS variable. The results are reported in Table 4 (FORECAST $_{FIRST}$ regression) and 5 (FORECAST $_{LAST}$ regression). The table clearly shows that in the loss firms, analysts use cash-driven prediction, and in the non-loss firms, analysts use earnings-driven prediction. First, in the loss firm sample, PREDICT $_{CFO}$ is significantly positively associated (coefficient = 0.241, p-value < 0.001) in Table 4 Panel A. On the other hand, PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$ are positively associated, but the association is not significant at any level (0.043 and 0.013, respectively). The same pattern is observed in the FORECAST $_{LAST}$ regression in Table 5 Panel A, although the value of the coefficient for PREDICT $_{CFO}$ decreased (coefficient = 0.207, p-value < 0.001). Similar to the FORECAST $_{FIRST}$ regression, PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$ are positively associated, but their coefficient is not significant at any level (0.029 and 0.015, respectively). Both Table 4 Panel B and Table 5 Panel B shows that the coefficient on PREDICT $_{CFO}$ is significantly different from that on PREDICT $_{CFO\ ACC}$ or PREDICT $_{EARN}$, based on $\chi^2$ statistics, whereas the coefficient on PREDICT $_{CFO\ ACC}$ is not significantly different from that on PREDICT $_{EARN}$. For example, in Table 4 Panel B, $\chi^2$ statistics to test the coefficient on PREDICT $_{CFO}$ and that on PREDICT $_{EARN}$ is 16.56 (p-value <0.001), but $\chi^2$ statistics to test the coefficient on PREDICT $_{CFO\ ACC}$ and that on PREDICT $_{EARN}$ is 1.94 (p-value = 0.164). This result indicates that analysts use cash-driven prediction for future forecasting, ignoring accrual or earnings information if firms report losses in the current quarter. The question arises as to whether this analyst response is irrational. One empirical observation is that for loss firms, on average, accruals do not contribute to the prediction of future earnings.

**TABLE 4. Regression of analysts' first forecasts at t+1 on cash-driven, accruals-driven and earnings-driven predictions using two subsamples – non-loss and loss firms (N obs. = 40,452)**

$$
\begin{aligned}
&FORECAST_{FIRST\ i,t+1} \\
&\quad = \alpha + \beta_1 PREDICT_{i,t} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 NUMEST_{FIRST\ i,t} \\
&\quad + \beta_6 STDEV_{FIRST\ i,t} + \beta_7 \Delta ACTUAL_{i,t} + \beta_8 VOLEARN_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

## Panel A. Estimation of regression

| | | Non-loss firm sample (N=34,543) | | | Loss firm sample (N=5,909) | | |
|---|---|---|---|---|---|---|---|
| **CONSTANT** | α | 0.019 | 0.021 | 0.021 | -0.124 | -0.127 | -0.130 |
| | | (2.52)* | (2.64)** | (2.60)** | (3.54)*** | (3.85)*** | (3.83)*** |
| **PREDICT $_{CFO}$** | $\beta_1$ | 0.109 | | | 0.241 | | |
| | | (10.02)*** | | | (5.09)*** | | |
| **PREDICT $_{CFO\ ACC}$** | $\beta_1$ | | 0.134 | | | 0.043 | |
| | | | (13.81)*** | | | (0.88) | |
| **PREDICT $_{EARN}$** | $\beta_1$ | | | 0.167 | | | 0.013 |
| | | | | (14.76)*** | | | (0.31) |
| **BTM** | $\beta_2$ | 0.004 | 0.005 | 0.005 | 0.020 | 0.021 | 0.021 |
| | | (4.70)*** | (5.27)*** | (5.23)*** | (3.96)*** | (4.09)*** | (4.09)*** |
| **RET** | $\beta_3$ | -0.001 | -0.001 | -0.001 | -0.003 | -0.003 | -0.003 |
| | | (2.06)* | (2.08)* | (1.95)$ | (0.46) | (0.50) | (0.49) |
| **SIZE** | $\beta_4$ | -0.002 | -0.002 | -0.002 | 0.018 | 0.019 | 0.019 |
| | | (3.95)*** | (4.32)*** | (4.64)*** | (4.20)*** | (4.69)*** | (4.64)*** |
| **NUMEST $_{FIRST}$** | $\beta_6$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (2.65)** | (3.34)*** | (3.15)** | (0.31) | (0.04) | (0.05) |
| **STDEV $_{FIRST}$** | $\beta_7$ | 0.035 | 0.035 | 0.034 | -0.071 | -0.072 | -0.072 |
| | | (5.94)*** | (5.88)*** | (5.78)*** | (1.79)$ | (1.79)$ | (1.80)$ |
| **ΔACTUAL** | $\beta_8$ | -0.022 | -0.024 | -0.019 | -0.035 | -0.049 | -0.056 |
| | | (3.65)*** | (4.02)*** | (3.11)*** | (0.96) | (1.29) | (1.50) |
| **VOLEARN** | $\beta_8$ | 0.004 | 0.003 | 0.003 | 0.001 | 0.001 | 0.001 |
| | | (8.64)*** | (6.63)*** | (6.44)*** | (0.21) | (0.24) | (0.28) |
| **Fixed effects** | | Firm, industry (two-digit SICs) and time effects | | | | | |
| **Adjusted R-squared** | | 0.355 | 0.362 | 0.362 | 0.120 | 0.117 | 0.117 |

$ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%.
The non-loss (loss) sample contains firm-quarter observations in which a firm reports profits (losses) in quarter t.
The table reports the coefficient and t-stat in parentheses.
Variables are defined in the glossary.

**Panel B. Results of testing the equality of coefficients**

| | Non-loss firm sample (N=34,543) | | | Loss firm sample (N=5,909) | | |
|---|---|---|---|---|---|---|
| | **$PREDICT_{CFO}$** | **$PREDICT_{CFO\ ACC}$** | **$PREDICT_{EARN}$** | **$PREDICT_{CFO}$** | **$PREDICT_{CFO\ ACC}$** | **$PREDICT_{EARN}$** |
| **Coefficient** | 0.109 | 0.134 | 0.167 | 0.241 | 0.043 | 0.013 |
| **$\chi^2$ statistics and p-value to test coefficients on $PREDICT_{CFO}$ and $PREDICT_{CFO\ ACC}$** | 7.25<br>0.007 | | | 10.81<br>0.001 | | |
| **$\chi^2$ statistics and p-value to test coefficients on $PREDICT_{CFO\ ACC}$ and $PREDICT_{EARN}$** | | 14.57<br>0.000 | | | 1.94<br>0.164 | |
| **$\chi^2$ statistics and p-value to test coefficients on $PREDICT_{CFO}$ and $PREDICT_{EARN}$** | | | 16.13<br>0.000 | | | 16.56<br>0.000 |

The non-loss (loss) sample contains firm-quarter observation in which a firm reports profits (losses) in quarter t.

**TABLE 5. Regression of analysts' last forecasts at t+1 on cash-driven, accruals-driven and earnings-driven predictions using two subsamples – non-loss and loss firms (N obs. = 40,452)**

$$FORECAST_{LAST\ i,t+1} = \alpha + \beta_1 PREDICT_{i,t} + \beta_2 BTM_{i,t} + \beta_3 RET_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 NUMEST_{LAST\ i,t} + \beta_6 STDEV_{LAST\ i,t} + \beta_7 \Delta ACTUAL_{i,t} + \beta_8 VOLEARN_{i,t} + \epsilon_{i,t}$$

## Panel A. Estimation of regression

| | | Non-loss firm sample (N=34,543) | | | Loss firm sample (N=5,909) | | |
|---|---|---|---|---|---|---|---|
| **CONSTANT** | α | 0.021 | 0.022 | 0.022 | -0.187 | -0.190 | -0.191 |
| | | (2.43)* | (2.57)* | (2.57)* | (5.60)*** | (5.97)*** | (5.85)*** |
| **PREDICT $_{CFO}$** | $\beta_1$ | 0.100 | | | 0.207 | | |
| | | (10.25)*** | | | (4.65)*** | | |
| **PREDICT $_{CFO\ ACC}$** | $\beta_1$ | | 0.136 | | | 0.029 | |
| | | | (14.75)*** | | | (0.64) | |
| **PREDICT $_{EARN}$** | $\beta_1$ | | | 0.186 | | | 0.015 |
| | | | | (17.59)*** | | | (0.36) |
| **BTM** | $\beta_2$ | 0.004 | 0.004 | 0.004 | 0.027 | 0.028 | 0.028 |
| | | (4.37)*** | (4.94)*** | (4.91)*** | (5.23)*** | (5.36)*** | (5.35)*** |
| **RET** | $\beta_3$ | -0.006 | -0.006 | -0.006 | 0.011 | 0.011 | 0.011 |
| | | (12.60)** | (12.63)*** | (12.45)*** | (1.81)$ | (1.75)$ | (1.77)$ |
| **SIZE** | $\beta_4$ | -0.002 | -0.002 | -0.002 | 0.023 | 0.024 | 0.024 |
| | | (4.05)** | (4.64)*** | (5.26)*** | (6.52)*** | (7.18)*** | (7.04)*** |
| **NUMEST$_{FIRST}$** | $\beta_6$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (1.37) | (1.97)* | (1.84)$ | (1.15) | (0.94) | (0.95) |
| **STDEV$_{FIRST}$** | $\beta_7$ | 0.034 | 0.034 | 0.033 | -0.084 | -0.087 | -0.087 |
| | | (6.40)** | (6.41)*** | (6.30)*** | (3.01)*** | (3.11)*** | (3.11)*** |
| **ΔACTUAL** | $\beta_8$ | -0.022 | -0.023 | -0.017 | -0.041 | -0.055 | -0.058 |
| | | (3.72)** | (4.00)*** | (2.91)** | (1.21) | (1.53) | (1.63) |
| **VOLEARN** | $\beta_8$ | 0.007 | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 |
| | | (15.60)*** | (13.43)*** | (13.27)*** | (1.84)$ | (1.90)$ | (1.90)$ |
| **Fixed effects** | | Firm, industry (two-digit SICs) and time effects | | | | | |
| **Adjusted R-squared** | | 0.412 | 0.418 | 0.421 | 0.257 | 0.254 | 0.254 |

$ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%.
The non-loss (loss) sample contains firm-quarter observations in which a firm reports profits (losses) in quarter t.
The table reports the coefficient and t-stat in parentheses. Variables are defined in the glossary.

**Panel B. Results of testing for the equality of coefficients**

| | Non-loss firm sample (N=34,543) | | | Loss firm sample (N=5,909) | | |
|---|---|---|---|---|---|---|
| | PREDICT $_{CFO}$ | PREDICT $_{CFO\ ACC}$ | PREDICT $_{EARN}$ | PREDICT $_{CFO}$ | PREDICT $_{CFO\ ACC}$ | PREDICT $_{EARN}$ |
| **Coefficient** | 0.100 | 0.136 | 0.186 | 0.207 | 0.029 | 0.015 |
| **$\chi^2$ statistics and p-value to test coefficients on PREDICT $_{CFO}$ and PREDICT $_{CFO\ ACC}$** | 18.58<br>0.000 | | | 9.63<br>0.001 | | |
| **$\chi^2$ statistics and p-value to test coefficients on PREDICT $_{CFO\ ACC}$ and PREDICT $_{EARN}$** | | 40.94<br>0.000 | | | 0.42<br>0.515 | |
| **$\chi^2$ statistics and p-value to test coefficients on PREDICT $_{CFO}$ and PREDICT $_{EARN}$** | | | 40.89<br>0.000 | | | 12.53<br>0.000 |

Specifically, untabulated result shows that ACCCONTRIB, the contribution of accruals to predicting future earnings, is -0.005 (relative to assets at t) in the loss firm sample. On the other hand, in the non-loss firm sample, the contribution of accruals is 0.016 (relative to the asset at t). It is possible that analysts already know this empirically and do not use accrual information.

In the non-loss firm sample, analysts' forecasts are more associated with earnings-driven prediction. For the FORECAST $_{FIRST}$ regression in Table 4 Panel A, the coefficient of PREDICT $_{EARN}$ is 0.167 (p-value < 0.001), which is significantly larger than those of PREDICT $_{CFO}$ (coefficient = 0.109, p-value < 0.001) and PREDICT $_{CFO\ ACC}$ (coefficient = 0.134, p-value < 0.001). The coefficient on PREDICT $_{EARN}$, 0.167, is significantly different from the coefficients on PREDICT $_{CFO\ ACC}$, 0.134 and PREDICT $_{CFO}$, 0.109 (Table 4 Panel B), at the 0.1% level. These results suggest that for profitable firms, analysts tend to use current earnings to predict future earnings but may ignore lower persistence of accruals. Analysts could react rationally to the signal that earnings are smoothed. In income smoothing, both accruals and cash flows can be used to maintain smooth and steady growth in earnings. It is well known that ROA and changes in I/B/E/S reported earnings are negatively associated with analysts' forecast error (AFE). Hence, analysts find it easier to forecast for profitable firms or for firms with increases in profitability. Analysts expect that firms will manage earnings optimally to avoid losses. Thus, as long as a firm avoids losses, accruals are useful, but they are useful in the sense that they are a mechanism to smooth earnings; analysts may conclude that lower persistence of accruals does not matter in their forecasts. This argument is improved because in the FORECAST $_{LAST}$ regression, the association with PREDICT $_{EARN}$ became stronger (the coefficient = 0.186, p-value < 0.001). In income smoothing, the coefficient may increase when analysts understand such income smoothing gradually. Similar to the result in Table 4, the coefficient on PREDICT $_{EARN}$, 0.186, is significantly different from those on PREDICT $_{CFO\ ACC}$, 0.136, and PREDICT $_{CFO}$, 0.100, at the 0.1% level (Table 5 Panel B).

Finally, Table 6 reports the result of the estimation in (5). Using the entire sample, ACCCONTRIB is not associated with AFE $_{FIRST}$ (the coefficient = -0.058, p-value = 0.21), but it is significantly negatively associated with AFE $_{LAST}$ (the coefficient = -0.099, p-value =0.06). The nonsignificant association implies that analysts' forecast error does not involve a contribution of accruals. Since accruals, on average, improve the precision of future earnings prediction and analysts' first forecast, FORECAST $_{FIRST}$, relates to cash-driven prediction, I interpret this result as indicating that analysts fail to recognize the contribution of accruals at first. On the other hand, FORECAST $_{LAST}$ is more equally associated with earnings and accruals-driven prediction in Table 3, which implies that analysts use accrual information more. Given the negative association between AFE $_{LAST}$ and ACCCONTRIB (the coefficient = -0.099), analysts then realize the contribution of accrual, thus reducing their forecast error.

When the sample is divided into loss firms and non-loss firms and regression (5) is estimated again, the contribution of accruals, ACCCONTRIB, is significantly negatively

**Table 6. Regression of analysts' forecast errors for t+1 on the contribution of accruals (N obs.= 46,698)**

$$AFE_{i,t+1} = \alpha + \beta_1 ACCCONTRIB_{i,t+1} + \beta_2 STDEV_{i,t+1} + \beta_3 NUMEST_{i,t+1} + \beta_4 SIZE_{i,t} + \beta_5 ABSDISCACC_{i,t} + \beta_6 ABSRMPROXY_{i,t} + \beta_7 ROA_{i,t} + \beta_8 VOLEARN_{i,t} + \beta_8 \Delta ACTUAL_{i,t} + \beta_8 LOSS_{i,t} + \epsilon_{i,t}$$

| Dependent variable | | AFE FIRST | AFE LAST | | |
|---|---|---|---|---|---|
| Sample | | Entire (N=40,452) | Entire (N=40,452) | Loss firms (N=5,909) | Non-loss firms (N=34,543) |
| **CONSTANT** | α | 0.038 | 0.034 | 0.073 | 0.023 |
| | | (8.16)*** | (7.10)*** | (3.31)*** | (6.30)*** |
| **ACCCONTRIB** | β1 | -0.058 | -0.099 | -0.138 | -0.022 |
| | | (1.78)$ | (1.88)$ | (0.94) | (2.22)* |
| **STDEV FIRST** | β2 | 0.043 | 0.034 | | |
| | | (8.04)*** | (6.11)*** | | |
| **NUMEST FIRST** | β3 | 0.000 | 0.000 | | |
| | | (1.04) | (1.79)$ | | |
| **STDEV LAST** | β2 | | | 0.051 | 0.023 |
| | | | | (2.05)* | (11.66)*** |
| **NUMEST LAST** | β3 | | | 0.000 | 0.000 |
| | | | | (0.312) | (2.92)** |
| **SIZE** | β4 | -0.004 | -0.004 | -0.012 | -0.003 |
| | | (12.91)*** | (9.58)*** | (6.57)*** | (20.43)*** |

| | | | | | |
|---|---|---|---|---|---|
| **ABSDISCACC** | β5 | 0.013 | 0.001 | -0.013 | 0.003 |
| | | (1.45) | (0.05) | (0.20) | (1.35) |
| **ABSRMPROXY** | β6 | 0.022 | 0.033 | 0.036 | 0.004 |
| | | (2.625)** | (1.87)$ | (0.67) | (2.06)* |
| **ROA** | β7 | -0.060 | -0.077 | -0.193 | 0.031 |
| | | (4.198)*** | (3.35)*** | (5.19)*** | (6.10)*** |
| **VOLEARN** | β8 | 0.034 | 0.034 | 0.068 | 0.013 |
| | | (4.537)*** | (4.53)*** | (1.21) | (3.54)*** |
| **ΔACTUAL** | β9 | -0.004 | -0.004 | -0.025 | 0.002 |
| | | (4.54)*** | (2.50)* | (3.20)*** | (5.93)*** |
| **Loss** | β10 | 0.001 | 0.000 | | |
| | | (2.67)** | (0.13) | | |
| **Adjusted R-squared** | | 0.214 | 0.117 | 0.038 | 0.298 |

$ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%.
The non-loss (loss) sample contains firm-quarter observations in which a firm reports profits (losses) in quarter t.
The table reports the coefficient and t-stat in parentheses. Variables are defined in the glossary.

associated with AFE $_{LAST}$ for non-loss firms (the coefficient = -0.022, p-value = 0.009).[14] For loss firms, the contribution of accruals is not significant (the coefficient = -0.138, p-value = 0.34). Accruals-driven prediction is not associated with analysts' forecasts (from FORECAST $_{FIRST}$ or FORECAST $_{LAST}$ regression for the loss firm sample in Tables 4 and 5). Therefore, the contribution of accruals is not incorporated into analysts' forecast error for loss firms.

## 6. Conclusion

This paper shows how analysts use information from financial reports. Specifically, I show that cash-driven prediction of future earnings is at least as strongly associated with analysts' forecasts as accruals-driven or earnings-driven predictions. This result is interesting since it shows how analysts find accruals to be informative predictors in their forecasts, and it seems that analysts discount the value of accruals. However, the subsequent results show that the documented stronger association between analysts' forecast and cash-driven prediction is pronounced for firms reporting losses. Additionally, while accruals can contribute to reducing errors in predicting future earnings, the contribution of accruals is negative for loss firms. This may lead analysts not to use accrual information in their forecasts. Overall, the financial reporting incentive for firms reporting losses is different to the extent that analysts do not consider accruals to be valuable information when firms report losses.

While this study documents the importance of the occurrence of losses to analysts, further research should be done to determine how analysts make forecasts for firms with losses. For

[14] The result of estimation of (5) using AFE $_{FIRST}$ as the dependent variable for the Loss firms and Non-Loss firms is omitted in Table (5) since accruals contribution (ACCCONTRIB) is not significant for both samples.

example, the adjusted R-squared value for estimating analysts' forecasts is significantly lower and constant ($\alpha$) is much more negative for loss firms than for non-loss firms. This result indicates that the explanatory power of the independent variables is significantly lower for firms reporting losses. It would be worthwhile to investigate what other variables explain analysts' forecasts for loss firms.

**Reference:**

Abarbanell, J. (1991). Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics* 14 (2): 147-165.

Ahmed, A. S., Nainar, S. M., & Zhou, J. (2005). Do Analysts' Earnings Forecasts Fully Reflect Information in Accruals? *Canadian Journal of Administrative Sciences*, 22(4), 329-342.

Bailey, W., Li, H., Mao, C., and Zhong, R. (2003). Regulation Fair Disclosure and earnings information: Market, analyst and corporate responses. *Journal of Finance*, 63(6), 2487−2514.

Barth, M., & Hutton, A. P. (2004). Analysts earnings forecast revisions and the pricing of accruals. *Review of Accounting Studies,* 9(1), 59-96

Bartov, E., & Cohen, D. A. (2009). The "Numbers Game" in the Pre- and Post-Sarbanes-Oxley Eras. *Journal of Accounting, Auditing & Finance,* 24(4), 505-534.

Basu, S., L. S., Hwang, & Jan, C. (2005) Auditor Conservatism and Analysts' Fourth Quarter Earnings Forecasts. *Journal of Accounting and Finance Research,*13(5) 211-235.

Beaver, W. H., McNichols, M. F., & Nelson, K. K. (2003). Management of the Loss Reserve Accrual and the Distribution of Earnings in the Property-casualty Insurance Industry. *Journal of Accounting and Economics,* 35(3), 347-376.

Bernstein, L. (1993). Financial Statement Analysis. 5th ed. Homewood, IL: Irwin.

Bradshaw, M.T., Richardson, S. A., & Sloan, R. G. (2002). Do analysts use information in accruals? *Journal of Accounting Research,* 39(1), 45-74.

Bradshaw, M.T. (2011) Analysts' Forecasts: What Do We Know after Decades of Work? Retrived from SSRN: https://ssrn.com/abstract=1880339

Brochet, F., Nam, S., & Ronen, J. (2012). The predictive value of accruals and consequences for market anomalies. *Journal of Accounting, Auditing & Finance,* 27(2), 151-176.

Brown, L. D., Hagerman, R., Griffin, P. A., & Zmijewski, M. (1987). An Evaluation of Alternative Proxies for the Market's Assessment of Unexpected Earnings. *Journal of Accounting and Economics,* 9(2), 159-193.

Brown, L., & Sivakumar, K. (2003). Comparing the value relevance of two operating income measures. *Review of Accounting Studies*, 8(4), 561−572.

Bugstahler, D., & Eames, M. (2003). Earnings management to avoid losses and earnings decrease: Are analysts fooled? *Contemporary Accounting Research*, 20(2), 253−294.

Chandra, U., Procassini, A., & Waymire, G. (1999). The use of trade association disclosures by investors and analysts: evidence from the semiconductor industry. *Contemporary Accounting Research*, 16(4), 643−670.

Ciccone, S. (2005). Trends in analyst earnings forecast properties. *International review of Financial Analysis,* 14(1), 1-22.

Cohen, D., Dey, A., & Lys, T. (2008). Real and accrual-based earnings management in the pre and post- Sarbanes-Oxley period. *The Accounting Review*, 83(3), 757–787.

Dechow, P. M., & Dichev, I. D. (2002), The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review,* 77(supplement): 35-59.

Dowen, R.J. (1996). Analyst reaction to negative earnings for large well-known firms. The *Journal of Portfolio Management,* 23(1), 49-55.

Easterwood, J., and Nutt, S. (1999). Inefficiency in analysts' earnings forecasts: systematic misreaction or systematic optimism? *Journal of Finance*, 54(5), 1777−1797.

Ertimur, Y. (2004). Accounting Numbers and Information Asymmetry: Evidence from Loss Firms. Retrieved from SSRN: https://ssrn.com/abstract=572284

Fairfield, P. M, Whisenant, J. S., & Yohn, T. L. (2003). The differential persistence of accruals and cash flows for future operating income versus future profitability. *The Review of Accounting Studies*, 8 (2-3), 221-243.

Francis, J., & Smith, M. (2004). A Re-examination of the Persistence of Accruals and Cash Flows. *Journal of Accounting Research*, 43(3), 413-451.

Gu, Z., and Chen, T. (2004). Analysts' treatment of nonrecurring items in street earnings. *Journal of Accounting and Economics*, 38, 129−170.

Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics*, 20(2), 125-153.

Jones, J. (1991). Earnings management during import relief investigations. *Journal of Accounting Research,* 29(2), 193-228.

Lewellen, J, & Restek, R. J. (2018). Why do accruals predict earnings? Retrieved from http://faculty.tuck.dartmouth.edu/images/uploads/faculty/jonathan-lewellen/Persistence_4-2014.pdf

Lim, T. (2001). Rationality and analysts' forecast bias. *Journal of Finance,* 56(1), 369-385.

Liu, X. (2005). Analysts' Response to Earnings Management. Available at SSRN: https://ssrn.com/abstract=622404

Lys, T., & Sohn, S. (1990). The association between revisions of financial analysts' earnings forecasts and security-price changes. *Journal of Accounting and Economics*,13(4): 341-363.

McNichols, M., & O'Brien, P. (1997). Self-selection and analyst coverage. *Journal of Accounting Research*, 35, 167−199.

Mest, D., & Plummer, E. (1999). Transitory and persistent earnings components as reflected in analysts' short-term and long-term earnings forecasts: evidence from a nonlinear model. *International Journal of Forecasting*, 15(3), 291−308.

Nam, S. (2019). The role of accruals in the prediction of future earnings. Retrieved from https://efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/2019-Azores/papers/EFMA2019_0340_fullpaper.pdf

Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24(1), 34-75.

Richardson, S., Teoh, S., & Wysocki, P. (2004). The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research*, 21(4), 885−924.

Sinha, P., Brown, L., & Das, S. (1997). A re-examination of financial analysts' differential earnings forecast accuracy. *Contemporary Accounting Research*, 14(1), 1−42.

Sloan, R., (1996). Do stock prices fully reflect information in cash flows and accruals about future earnings? *The Accounting Review,* 71(3), 289-315.

Teoh, S., & Wong, T. (2002). Why new issues and high-accrual firms underperform: The role of analysts' credulity. *The Review of Financial Studies*, 15(3), 869−900.

Xie, H. (2001). The Mispricing of Abnormal Accruals. *The Accounting Review*, 76(3), 357- 373.

Zhang, F. (2006) Information Uncertainty and Analyst Forecast Behavior. *Contemporary Accounting Research*, 23(2), 565-590.

Zhang, X. F., (2007). Accruals, investment, and the accrual anomaly. *The Accounting Review*, 82 (5), 1333-1363.