The Role of Accruals in the Prediction of Future Earnings

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Although past accruals can explain current earnings, whether current accruals can predict future earnings has not been examined. I introduce three regression-based prediction models to predict future earnings: using only cash flows only, both cash flows and accruals, and earnings, to determine whether current accruals contribute to the prediction of future earnings. I find a cash flows and accruals model is more precise than a cash flows-only model, but the earnings model is the most precise. This result suggests that current earnings are a more accurate predictor of future earnings, and that accruals' persistence is less important in prediction of future earnings. I also document that predictions based on these models are more precise than time series-based predictions, but not as precise as analysts' forecasts. Additionally, I investigate how current earnings management negatively affects prediction of future earnings and hypothesize that current accrual management and real earnings management are positively associated with the prediction errors of the three models. The result shows that only the measure of real earnings management is positively associated with prediction error.

Keywords: Earnings prediction, Cash flows, Accruals, Accruals management, Real earnings management

INTRODUCTION

Although the in-sample explanatory power of past accruals in current earnings is well documented (Sloan 1996; Collins and Hribar 2000), the predictive power of current accruals in predicting future earnings in out-of-sample settings is not. In this research, I examine whether current accruals contribute to the prediction of future earnings. To be more specific, I investigate whether current cash flows and current accruals can be more effective in predicting future earnings than current earnings (sum of cash flows and accruals) alone or cash flows alone.

In prior research, earnings have been predicted using random walk, seasonal random walk, Foster's (1977) ARIMA model, and Brown and Rozeff's (1979) ARIMA model. While these models have been successful in predicting future earnings, they do not predict future earnings using the components of earnings, cash flows, and accruals as predictors. Therefore, I construct three regression-based predictions of future earnings. The regression-based models use, as predictor(s): 1. Only current cash flows (CFO-only model, hereafter), 2. current cash flows and accruals (CFO & ACC model, hereafter), and 3. current earnings (Earnings model, hereafter). The comparison of prediction errors allows me to determine which prediction is more accurate and to determine whether accruals are an effective independent predictor.

Prior research (e.g. Sloan 1996) suggests that future earnings prediction based on current cash flows and accruals is most accurate. Studies have shown that current earnings are explained better by including past cash flows and accruals separately, than including past earnings alone. Past cash flows and accruals have different persistence; specifically, accruals are less persistent. Francis and Smith (2005) argue that the accruals used in research have implications in both current and non-current transactions and that the portion from non-current periods leads to lower persistence. In other words, current accruals, defined as earnings less cash flows, should have different (lower) persistence compared to current cash flows. This leads to the conjecture that earnings alone are not a better predictor than cash flows and accruals combined. Barth et al. (2001) argue that disaggregated accrual components can have a different impact on future cash flows and that earnings can mask the impact. Thus, the prior literature suggests that predictions based on cash flows and accruals separately (or cash flows and the components of accruals, Components model, hereafter) would also be more accurate predictors of future earnings in an out-of-sample setting.

In contrast, in an out-of-sample setting, if a firm engages in earnings smoothing, regardless of earnings components, such as cash flows, accruals or components of accruals, this would produce a stable earnings trend. Therefore, prediction based on earnings alone can be a more accurate predictor in this context. Prediction based on cash flows alone ignores accruals and their persistence completely. Therefore, its accuracy should be lower, in theory. However, if accruals are only noise in the earnings, or are managed opportunistically, then cash flows-based prediction can be more accurate. If earnings management through accrual management is widespread, then accruals, on average, will be ineffective for forecasting.

Next, I examine the association of earnings management in the current period and errors in predicting future earnings based on these models. The accounting literature, including work from Cohen et al. (2008) and Jones (1991), provides two earnings management mechanisms: accruals management and real earnings management. If current earnings are managed opportunistically by managing accruals or cash flows, then the future earnings predictions of these models would suffer higher prediction errors. For example, under opportunistic accruals management in the current period, accruals tend to reverse and can be less effective in forecasting future earnings. This will be revealed in the association of accruals management proxy in the current period and prediction error. A positively significant association between current accruals management measures and prediction error provides direct evidence implying that accruals management interferes in accurate prediction of future earnings based on financial statements.

Real earnings management can also harm predictions of future earnings. Real earnings management, which can be achieved by changing a firm's operations to obtain favorable financial reporting, affects cash flows. By adjusting the timing of investments, Research &Development expenditures, and Selling, General &Administration expenses in current period, a firm's cash flows may increase, thus increasing earnings. However, this will obscure the true relationship between current cash flows and future earnings, thereby increasing the prediction error of the forecast when using cash flows as a predictor. Using the well-established proxy for accruals management (discretionary accruals, Jones 1991) and real earnings management (RMproxy, Cohen et al. 2008), I test whether these proxies in the current period are positively associated with error in predicting future earnings.

The result shows that accruals have predictive power beyond cash flows in out-of-sample prediction. The CFO & ACC model's prediction is more accurate than that of the CFO-only model in predicting future earnings. The Earnings model, however, is more accurate than the CFO & ACC model. The Components model is the least accurate in predicting future earnings, though the in-sample R-squared of this model is highest. Thus, there is evidence that current accruals contribute to the prediction of future earnings beyond cash flows; however, current earnings are the most accurate predictor of future earnings.

I also document following characteristics that have not been previously described in the literature. First, the four regression-based predictions described above outperform the random walk and seasonal random walk method by an average of 30%. Most time series earnings forecasts in the literature tend to focus on a specific industry or group of firms (see Bradshaw et al. 2012 for a summary). Using a relatively larger sample that represents overall populations, the CFO-only, CFO & ACC, Earnings and Components models are shown to outperform time series earnings prediction. This shows that regression-based prediction can be more effective in predicting future earnings.

Second, I show that the driving force of these models' improvement over time series earnings prediction is the coefficients from firm-specific regressions. If the regression coefficients are from cross-sectional regressions, then the four regression-based predictions perform poorly. Third, even with the average 30% improvements over time series predictions offered by these regression models, analyst forecasts remain far more precise[1].

To determine whether prediction errors are associated with accruals management and real earnings management, I regress the prediction errors from the CFO-only, CFO & ACC, and Earnings models on a proxy for discretionary accruals and real earnings management. If current accruals management or real earnings management distorts the earnings, future earnings predictions based on the models can be less accurate; therefore, I predict that the coefficients of discretionary accruals and RMProxy are positive. The result shows that discretionary accruals are positively associated with the prediction error based on the CFO-only model.[2] For both the prediction errors of the CFO & ACC and the Earnings model, discretionary accruals are not significantly associated. This suggests that accruals distortion based on accruals management is not severe enough to harm the ability of financial reporting to predict future earnings.

In contrast, RMproxy is consistently positively associated with the prediction error of the CFO & ACC and Earnings models. This result is consistent with the conjecture that real earnings management negatively affects future earnings by artificially increasing current cash flows. Real earnings management can distort the true relationship between current earnings and past accounting information used in coefficient estimation, resulting in the use of unreliable current information in predicting future earnings.

This paper contributes to the accruals literature by showing that accruals can be useful in predicting future earnings. One of the objectives in financial reporting is to provide predictive value, and it appears that accruals information provides such predictive value. It is earnings, however, that are a more accurate predictor than the components of earnings, cash flows, and accruals are. In addition, the result in this paper shows that accruals management (discretionary accruals) is not a significant obstacle in predicting future earnings but, rather, that RMproxy is. I also show that the regression-based predictions used in this paper outperform time series methods such as random walk and seasonal random walk.

The remainder of the paper is organized as follows. Section 2 offers a review of the literature and introduces regression-based prediction models. Section 3 develops hypotheses. Section 4 describes the data and sample construction. Section 5 discusses the descriptive statistics and the univariate results of the prediction errors, including comparison with time series-based prediction and analyst forecasts. Section 6 presents the results of multivariate regression analysis of prediction error on discretionary accruals and a proxy for real earnings management. Section 7 concludes the paper.

LITERATURE REVIEW AND OVERVIEW OF REGRESSION-BASED PREDICTION MODELS

The relationship between current earnings and past cash flows and accruals has been well explored in the literature (Chan et al., 2004; Collins and Hribar, 2000; Sloan, 1996; Xie 2001). This line of research finds the explanatory power of accruals, albeit with lower regression coefficients on past accruals, and concludes that accruals are less persistent than cash flows. Given that prior research shows accruals' explanatory power, a natural question would be whether current accruals provide predictive power in predicting future earnings in the out-of-sample setting.[3] In the earnings forecast literature (e.g., Brown and Rozeff 1979; Foster 1997; Bradshaw et al. 2012), earnings are predicted in a time series setting. Since the only predictor in time series-based prediction is past earnings, the contribution of earnings components, cash flows and accruals, cannot be determined. Therefore, I seek to determine the value of accruals in the prediction of future earnings with regression-based predictions.

Current accruals can be helpful in predicting future earnings. Accruals are an adjustment for current earnings but also can affect future earnings through a change in future cash flows. Barth et al. (2001) show the (in-sample) predictive ability of past accruals and components of accruals in current cash flows, and that components of past accruals have different associations with current cash flows. Further, it is plausible to expect a positive relationship between current accruals and future accruals, due to business practice, contracts, and commitment.

To the extent that accruals are managed subjectively or opportunistically to meet current earnings targets, however, their predictive ability may decrease. For example, increased revenue or decreased expense at past period, t-1, obtained by managing timing causes an increase in earnings at t-1 by increasing accruals at t-1. Such an artificial increase in accruals at t-1 will be reversed in the current period t, and earnings at t will decrease. In estimating the regression of earnings at t on cash flows at t-1 and accruals at t-1, accruals can be more persistent than normal; in other words, the coefficient on accruals is more positive than it should be. Accruals at current period, t, however, will be lower; therefore, the prediction error may be higher when predicting earnings at future period, t+1.

To determine the extent to which accruals contribute to predictions of earning, I use parsimonious models to predict future earnings. The following two models are employed:

CFO & ACC model: $\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha + \beta_1 \frac{CFO_{t-1}}{Total\ assets_{t-1}} + \beta_2 \frac{ACC_{t-1}}{Total\ assets_{t-1}} + \varepsilon$ (1)

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

where ACC is accruals, which is Earnings – CFO (cash flows from operations).

To predict future earnings at t+1, models (1) and (2) would produce the following:

$$\text{PREDICT}_{\text{CFO ACC, t+1}} = \hat{\alpha} + \hat{\beta}_1 \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2 \frac{ACC_t}{Total\ assets_t},$$

where $\hat{\alpha}$, $\hat{\beta}_1$and $\hat{\beta}_2$ are estimated in (1)

$$\text{PREDICT}_{\text{CFO, t+1}} = \hat{\alpha}_1 + \hat{\beta}_{11} \frac{CFO_t}{Total\ assets_t},$$

where $\hat{\alpha}_1$ and $\hat{\beta}_{11}$ are estimated in (2)

Then, the out-of-sample prediction errors are calculated.

CFO & ACC model's prediction error: $ABSE_{CFO\ ACC} = \left|\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO\ ACC,t+1}\right|$

CFO-only model's prediction error: $ABSE_{CFO} = \left|\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO,t+1}\right|$

These models are parsimonious; their purpose is not to predict future earnings in the most precise possible way, but rather, to determine the extent to which accruals contribute to the prediction of earnings. Nonetheless, it is important to note differences from the prediction methods used in prior research.

Prior research suggests prediction of future earnings can be made using various time series methods, such as 1. random walk, E(Earnings $_t$) = Earnings $_{t-1}$ + δ; 2. seasonal random walk, E(Earnings $_t$) = Earnings $_{t-4}$ + δ; 3. Foster's (1977) ARIMA model, E(Earnings $_t$) = Earnings $_{t-4}$ + β (Earnings $_{t-1}$ - Earnings $_{t-5}$) +δ, where β is an autoregressive parameter; and 4. Brown and Rozeff's (1979) ARIMA model, E(Earnings $_t$) = Earnings $_{t-4}$ + β_1 (Earnings $_{t-1}$ - Earnings $_{t-5}$) - β_2 a_{t-4} +δ, where β_1 is the autoregressive parameter, β_1 is the seasonal moving-average parameter and a_{t-4} is the disturbance term at time *t-4*.

These models predict future earnings well. However, there are two issues: first, the predictors of these models are earnings, and second, they do not incorporate the lower persistence of accruals. The CFO &

ACC model (1) can overcome these issues by using cash flows and accruals as separate predictors and incorporating different coefficients (persistence) in each predictor.

The CFO-only model (2) is mis-specified. Accruals are not included as a predictor, and consequently, the lower persistence of accruals is also missing. In addition, it is likely that β11 in (2) is larger than β1 in (1) due to the omitted variable. The CFO & ACC model (1) can be reduced or expanded. The reduced form uses only earnings, the sum of cash flows and accruals, as a predictor. In this case, the coefficients on cash flows and accruals are equal, implying that the persistence of cash flows and accruals are the same. Past accruals' association with current earnings can be different from that as cash flows' association, as past literature (Sloan 1996) shows. Further, Barth et al. (2001) show that accruals alone mask the different contribution of the components of accruals in predicting cash flows; therefore, including the components of accruals also can be useful in forecasting future cash flows. Thus, I consider the following models for comparison:

Earnings model: $\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha_2 + \beta_{21} \frac{Earnings_{t-1}}{Total\ assets_{t-1}} + \partial$ (3)

Components model: $\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha_3 + \beta_{31} \frac{CFO_{t-1}}{Total\ assets_{t-1}} + \beta_{32} \frac{\Delta AR_{t-1}}{Total\ assets_{t-1}} + \beta_{33} \frac{\Delta AP_{t-1}}{Total\ assets_{t-1}} + \beta_{34} \frac{\Delta Inv_{t-1}}{Total\ assets_{t-1}} + \beta_{35} \frac{\mathrm{DEPAMOR}_{t-1}}{Total\ assets_{t-1}} + \beta_{36} \frac{\mathrm{Other}_{t-1}}{Total\ assets_{t-1}} + \mu$, (4)

where AR is accounts receivable, AP is accounts payable, Inv is inventory, DEPAMOR is depreciation and amortization, and $Other = \mathrm{ACC} - (\Delta AR_{t-1} + \Delta AP_{t-1} + \Delta Inv_{t-1} + \mathrm{DEPAMOR}_{t-1})$, which represent the rest of the accruals.

Following the estimation of the coefficients, the predictions are formed, and the out-of-sample prediction errors are calculated similarly to the *CFO & ACC* and *CFO-only* models.

PREDICT $_{\mathrm{EARN},\ t+1} = \hat{\alpha}_2 + \hat{\beta}_{21} \frac{Earning_t}{Total\ assets_t}$, where $\hat{\alpha}_2$ and $\hat{\beta}_{21}$ are estimated in (3)

PREDICT $_{\mathrm{COMPONENTS},\ t+1} = \hat{\alpha} + \hat{\beta}_{31} \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_{32} \frac{\Delta AR_t}{Total\ assets_t} + \hat{\beta}_{33} \frac{\Delta AP_t}{Total\ assets_t} + \hat{\beta}_{34} \frac{\Delta Inv_t}{Total\ assets_t} + \hat{\beta}_{35} \frac{\mathrm{DEPAMOR}_t}{Total\ assets_t} + \hat{\beta}_{36} \frac{\mathrm{Other}_t}{Total\ assets_t}$,

where $\hat{\alpha}$, $\hat{\beta}_{31}$, $\hat{\beta}_{32}$, $\hat{\beta}_{33}$, $\hat{\beta}_{34}$, $\hat{\beta}_{35}$ and $\hat{\beta}_{36}$ are estimated in (4).

The *Earnings* model's prediction error is $ABSE_{EARN} = \left|\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{EARN,t+1}\right|$ and the *Components* model's prediction error is $ABSE_{COMPONENTS} = \left|\frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{COMPONENTS,t+1}\right|$.

The Earnings model (3) assumes that the persistence of accruals and cash flows is equal; therefore, investors need only current earnings from financial reports in the prediction of future earnings. This already has been shown not to be the case in the regression setting in prior research (Chan et al. 2004; Collins and Hribar 2000; Sloan, 1996; Xie 2001). On the other hand, Francis and Smith (2005) re-examine accrual persistence and find that, based on firm-specific estimation, in 85% of firms, the persistence of accruals' persistence is similar to that of cash flows. If that is the case, then it is possible that Earnings model (3) may be more precise than CFO & ACC model (1).

In the Components model, the coefficients on the components of accruals are allowed to be different. The model would have higher explanatory power in the in-sample regression, as it incorporates the different persistence of the accruals' components (Barth et al 2001). Based on such empirical findings, the most accurate model for regression would be the Components model (4). My conjecture, based on in-sample results in prior research, is that the Components model (4) should provide the most accurate prediction, followed by the CFO & ACC model (1), the Earnings model (3), and, finally, the CFO-only model (2).

HYPOTHESIS

The prediction error is subject to the quality of accruals and cash flows. If the accruals are opportunistically managed to meet private gains, they can be less useful in the prediction of future earnings. If management tries to smooth income through accruals management, however, and opportunistic and excessive accruals management is not widespread, then discretionary accruals will not have a negative association with prediction error. To be more specific, several factors play roles in this research question: coefficients in estimating regression, current accruals at *t*, and future earnings at *t+1*. Let us suppose that current accruals at *t* are opportunistically managed higher and consequently current earnings at *t* are also higher than the range of income smoothing. This can produce lower coefficients, $\hat{\beta}_1$ and $\hat{\beta}_2$ in the *CFO & ACC* model's regression. Note that prediction of future earnings in the *CFO & ACC* model is PREDICT $_{\text{CFO ACC, t+1}}$, which is calculated by $\hat{\alpha} + \hat{\beta}_1 \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2 \frac{ACC_t}{Total\ assets_t}$. For the third term in the prediction, $\hat{\beta}_2 \frac{ACC_t}{Total\ assets_t}$, it is difficult to predict the impact. $\hat{\beta}_2$ is lower and ACC_t is higher. It is likely that the second term, $\hat{\beta}_1 \frac{CFO_t}{Total\ assets_t}$, is underestimated, possibly resulting in higher prediction error. Finally, future earnings at *t+1* play a role. If opportunistic accruals management at *t* reverses at t+1, earnings at *t+1* will be lower. Overall, it is difficult to predict the association of current accruals and error in predicting future earnings; it is an empirical question.

H1: *Current discretionary accruals have a negative association with prediction error in predicting future earnings*.

Real earnings management may also have a negative impact on prediction error, as it affects the cash flows component of earnings. Gunny (2005) identifies the typical earnings management activities: R&D spending, SG&A, the timing of disposal of assets, and reducing the price, such as offering products and services at a discount. All of these activities affect cash flows, instead of accruals. A similar argument to that made regarding accruals management can be made here. If real earnings management is an event at t to overstate current cash flows at t, then current earnings at t will be overstated and future cash flows at t+1 will be understated compared to real value. Then, future earnings at t+1 will be understated as well. Under such real earnings management, estimates of both the coefficient of past cash flows and past accruals will be lower. Overall, under real earnings management at t, where current cash flows at t is overstated, there will be lower future earnings at t+1, lower coefficients in estimating models (1)–(3), and higher current cash flows at t. It is, again, difficult to predict the direction of association between real earnings management and prediction errors in (1)–(3).

H2: *The current real earnings management proxy has a negative association with prediction error in predicting future earnings*.

I use RMProxy (defined in Section 3) as a proxy of real earnings management.

DATA AND SAMPLE

To form a prediction of future earnings based on the four models, I first estimate the regressions in models (1)–(4). Accruals policy is distinct for each firm; thus, it is desirable to estimate (1)–(4) in a firm-specific regression, instead of a cross-section regression. To achieve a firm-specific estimation, I use quarterly data instead of annual data. The typical study that estimates firm-specific regression uses 20–40 years of observations. (e.g., Francis and Smith 2005). An annual setting that requires a long time period would limit the sample significantly. Besides, accrual accounting is based on management's discretionary inputs and judgement. Over time, different managers employ different estimates and accounting methods; therefore, running a firm-specific regression using such a long period may not capture the true relationship between current earnings and past accounting data. A quarterly setting also facilitates the direct comparison of models (1)–(4) with time series-based prediction methods, such as random walk. Additionally, the quarterly setting is more practical for a short investment horizon, since the most imminent investment decision is based on next quarter's earnings. The sample requirement for the firm-specific regression in this study is eight years or 32 quarters.[4]

Quarterly data, however, can suffer from seasonality. The accounting literature typically deals with seasonality by regressing quarter t's dependent variables on t-4 independent variables. Instead, in this study, I use the X11 method to remove seasonality from the quarterly data.

The X11 method is based on U.S Bureau of the Census X-11 seasonal adjustment program, and it adjusts monthly or quarterly time series for seasonality, by taking out the seasonal component from the seasonal data.[5] For example, if the original series is Ot, t=1,…n, then X11 decomposes Ot into four components: Ot = St + Ct + Dt + It.

St represents the seasonal components; Ct is known as trend cycle components that can be explained by long-term trend, business cycle, and other long-term cyclical factors; Dt is the variation that can be attributable to calendar composition; and It is the irregular component, residual variation. The seasonally adjusted series would be Ct + It. X11 also predicts the seasonal components in t+1, St+1.

Thus, in the prediction of earnings at *t+1*, the estimation of models (1)–(4) is based on seasonally adjusted data. However, I predict actual earnings. To illustrate, in the *CFO & ACC* model, $\frac{Earnings_t}{Total\ assets_{t-1}} = \alpha + \beta_1 \frac{CFO_{t-1}}{Total\ assets_{t-1}} + \beta_2 \frac{ACC_{t-1}}{Total\ assets_{t-1}} + \varepsilon$, estimation uses the seasonally adjusted data of Earnings and CFO (where ACC, accruals = Earnings – CFO). In the prediction of earnings at *t+1*, using the seasonally adjusted CFO_t and ACC_t, seasonally adjusted earnings at *t+1*, $C_{t+1} + I_{t+1}$, are predicted. Then, prediction error is the difference between actual earnings at *t+1* and the sum of predicted seasonal component of earnings at *t+1* (S_{t+1}) to the prediction (predicted $C_{t+1} + I_{t+1}$). To the extent that earnings, CFO and accruals are unstable in the X11 procedure, or the predicted seasonal component of earnings at *t+1* is unstable, this process would suffer, leading to less precise prediction of earnings at *t+1*. To check the reliability of the X11 process and prediction methodology used in this research, I employ models based on regressing earnings at *t* and CFO, accruals or components of accruals at *t-4* (seasonal method). The results based on the two different methods, X11 and seasonal, are compared in Table 2b.

Discretionary accruals are measured by the modified Jones (1991) model, a well-known proxy.

$$\frac{ACC_t}{TA_{t-1}} = \alpha \frac{1}{TA_{t-1}} + \beta_1 \left(\frac{\Delta REV_t - \Delta REC_t}{TA_{t-1}}\right) + \beta_2 \frac{PPE_t}{TA_{t-1}} + \varepsilon_t$$

where ACC is accruals, measured by the difference between earnings before the discontinued operations and extraordinary items and CFO before discontinued operations and extraordinary items; TA is total assets; REV is sales; REC is accounts receivable; and PPE is gross property, plant, and equipment.

The fitted value of the modified Jones model is non-discretionary accruals, and the residual is discretionary accruals. I estimate the modified Jones model by firm-specific regression. Since the sample already requires 32 past observations for each firm in the firm-specific regression, the estimation of discretionary accruals does not reduce sample size. It is argued that estimating the modified Jones model by cross-sectional industry regression captures the industry effect (Defond and Jiambalvo 1994 and Kasznik 1999). However, the discretionary accruals are firm-specific, and capturing such an effect is more important in this study. Among the variables in the modified Jones model, the income statement variables (ACC and REV) are seasonally adjusted using X11, whereas balance sheet variables (REC, PPE and total assets) are not.[6]

The proxy for real earnings management follows Cohen et al. (2008), which focuses on three manipulation models: 1. Acceleration of timing of sale through increased price discount; 2. Firms reporting a lower cost of goods through increased production; and 3. Decreases in discretionary expense, such as advertising expense, R&D expenditure and SG&A expense. I calculate RMproxy as the sum of the residual from the three models. Specifically, the real earnings managements' three models are the following:

$$\frac{CFO_t}{TA_{t-1}} = \alpha\frac{1}{TA_{t-1}} + \beta_1\frac{REV_t}{TA_{t-1}} + \beta_2\frac{\Delta REV_t}{TA_{t-1}} + \varepsilon_t$$
$$\frac{Production\ cost_t}{TA_{t-1}} = \alpha\frac{1}{TA_{t-1}} + \beta_1\frac{REV_t}{TA_{t-1}} + \beta_2\frac{\Delta REV_t}{TA_{t-1}} + \beta_3\frac{\Delta REV_{t-1}}{TA_{t-1}} + \varepsilon_t$$
$$\frac{Discretionary\ expense_t}{TA_{t-1}} = \alpha\frac{1}{TA_{t-1}} + \beta_1\frac{REV_t}{TA_{t-1}} + \varepsilon_t$$

where CFO is cash flows from operations, TA is total assets, REV is sales, the production cost is the sum of the cost of goods sold and change in inventory, and discretionary expense is the sum of advertising expense, R&D expense and SG&A expense. The difference between actual and fitted values from these models proxies for real earning management, and RMproxy is the sum of abnormal CFO, abnormal production costs and abnormal discretionary expense. Again, the income statement variables (CFO, REV, production costs, discretionary expense) are seasonally adjusted using X11 procedure, whereas the balance sheet variable (TA) is not.

The sample is gathered from CompuStat Quarterly (1995–2017), requiring that the following are available: 1. Thirty-two past observations of earnings (data item NIQ, earnings – XIDOQ, Extraordinary items and discontinued operations in income statement), cash flows (data item OANCFY, operating activities – Net cash flows, less XIDOCY, Extraordinary items and discontinued operations in Statement of Cash Flows); 2. Earnings data for one quarter ahead; 3. Sufficient data to provide the dependent and independent variables for the modified Jones model and real earnings management models (data items are described above)[7]; 4. Control variables for regression to test H1 and H2, SIZE, LOSS, ROA, BTM, LEV, VOLEARN and VOLCFO (variables defined in Section 5). I also require market capitalization to be higher than \$100 million. The final sample has 72,038 firm-quarter observations for 2,896 firms. On average, in each quarter, 1,254 firms are included in the sample. The sample requirement of past 35 quarters (or approximately 9 years) of earnings and cash flows is not as restrictive as prior research; for example, Chan et al. (2004) use a Vector Autoregression (VAR) based approach to predict earnings and use annual data. Its sample requirement is 11 consecutive earnings and accruals data. To run their VAR system, they use ten time series annual observations. The dataset I use in the present work thus provides a relatively large amount of time series data to run the regressions in models (1)–(4).

DESCRIPTIVE STATISTICS AND THE UNIVARIATE RESULT

Table 1 describes the sample and univariate result of prediction errors of the four models for the sample period, 1995–2017. First, the firms in the sample have average total assets of \$6.7 billion and \$8.2 billion in market capitalization. Some 18.3% of firms had a loss in quarter t. On average, the return on assets (ROA) is 1.0%, and book-to-market is 0.474. Leverage (LEV), measured as total debt divided by total assets, is 22.3%.

TABLE 1
DESCRIPTIVE STATISTICS (N Obs. = 72,038)

Variables	Mean	Standard Deviation	1st Percentile	10th Percentile	Median	90th Percentile	99th Percentile
ABSE $_{CFO}$	1.75%	5.59%	0.01%	0.13%	0.78%	3.52%	15.55%
ABSE $_{CFO\ ACC}$	1.69%	6.19%	0.01%	0.09%	0.62%	3.36%	16.77%
ABSE $_{EARN}$	1.64%	5.94%	0.01%	0.09%	0.61%	3.28%	16.46%
ABSE $_{COMPONENTS}$	1.88%	6.51%	0.01%	0.10%	0.70%	3.96%	18.61%
R-Squared $_{CFO}$	8.69%	15.48%	-3.33%	-3.14%	2.37%	30.98%	65.54%
R-Squared $_{CFO\ ACC}$	27.44%	27.66%	-6.68%	-4.10%	21.27%	70.15%	90.43%
R-Squared $_{EARN}$	25.45%	27.38%	-3.33%	-2.96%	17.25%	68.85%	89.90%
R-Squared $_{COMPONENTS}$	28.53%	27.96%	-9.83%	-4.76%	23.46%	70.93%	90.57%
LOSS	0.183	0.387	0.000	0.000	0.000	1.000	1.000
MKTCAP	8,276.25	28,647.64	107.19	187.36	1,276.22	16,161.82	140,618.15
TA	6,763.61	23,267.09	42.40	164.10	1,186.97	13,573.00	104,922.00
ROA	0.010	0.072	-0.142	-0.013	0.014	0.038	0.083
BTM	0.474	0.465	-0.354	0.134	0.408	0.918	1.794
LEV	0.223	0.212	0.000	0.000	0.198	0.473	0.887
ABSDISCACC	0.017	0.018	0.000	0.002	0.011	0.038	0.086
ABSRM	0.026	0.030	0.000	0.003	0.017	0.058	0.142
VOLEARN	0.022	0.092	0.002	0.004	0.011	0.045	0.153
VOLCFO	0.034	0.096	0.006	0.011	0.023	0.059	0.164

Variables are defined in the glossary

Models (1)–(4) are estimated using seasonally adjusted earnings, cash flows and accruals. The R-squared value of the CFO-only model (1) is much smaller (8.7%) than the CFO & ACC model (2; 27.4%). The R-squared value of the Earnings model (3) is smaller (25.4%), and the Components model (4) has the highest R-squared (28.5%). Therefore, I confirm the results described in the prior literature: current earnings are explained by the accruals beyond the cash flows. The Earnings model has less explanatory power than the CFO & ACC model. Although the degree of freedom is smaller, Components model, which incorporates the different impact of accruals' components, explains current earnings better than the other three models, in terms of R-squared. The coefficients on the CFO & ACC model, which much prior research has estimated in cross-sectional regressions, show less-persistent accruals. On average, the coefficient on ACC is 0.413, compared to 0.543 for the coefficient on CFO; the coefficient on CFO was generally (67.2% of the time) larger (untabulated).

The out-of-sample prediction shows different results. ABSE is the absolute value of the difference between actual earnings and predicted earnings using models (1) – (4), scaled by the total assets at quarter t. I expect that the CFO-only model would perform worst. This is confirmed by the mean of ABSECFO (1.75%) or the median (0.78%). Compared to the CFO-only model, the mean and median of ABSE CFO ACC (1.69% and 0.62%, respectively) are smaller for the CFO & ACC model (2). However, the most precise result is offered by the Earnings model. ABSE EARN has a mean of 1.64% and a median of 0.61%.

While the current earnings are explained by past cash flow and accruals separately, the best predictor for future earnings is current earnings. The two means and medians of ABSE CFO ACC and ABSE EARN are significantly different from each other at the 0.1% level (based on pairwise t-test and

Wilcoxon signed rank test, respectively). This suggests that earnings are smoothed, rather than opportunistically managed. Quarter-to-quarter, management could be attempting to smooth earnings using either cash flows or accruals or both. Therefore, in one period, accruals may be used to meet a certain expectation of earnings, but in the next period, cash flows could be used. The Components model results in higher mean (1.88%) and median (0.70%) prediction error than the CFO & ACC and Earnings models. One possible explanation is that this is due to the volatility of the components being higher than its sum. In other words, the noise in the components in accruals are more significant than sum, accruals. While the past components can explain current earnings better, using the current components in prediction could result in more volatile prediction, if the components are more volatile.[8]

In Table 2a, I show the significance of coefficients in firm-specific regressions. The coefficients in models (1)–(4) are estimated in firm-specific regression. Cross-sectional regression is often used to estimate coefficients. For example, Jones's (1991) discretionary accruals and Sloan's (1996) estimation of regressing current earnings on past cash flows and accruals use cross-sectional regressions. If cross-sectional regression is run among firms in the same industry each quarter, then the implication is that coefficients are set equal across all firms in a given quarter and industry (industry in this case defined by 2-digit SIC code). To the extent that firm-specific characteristics are important, a prediction based on coefficients from cross-sectional regression would be less accurate, since the regression coefficients ignore the firm-specific persistence of cash flows and accruals or earnings. The results in Table 2a confirms this conjecture. The prediction errors (ABSEI) using the coefficients from industry-pooled quarterly regression are approximately ten times bigger than when coefficients from firm-specific regressions are used. For example, the mean of ABSEI CFO ACC, in which future earnings are predicted using the CFO & ACC model and the coefficients are from industry-pooled quarterly regression, is 17.58%, compared to ABSE CFO ACC, 1.69%. In ABSE CFO ACC, future earnings at t+1 are predicted using same CFO & ACC model and the coefficients are from firm-specific regression. Additionally, the pattern among the ABSEIs is different: The prediction error of the CFO-only model (ABSEI CFO), is smaller than that of the CFO & ACC model (ABSEI CFO ACC), whether it is a comparison of the mean (16.77% versus 17.58%) or median (5.86% versus 6.40%), and the prediction error of the Components model (ABSE Component) has the lowest prediction error (mean = 8.33%, median = 2.12%). Therefore, the firm-specific coefficient is important; not only can the coefficients of firm-specific regression significantly reduce prediction error, but the conclusion that can be drawn from the statistics may be influenced.

TABLE 2A
COMPARISON OF PREDICTION ERROR OF PREDICTION BASED ON COEFFICIENTS FROM FIRM-SPECIFIC AND INDUSTRY-POOLED REGRESSION (N obs. = 72,038)

Variable	Mean	Standard Deviation	1st Percentile	10th Percentile	Median	90th Percentile	99th Percentile
Panel A. Predictions that use coefficients from firm-specific regression							
ABSE $_{CFO}$	1.75%	5.59%	0.01%	0.13%	0.78%	3.52%	15.55%
ABSE $_{CFO\ ACC}$	1.69%	6.19%	0.01%	0.09%	0.62%	3.36%	16.77%
ABSE $_{EARN}$	1.64%	5.94%	0.01%	0.09%	0.61%	3.28%	16.46%
ABSE $_{COMPONENTS}$	1.72%	5.91%	0.01%	0.10%	0.64%	3.48%	16.82%
Panel B. Predictions that use coefficients from industry-pooled regression							
ABSEI $_{CFO}$	16.77%	44.21%	0.09%	0.89%	5.86%	43.43%	148.83%
ABSEI $_{CFO\ ACC}$	17.58%	51.07%	0.07%	0.72%	6.42%	43.60%	158.45%
ABSEI $_{EARN}$	13.86%	37.30%	0.05%	0.55%	5.50%	34.04%	113.12%
ABSEI $_{COMPONENTS}$	8.33%	48.84%	0.03%	0.32%	2.12%	12.92%	112.08%

Variables are defined in the glossary.

To test the usefulness of X11 procedure in this study, I also use the *seasonal method* to predict future earnings at *t+1* and compare it with the main result in Table 1. In Table 2b, models (1)–(4) use independent variables at *t-4* that have not been adjusted for seasonality (seasonal method regression). For example, the *CFO-only* model (2) is run as: $\frac{Earnings_t}{Total\ assets_{t-4}} = \alpha_1 + \beta_{21}\frac{CFO_{t-4}}{Total\ assets_{t-4}} + \theta$ and CFO, and earnings are not seasonally adjusted. Then , $ABSEQ_{CFO} = \left|\frac{Earnings_{t+1}}{Total\ assets_{t-3}} - \left(\hat{\alpha}_1 + \hat{\beta}_{21}\frac{CFO_{t-3}}{Total\ assets_{t-3}}\right)\right|$.[9] Therefore, instead of adjusting the variables in (2) for seasonality, data from the four quarters prior to t are used to control for seasonality. All other data requirements remain the same, and the same sample is used to preserve the comparison. The result in Table 2b largely shows that the prediction errors of models (1)–(4) increase. For example, the mean (median) of ABSEQ CFO ACC is 1.86% (0.72%), compared to ABSE CFO ACC 1.69% (0.62%) when the variables are adjusted for seasonality. The improvement from using seasonally adjusted earnings and CFO based on X11 is 10% (1.86% versus 1.69%). The difference in the means and the medians are significant at 0.1% (based on pairwise t-test and Wilcoxon signed rank test respectively). More importantly, this approach also shows that ABSEQ CFO (mean = 1.80%) is smaller than ABSEQ CFO ACC (1.85%) or ABSEQ EARN (1.82%), which implies the CFO-only model is more precise than the CFO & ACC or the Earnings model. Therefore, based on this approach, one could conclude that current cash flows alone better predict future earnings, when this is not the case. Overall, the X11 method works well in terms of yielding lower prediction error.

TABLE 2B
PREDICTION ERROR OF PREDICTION BASED ON COEFFICIENTS FROM SEASONAL METHOD REGRESSION (N obs. = 72,038)

Variable	Mean	Standard Deviation	1st Percentile	10th Percentile	Median	90th Percentile	99th Percentile
ABSEQ $_{CFO}$	1.80%	5.64%	0.01%	0.14%	0.84%	3.69%	15.09%
ABSEQ $_{CFO\ ACC}$	1.86%	9.85%	0.01%	0.11%	0.72%	3.71%	17.73%
ABSEQ $_{EARN}$	1.82%	8.21%	0.01%	0.10%	0.70%	3.55%	17.53%
ABSEQ $_{COMPONENTS}$	2.25%	15.88%	0.01%	0.13%	0.84%	4.42%	20.69%

Variables are defined in the glossary.

In Table 3, I compare accuracy of models (1)–(4) with that of time series prediction. Predictions and their errors in (1)–(4) are scaled by total assets, whereas time series prediction and its accuracy are based on earnings per share. Therefore, it is impossible to directly compare models (1)–(4) with time series-based prediction without converting the prediction errors to a per-share basis. To do this, I first multiply the predictions of (1)–(4) by total assets, and then divide that value by common shares used to calculate predicted basic earnings per share at t+1. Then, I define ABSEEPS as $\left|\frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{PREDICT \times Total\ assets_t}{SHARES_t}\right|$ For example, the *CFO & ACC* model's prediction of future earnings at *t+1* is $PREDICT_{CFO\ ACC} = \hat{\alpha} + \hat{\beta}_1 \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2 \frac{ACC_t}{Total\ assets_t}$ and ABSEEPS $_{CFO\ ACC}$ is calculated as $\left|\frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{PREDICT_{CFO\ ACC} \times Total\ assets_t}{SHARES_t}\right|$.[10]

TABLE 3
COMPARISON OF ACCURACY OF REGRESSION-BASED PREDICTION WITH TIME SERIES BASED PREDICTION AND ANALYSTS FORECAST (N obs. = 60,846)

Variable	Mean	Standard deviation	1st Percentile	10th Percentile	Median	90th Percentile	99th Percentile
ABSEEPS $_{CFO}$	0.37	0.87	0.00	0.03	0.17	0.77	3.40
ABSEEPS $_{CFO\ ACC}$	0.37	1.46	0.00	0.02	0.13	0.73	3.81
ABSEEPS $_{EARNINGS}$	0.36	1.33	0.00	0.02	0.13	0.71	3.60
ABSEEPS $_{COMPONENTS}$	0.43	1.51	0.00	0.02	0.15	0.86	4.49
ABSEEPS $_{RW}$	0.56	1.03	0.01	0.06	0.37	1.17	3.35
ABSEEPS $_{SEASONAL\ RW}$	0.54	1.08	0.01	0.06	0.35	1.13	3.23
AFE	0.09	0.22	0.00	0.00	0.04	0.19	0.73

Variables are defined in the glossary.

While it is established that analyst forecasts are superior to time series-based predictions (Bradshaw et al. 2012), it would be interesting to see how the accuracy of the predictions of models (1)–(4) compare with analysts' forecast accuracy. The comparison with analysts' forecast error requires analyst forecasts be available from I/B/E/S.[11] This restriction reduces the sample size to 60,846.

The result of the per-share basis prediction comparison is reported in Table 3. First, the regression-based prediction based on models (1)–(4) outperforms time series predictions. For example, on average, the Earnings model's prediction error is 36 cents, whereas the seasonal random walk's prediction error is 54 cents (33.9% improvement). Comparing the medians makes the improvement more evident. On median, the Earnings model's prediction is 13 cents, whereas the seasonal random walk's prediction error is 35 cents. All four regression-based predictions outperform random walk or seasonal random walk. On the other hand, analysts' forecast error is far smaller. Analysts' average (median) forecast error[12] is 9 cents (4 cents). Therefore, while the regression-based predictions of models (1)–(4) improve upon time series-based prediction, they are still less precise than analysts' forecasts. This is not a disappointing result; analysts have more resources, experience and timing advantages in forecasting earnings.[13] The only information that the regression-based predictions use is key variables in financial statement, such as earnings, cash flows and accruals.

MULTIVARIATE REGRESSION ANALYSIS

I turn here to the multivariate analysis, where the association between prediction errors and accruals management and real earnings management is examined. I run following OLS regression model:

$$ABSE_{it+1} = \alpha + \beta_1 SIZE_{it} + \beta_2 LOSS_{it} + \beta_3 ROA_{it} + \beta_4 BTM_{it} + \beta_5 LEV_{it} + \beta_6 ABSDISCACC_{it} + \beta_7 ABSRM_{it} + \beta_8 VOLEARN_{it} + \beta_9 VOLCFO_{it} + \nu_{it} \quad (5)$$

The dependent variables are the prediction errors from models (1)–(3), ABSE CFO, ABSE $_{\text{CFO ACC}}$ and ABSE $_{\text{EARN}}$.[14] Discretionary accruals captured in ABSDISCACC (absolute value of discretionary accruals, DiscACC) and ABSRM (absolute value of RMproxy) serve as proxies for the accruals management and real earnings management. Based on *H1* and *H2*, I predict that ABSDISCACC is positively associated with the two of the dependent variables, ABSE $_{\text{CFO ACC}}$ and ABSE $_{\text{EARN}}$, and ABSRM is positively associated with all dependent variables, ABSE CFO, ABSE $_{\text{CFO ACC}}$ and ABSE $_{\text{EARN}}$.

To control for the other variables that explain the predictability of future earnings, I use the firm's size, loss indicator, profitability, book-to-market value, leverage, volatility of earnings and volatility of cash flows, along with firm and time fixed effects. First, SIZE, firm size (measured as the log of market capitalization at quarter t+1) indicates how mature and successful firm is. It is likely that size proxies for a stable operating environment for a firm. Therefore, better accuracy of the prediction of future earnings is expected for larger firms. I expect SIZE to be negatively associated with prediction errors. LOSS (equals 1 when earnings at t are negative, otherwise 0) could make prediction difficult, directly or indirectly. Hayn (1995) implies that firms with losses are characterized by a higher degree of information asymmetry, and that this asymmetry can apply to firm itself. Also, in the prediction environment, the current negative earnings at t would imply that the regression for the prediction models (1)–(4) has a negative dependent variable; such a variable can cause the coefficients in (1)–(4) to be volatile, when loss can be temporary. Also, the predictor earnings at t are negative, especially in the Earnings model (3). If the future earnings at t+1 are positive, then the prediction error will increase. Therefore, I expect that LOSS is positively associated with the prediction error.

Accounting profitability is measured by ROA (defined as earnings at t, divided by the average of total assets at t-1 and t). It is difficult to predict the sign of association for ROA. One could argue that the information environment for a profitable firm is better and earnings are smoothed; therefore, prediction error is smaller for profitable firms. However, it is possible that a successful firm could engage in riskier projects or that its profitability could revert under high competition (Stigler 1963). Mean reversion means that the future earnings at t+1 will be reduced, and if the prediction is made based on past growth, it will be less accurate. Therefore, under mean reversion, profitability should have a negative association with prediction error. The prediction horizon is a quarter, and mean reversion may not occur in a short period.

BTM is book-to-market (book value, equity at t, divided by market capitalization at t) is a measure of growth. For firms in a stage of high growth, the regression coefficient in the model could be understated, thus causing higher prediction error. I expect book-to-market to be negatively associated with prediction errors. LEV is leverage (measured as total debt at t divided by total assets at t). High leverage could either imply fewer risky projects (Myers, 1977) or higher financial risk. It is difficult to forecast the direction of the association for this variable. VOLEARN is volatility of earnings (measured as the standard deviation of past 16 quarters' earnings at t divided by the average of beginning and ending total assets at t). Higher earnings volatility can reduce the predictive ability of earnings, CFO and accruals; thus, I expect VOLEARN to be positively associated with prediction errors. VOLCFO is the volatility of CFO (measured as the standard deviation of the past 16 quarters' cash flows from operations at t divided by the average of beginning and ending total assets at t). This considers the volatility of a predictor variable, cash flows. If the cash flows are volatile, then so are the predictions of models (1)–(3). While I expect VOLCFO to be positively associated with prediction errors, VOLEARN and VOLCFO are positively correlated. Therefore, VOLCFO may be spuriously associated due to correlations. Finally, for robust estimation, I include firm- and time-fixed effects.[15] The prediction errors can be affected by firm-specific factors that I do not control for, as well as macro events, for which time-fixed effects can control.

Table 4 shows the correlations of dependent variables (ABSECFO, ABSECFO ACC, and ABSEEARN) and independent variables. As expected, ABSDISCACC and ABSRM are positively correlated with the dependent variables (significant at the 0.1% level). ABSDISCACC (0.135, significant at 0.1%,) and ABSRM (0.212, significant at 0.1%) are positively correlated with ABSECFO ACC. These correlations support hypotheses 1 and 2: accruals management and real earnings management are associated with higher prediction errors. ABSDISCACC and ABSRM are not positively correlated, suggesting that management does not engage in both accruals management and real earnings management.

TABLE 4
CORRELATION TABLE (N obs = 72,038; PEARSON'S CORRELATIONS IN THE LOWER TRIANGLE AND SPEARMAN'S CORRELATIONS IN THE UPPER TRIANGLE)

	$ABSE_{CFO}$	$ABSE_{CFO\ ACC}$	$ABSE_{EARN}$	SIZE	TA	LOSS	ROA	BTM	LEV	ABSDICSACC	ABSRM	VOLEARN	VOLCFO	Lag($ABSE_{CFO}$)	Lag($ABSE_{CFO\ ACC}$)	Lag($ABSE_{EARN}$)
$ABSE_{CFO}$	1	0.767	0.687	-0.177	-0.194	0.206	-0.086	-0.026	-0.088	0.169	0.186	0.433	0.344	0.416	0.360	0.365
$ABSE_{CFO\ ACC}$	0.731	1	0.885	-0.169	-0.154	0.251	-0.144	0.008	-0.048	0.160	0.198	0.456	0.347	0.368	0.407	0.408
$ABSE_{EARN}$	0.720	0.964	1	-0.160	-0.149	0.247	-0.136	-0.005	-0.047	0.146	0.193	0.454	0.342	0.370	0.408	0.423
SIZE	-0.110	-0.099	-0.099	1	0.879	-0.222	0.266	-0.360	0.179	-0.217	-0.191	-0.191	-0.331	-0.181	-0.174	-0.166
TA	-0.048	-0.038	-0.037	0.641	1	-0.104	0.016	-0.049	0.403	-0.228	-0.195	-0.195	-0.319	-0.198	-0.160	-0.155
LOSS	0.157	0.182	0.183	-0.213	-0.063	1	-0.640	0.136	0.073	0.104	0.152	0.304	0.222	0.311	0.315	0.321
ROA	-0.159	-0.240	-0.240	0.232	0.044	-0.659	1	-0.395	-0.240	-0.033	-0.057	-0.140	-0.118	-0.095	-0.148	-0.139
BTM	-0.002	0.018	0.018	-0.316	-0.033	0.173	-0.246	1	-0.071	0.014	0.014	-0.016	0.041	-0.030	0.003	-0.009
LEV	-0.011	-0.001	0.001	0.117	0.087	0.099	-0.165	-0.130	1	-0.107	-0.094	-0.096	-0.109	-0.088	-0.048	-0.047
ABSDISCACC	0.146	0.135	0.126	-0.218	-0.129	0.125	-0.082	0.004	-0.089	1	0.366	0.182	0.354	0.183	0.177	0.173
ABSRM	0.166	0.212	0.209	-0.194	-0.108	0.198	-0.207	0.015	-0.068	0.439	1	0.248	0.366	0.257	0.244	0.243
VOLEARN	0.322	0.339	0.331	-0.182	-0.080	0.270	-0.249	-0.015	-0.031	0.204	0.304	1	0.642	0.488	0.509	0.509
VOLCFO	0.275	0.279	0.270	-0.255	-0.137	0.212	-0.175	0.001	-0.054	0.351	0.385	0.781	1	0.371	0.374	0.369
Lag($ABSE_{CFO}$)	0.292	0.381	0.379	-0.163	-0.075	0.339	-0.351	-0.007	-0.028	0.241	0.417	0.523	0.425	1	0.768	0.686
Lag($ABSE_{CFO\ ACC}$)	0.270	0.378	0.373	-0.148	-0.061	0.324	-0.355	0.016	-0.001	0.225	0.386	0.534	0.422	0.878	1	0.883
Lag($ABSE_{EARN}$)	0.262	0.370	0.375	-0.144	-0.057	0.332	-0.356	0.014	0.000	0.224	0.391	0.523	0.410	0.824	0.942	1

Variables are defined in the glossary.

Among the control variables, the three with the strongest correlation with the dependent variables are VOLEARN, VOLCFO, and ROA. For example, with ABSECFO ACC, the Pearson correlations are 0.339, 0.279 and -0.240, respectively, all significant at 0.1%. Past volatile earnings or cash flows indicates the prediction based on models (1)–(3) will have a higher prediction error. Since VOLEARN and VOLCFO are positively correlated (0.781, significant at 0.1%), it could be VOLEARN that drives the correlations. ROA is negatively correlated with ABSEs, which shows that the higher the profitability, the easier it is to predict earnings, supporting the income smoothing argument.

Table 5 reports the results of regression. First, the coefficient on ABSDISCACC is positive and significant in regression of ABSECFO, (0.092, significant at 0.1% level). However, it is insignificant for ABSECFO ACC and ABSEEARN regression. The positive coefficient on ABSDISCACC in the ABSECFO regression is expected. Since the prediction in (2), PREDICT CFO, does not include accruals, accruals would remain in the prediction error. Overall, the statistical association between accruals management and prediction errors is mixed and possibly weak.

TABLE 5
REGRESSION OF PREDICTION ERROR ON DISCRETIONARY ACCRUALS AND REAL EARNINGS MANAGEMENT PROXY (N obs. = 72,038)

$$ABSE_{it+1} = \alpha + \beta_1 SIZE_{it} + \beta_2 LOSS_{it} + \beta_3 ROA_{it} + \beta_4 BTM_{it} + \beta_5 LEV_{it} +$$

$$ABSE_{it+1} = \alpha + \beta_1 SIZE_{it} + \beta_2 LOSS_{it} + \beta_3 ROA_{it} + \beta_4 BTM_{it} + \beta_5 LEV_{it} +$$

Dependent Variable		$ABSE_{CFO}$	$ABSE_{CFO\ ACC}$	$ABSE_{EARN}$
		Coeff (T-stat)		
Constant	α	0.014	0.005	0.007
		(3.02)**	-0.80	-1.18
SIZE	β_1	-0.001	0.000	0.000
		(3.05)**	-0.22	-0.28
LOSS	β_2	0.003	0.002	0.003
		(5.09)**	(2.25)*	(2.43)*
ROA	β_3	0.025	-0.253	-0.255
		-1.550	(6.34)**	(6.97)**
BTM	β_4	0.005	0.004	0.004
		(3.53)**	(2.42)*	(2.25)*
LEV	β_5	0.018	0.001	0.004
		(2.02)*	-0.17	-0.59
ABSDISCACC	β_6	0.093	0.066	0.036
		(4.54)**	-1.57	-1.42
ABSRM	β_7	0.043	0.151	0.151
		(2.50)*	(7.41)**	(7.68)**
VOLEARN	β_8	0.054	0.272	0.246
		(2.61)**	(7.50)**	(7.03)**
VOLCFO	β_9	0.025	-0.004	0.005
		(1.75)$	-0.17	-0.24
Fixed effect		Firm and Time		
Adj. R^2		0.300	0.258	0.253

$ significant at 10%; * significant at 5%; ** significant at 1%
Variables are defined in the glossary.

One possible explanation for the weak association is that some amount of discretion in accruals adds to the predictability of earnings, whereas opportunistic and excessive discretionary accruals that can harm the predictability are not widespread. This would happen when earnings are smoothed, and discretionary accruals are the primary tool for such income smoothing. Alternatively, it could be correlated with other variables (such as VOLEARN and VOLCFO) that better explain the variability of ABSEs. If discretionary accruals add to the volatility of earnings or cash flows, volatility could be absorbing the impact of discretionary accruals in the regression. In all, it is shown that discretionary accruals are not large enough to disrupt the predictive ability of accounting information in financial statements.

ABSRM, which is a proxy for real earnings management, is consistently positively associated with ABSEs, regardless of model. The magnitude of the coefficient is also consistent in both the ABSE CFO ACC and ABSE EARN regressions. In the ABSE CFO ACC and ABSEEARN regressions, the coefficient on ABSRM is 0.089 and 0.084, respectively (both significant at 1%). Therefore, the results suggest that real earnings management negatively affects the predictability of earnings.

The important variable among the control variables in the both ABSE CFO ACC and ABSE EARN regressions is ROA. The profitability is negatively associated with ABSE CFO ACC and ABSE EARN. It implies that higher profitability is associated with a more precise prediction. The coefficient on ROA is -0.222 (significant at 1%) in the ABSE CFO ACC regression and -0.226 (significant at 1%) in the ABSE EARN regression. The coefficient on ROA represents the case where a firm increases its profitability without accruals management and real earnings management; the positive coefficient implies that profitability enhances predictability.

In addition, I explore persistence of the accuracy of prediction models. In other words, if a particular model offers better predictions at t, does this quality hold in the next period, t+1? This question offers different way to validate which of models (1)–(3) serves as a better predictor for future earnings at t+1. Results in Table 1 show that Earnings model produces the lowest prediction error. Also, the ABSE t+1 is positively correlated with its own lag, ABSE t in table 3. The correlation is highest in the Earnings models (0.375) and lowest in the CFO-only model (0.292). To test this in multivariate regression, I estimate the following OLS regression:

$$ABSE_{it+1} = \alpha + \beta_1 SIZE_{it} + \beta_2 LOSS_{it} + \beta_3 ROA_{it} + \beta_4 BTM_{it} + \beta_5 LEV_{it} + \beta_6 ABSDISCACC_{it} + \beta_7 ABSRM_{it} + \beta_8 VOLEARN_{it} + \beta_9 VOLCFO_{it} + \beta_9 ABSE_{it} + \nu_{it} \quad (6)$$

Table 6 reports the result; it appears to show associations similar to those documented in Table 5. The coefficient on ABSDISCACC is significantly positive (0.073, significant at 1%) in the ABSECFO regressions, but not in the others. Also, ABSPM is positively associated with ABSECFO ACC and ABSEEARN (0.089 and 0.084 respectively, both significant at 1%). For each regression, the ABSEt+1 is positively associated with its lag, ABSEt. However, the magnitude of the coefficient is different. In the ABSECFO regression, the coefficient on lag(ABSECFO) is 0.096 (significant at 1%), while in the ABSECFO ACC regression, the coefficient on lag(ABSECFO ACC) is 0.331 (significant at 1%). Finally, in ABSEEARN regression, the coefficient on lag(ABSEEARN) is 0.373 (significant at 1%). These coefficients are also significantly different from each other at 1% level (based on a Z-test).[16] Based on this result, the Earnings model is most persistent and the CFO-only model least persistent. If the Earnings model predicts the current earnings well, then it is most likely to have lower errors in predicting future earnings, ceteris paribus.

TABLE 6
REGRESSION OF PREDICTION ERROR ON DISCRETIONARY ACCRUALS, REAL EARNINGS MANAGEMENT PROXY AND PAST ERROR (N obs = 72,038)

$$ABSE_{it+1} = \alpha + \beta_1 SIZE_{it} + \beta_2 LOSS_{it} + \beta_3 ROA_{it} + \beta_4 BTM_{it} + \beta_5 LEV_{it} + \beta_6 ABSDISCACC_{it} + \beta_7 ABSRM_{it} + \beta_8 VOLEARN_{it} + \beta_9 VOLCFO_{it} + \beta_9 ABSE_{it} + \nu_{it} \quad (6)$$

Dependent Variable		$ABSE_{CFO}$	$ABSE_{CFO\ ACC}$	$ABSE_{EARN}$
		Coeff (T-stat)		
Constant	α	0.009	0.004	0.006
		(1.92)$	-0.780	-1.087
SIZE	β_1	-0.001	0.00	0.00
		(3.38)**	-0.056	-0.501
LOSS	β_2	0.003	0.004	0.004
		(5.25)**	(3.19)**	(3.58)**
ROA	β_3	0.036	-0.222	-0.226
		(2.22)*	(5.86)**	(6.61)**
BTM	β_4	0.005	0.004	0.004
		(4.02)**	(2.41)*	(2.23)*
LEV	β_5	0.013	-0.003	0.000
		(1.66)$	-0.550	-0.04
ABSDISCACC	β_6	0.073	0.040	0.010
		(4.59)**	-1.61	-0.46
ABSRM	β_7	0.025	0.089	0.084
		(1.81)$	(5.25)**	(5.01)**
VOLEARN	β_8	-0.002	0.108	0.086
		-0.070	(3.34)**	(2.72)**
VOLCFO	β_9	0.025	0.010	0.019
		-1.630	-0.460	-0.920
Lag($ABSE_{CFO}$)	β_{10}	0.096		
		(5.65)**		
Lag($ABSE_{CFO\ ACC}$)	β_{10}		0.331	
			(11.29)**	
Lag($ABSE_{EARN}$)	β_{10}			0.373
				(11.21)**
Fixed effect		Time and Firm		
Adj. R^2		0.300	0.253	0.258

$ significant at 10%; * significant at 5%; ** significant at 1%
Variables are defined in the glossary.

CONCLUSION

This research examines the role of current accruals in predicting future earnings and shows that accruals can be useful in reducing prediction error. However, the more accurate predictor in terms of lowest prediction error is earnings. This suggests that accruals' lower persistence observed in-sample does not affect future earnings predictions. The Earnings model is more consistent, providing similar results over time.

I examine whether the accruals management or real earnings management in the current period is associated with the predictability of future earnings and find that accrual management has a weak significant association, but real earnings management in the current period is strongly positively associated with prediction error. Accruals management may not lead to higher prediction error, but real earnings management may decrease the quality of financial reports in terms of predictability.

ACKNOWLEDGEMENT

I would like to thank the participants at the American Association of Behavioral and Social Sciences Conference and the European Financial Management Association Annual meeting for their helpful comments.

ENDNOTES

1. Often, the prior literature (see Bradshaw et al. 2012 for a summary) compares the time series predictions with analyst forecasts and concludes the latter are superior.
2. Given that the *CFO-only* model does not use accruals, it is plausible that the documented positive association picks up the missing accruals.
3. Another reason I focus on out-of-sample prediction is that the prediction of future earnings is useful to investors. When investors read financial reports, they may use the information they provide to form a prediction of future earnings. Although there are other sources of information, such as analyst forecasts and management guidance, investors may be interested in developing expectation of future earnings by using the information in financial reports or by confirming analyst or management forecasts
4. Bradshaw et al. (2009) provide a comprehensive literature review on time series models in prior research, and a requirement of data from 32 quarters is among the least strenuous
5. The most up-to-date version is X13. Repeating the analysis using X13 instead of X11 results in virtually the same quantitative result, which is available upon request
6. Balance sheet variables such as total assets or accounts receivable can also suffer from seasonality issues. I examined the seasonality of variables on balance sheets and found that they are rarely affected by seasonality. Specifically, I tested, for each firm-quarter, whether seasonal components in total assets, accounts receivable, accounts payable and inventory are different from zero. Among the sample (N observations = 72,038) the incidence of significant seasonal components in these balance sheet variables is less than 0.1%. In addition, I repeated the entire set of tests with seasonally adjusted balance sheet variables and obtained a quantitatively similar result
7. Since the modified Jones model requires sales at t-1, and one of the real earnings management models requires sales at t-2, the data requirement is 35 consecutive quarters of data
8. It is possible that there may be seasonality in components of accruals, that drives the higher prediction errors. In Table 1, I do not adjust seasonality for balance sheet variables such as accounts receivable, accounts payable, and inventory. Thus, the change in those variables could contain seasonality. However, even with the potential seasonality in those variables, the R-squared of the components is significantly higher. Additionally, I ran the *Components* model (4) with the seasonally adjusted components and computed the $ABSE_{COMPONENTS}$. The result (untabulated) was qualitatively similar.
9. For other models' definition of ABSEQ, see glossary.
10. For other models' definition of ABSEEPS, see glossary.
11. Random walk's accuracy is defined as $\left|\frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{Earnings_t}{SHARES_t}\right|$, where earnings are defined as data item NIQ (earnings) – XIDOQ (extraordinary items and discontinued operations) and SHARE is common shares used to calculate basic earnings per share (CSHPRQ). Seasonal random walk's accuracy is defined as $\left|\frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{Earnings_{t-3}}{SHARES_{t-3}}\right|$,
12. Analysts' forecast error (AFE) 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, $|\text{Actual EPS}_{t+1} - \text{FORECAST}_{\text{FIRST}, t+1}|$,

13. In addition, analysts' forecasts can be a non-GAAP measure, which can exclude various accruals components, or may be guided by management forecasts.
14. I dropped ABSE $_{\text{COMPONENTS}}$ from the analysis because it is larger than other three, ABSE $_{\text{CFO}}$, ABSE $_{\text{CFO \& ACC}}$ and ABSE $_{\text{EARN}}$, therefore statistical inference that we can make can be spurious, when it is not.
15. Result without the fixed effects show much stronger results than those reported in Table 5. I estimated Equation (5) with industry fixed effect included as well and obtained a qualitatively similar result.
16. Z-test is based on Clogg et al. (1995). $Z = \frac{\beta_1 - \beta_2}{\sqrt{(SE_{\beta_1})^2 + (SE_{\beta_2})^2}}$

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APPENDIX

VARIABLE DEFINITION

$ABSE_{CFO}$	The absolute value of prediction error of the *CFO-only* model, $\left\vert \frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO} \right\vert$, where $PREDICT_{CFO} = \hat{\alpha}_1 + \hat{\beta}_{11} \frac{CFO_t}{Total\ assets_t}$. $\hat{\alpha}_1$ 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 32 past observations. Earnings are defined as data item NIQ (earnings) less XIDOQ (extraordinary items and discontinued operations, income statement), and CFO is data item OANCFY (operating activities – net cash flows) less XIDOCY (extraordinary items and discontinued operations, statement of cash flows) in CompuStat Quarterly. Earnings and CFO in the regression are adjusted for seasonality using the X11 procedure.
$ABSE_{CFO\ ACC}$	The absolute value of prediction error of the *CFO & ACC* model, $\left\vert \frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{CFO\ ACC} \right\vert$, where $PREDICT_{CFO\ ACC} = \hat{\alpha} + \hat{\beta}_1 \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2 \frac{ACC_t}{Total\ assets_t}$. $\hat{\alpha}$, $\hat{\beta}_1$ 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 32 past observations. Earnings and CFO are defined in $ABSE_{CFO}$. ACC is the difference between EARN and CFO. Earnings and CFO in the regression are adjusted for seasonality using the X11 procedure.
$ABSE_{EARN}$	The absolute value of prediction error of the *Earnings* model, $\left\vert \frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{EARN} \right\vert$, where $PREDICT_{EARN} = \hat{\alpha}_2 + \hat{\beta}_{21} \frac{Earning_t}{Total\ assets_t}$. $\hat{\alpha}_2$ 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 32 past observations. Variables in the regression are treated for seasonality using the X11 procedure. Earnings are defined in $ABSE_{CFO}$. Earnings in the regression are adjusted for seasonality using the X11 procedure.
$ABSE_{COMPONENTS}$	The absolute value of prediction error of the *Components* model, $\left\vert \frac{Earnings_{t+1}}{Total\ assets_t} - PREDICT_{COMPONENTS} \right\vert$, where $PREDICT_{COMPONENTS} = \hat{\alpha}_3 + \hat{\beta}_{31} \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_{32} \frac{\Delta AR_t}{Total\ assets_t} + \hat{\beta}_{33} \frac{\Delta AP_t}{Total\ assets_t} + \hat{\beta}_{34} \frac{\Delta Inv_t}{Total\ assets_t} + \hat{\beta}_{35} \frac{\mathrm{DEPAMOR}_t}{Total\ assets_t} + \hat{\beta}_{36} \frac{\mathrm{Other}_t}{Total\ assets_t}$. $\hat{\alpha}_3, \hat{\beta}_{31}, \hat{\beta}_{32}, \hat{\beta}_{33}, \hat{\beta}_{34}, \hat{\beta}_{35}$ and, $\hat{\beta}_{36}$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on $\frac{CFO_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta AR_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta AP_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta Inv_{t-1}}{Total\ assets_{t-1}}, \frac{\mathrm{DEPAMOR}_{t-1}}{Total\ assets_{t-1}}, \frac{\mathrm{Other}_{t-1}}{Total\ assets_{t-1}}$, using 32 past observations. Earnings and CFO are defined in $ABSE_{CFO}$. AR is accounts receivable (data item RECTQ), AP is accounts payable (data item APQ), Inv is inventory (data item INVTQ), DEPAMOR is depreciation and amortization (data item DPCY), and $Other = \mathrm{ACC} -$

	$(\Delta AR_{t-1} + \Delta AP_{t-1} + \Delta Inv_{t-1} + \text{DEPAMOR}_{t-1})$. Earnings and CFO in the regression are adjusted for seasonality using the X11 procedure.
R-Squared $_{\text{CFO}}$	Adjusted R-squared of the firm-specific regression used in calculation of ABSE $_{\text{CFO}}$.
R-Squared $_{\text{CFO ACC}}$	Adjusted R-squared of the firm-specific regression used in calculation of ABSE $_{\text{CFO ACC}}$.
R-Squared $_{\text{EARN}}$	Adjusted R-squared of the firm-specific regression used in calculation of ABSE $_{\text{EARN}}$.
R-Squared $_{\text{COMPONENTS}}$	Adjusted R-squared of the firm-specific regression used in calculation of ABSE $_{\text{COMPONENTS}}$.
ABSEI $_{\text{CFO}}$	The absolute value of prediction error of the *CFO-only* model using the coefficients from industry-pooled regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_t} - \left(\hat{\alpha}_1 + \hat{\beta}_{11}\frac{CFO_t}{Total\ assets_t}\right)\right\rvert$, where $\hat{\alpha}_1$ and $\hat{\beta}_{11}$are estimated in *a quarterly industry-pooled* (SIC 2-digit) regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on constant and $\frac{CFO_{t-1}}{Total\ assets_{t-1}}$, each quarter. Earnings are defined as data item NIQ (earnings) less XIDOQ (extraordinary items and discontinued operations, income statement), and CFO is data item OANCFY (operating activities – net cash flows) less XIDOCY (extraordinary items and discontinued operations, statement of cash flows) in CompuStat Quarterly. Earnings and CFO in the regression are treated for seasonality using the X11 procedure.
ABSEI $_{\text{CFO ACC}}$	The absolute value of prediction error of the *CFO & ACC* model using the coefficients from industry-pooled regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_t} - \left(\hat{\alpha} + \hat{\beta}_1\frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2\frac{ACC_t}{Total\ assets_t}\right)\right\rvert$, where $\hat{\alpha}$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are estimated in *a quarterly industry-pooled* (SIC 2-digit) regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on constant, $\frac{CFO_{t-1}}{Total\ assets_{t-1}}$ and $\frac{ACC_{t-1}}{Total\ assets_{t-1}}$, each quarter. Earnings and CFO are defined in $\text{ABSEI}_{\text{CFO}}$. ACC is defined as earnings less CFO. Earnings and CFO in the regression are treated for seasonality using the X11 procedure.
ABSEI $_{\text{EARN}}$	The absolute value of prediction error of the *Earnings* model using the coefficients from industry-pooled regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_t} - \left(\hat{\alpha}_2 + \hat{\beta}_{21}\frac{Earning_t}{Total\ assets_t}\right)\right\rvert$, where $\hat{\alpha}_2$ and $\hat{\beta}_{21}$are estimated in *a quarterly industry-pooled* (SIC 2-digit) regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on $\frac{Earnings_{t-1}}{Total\ assets_{t-1}}$. Variables in the regression are treated for seasonality using the X11 procedure. Earnings are defined in $\text{ABSEI}_{\text{CFO}}$ and Earnings in the regression are treated for seasonality using the X11 procedure.
ABSEI $_{\text{COMPONENTS}}$	The absolute value of prediction error of the *Components* model using the coefficients from industry-pooled regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_t} - \left(\hat{\alpha}_3 + \hat{\beta}_{31}\frac{CFO_t}{Total\ assets_t} + \hat{\beta}_{32}\frac{\Delta AR_t}{Total\ assets_t} + \hat{\beta}_{33}\frac{\Delta AP_t}{Total\ assets_t} + \hat{\beta}_{34}\frac{\Delta Inv_t}{Total\ assets_t} + \hat{\beta}_{35}\frac{\text{DEPAMOR}_t}{Total\ assets_t} + \hat{\beta}_{36}\frac{\text{Other}_t}{Total\ assets_t}\right)\right\rvert$, where $\hat{\alpha}_3, \hat{\beta}_{31}, \hat{\beta}_{32}, \hat{\beta}_{33}, \hat{\beta}_{34}, \hat{\beta}_{35}$ and, $\hat{\beta}_{36}$

	are estimated in *a quarterly industry-pooled* (SIC 2-digit) regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on $\frac{CFO_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta AR_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta AP_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta Inv_{t-1}}{Total\ assets_{t-1}}, \frac{\text{DEPAMOR}_{t-1}}{Total\ assets_{t-1}}, \frac{\text{Other}_{t-1}}{Total\ assets_{t-1}}$, using 32 past observations. Earnings and CFO are defined in $\text{ABSEI}_{\text{CFO}}$. AR is accounts receivable (data item RECTQ), AP is accounts payable (data item APQ), Inv is inventory (data item INVTQ), DEPAMOR (data item DPCY) is depreciation and amortization, and $Other = \text{ACC} - (\Delta AR_{t-1} + \Delta AP_{t-1} + \Delta Inv_{t-1} + \text{DEPAMOR}_{t-1})$. Earnings and CFO in the regression are treated for seasonality using the X11 procedure.
$\text{ABSEQ}_{\text{CFO}}$	The absolute value of prediction error of the *CFO-only* model using the coefficients from seasonal method regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_{t-3}} - \left(\hat{\alpha}_1 + \hat{\beta}_{11} \frac{CFO_{t-3}}{Total\ assets_{t-3}}\right)\right\rvert$, where $\hat{\alpha}_1$ and $\hat{\beta}_{11}$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-4}}$ on constant and $\frac{CFO_{t-4}}{Total\ assets_{t-4}}$ using 32 past observations. Earnings are defined as data item NIQ (earnings) less XIDOQ (extraordinary items and discontinued operations, income statement), and CFO is data item OANCFY (operating activities – net cash flows) less XIDOCY (extraordinary items and discontinued operations, statement of cash flows) in CompuStat Quarterly. None of the variables in the regression are adjusted for seasonality.
$\text{ABSEQ}_{\text{CFO ACC}}$	The absolute value of prediction error of *CFO & ACC* model using the coefficients from seasonal method regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_{t-3}} - \left(\hat{\alpha} + \hat{\beta}_1 \frac{CFO_{t-3}}{Total\ assets_{t-3}} + \hat{\beta}_2 \frac{ACC_{t-3}}{Total\ assets_{t-3}}\right)\right\rvert$, where $\hat{\alpha}$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-4}}$ on constant, $\frac{CFO_{t-4}}{Total\ assets_{t-4}}$ and $\frac{ACC_{t-4}}{Total\ assets_{t-4}}$ using 32 past observations. Earnings and CFO are defined in $\text{ABSEQ}_{\text{CFO}}$. ACC is defined as earnings less CFO. None of the variables in the regression are adjusted for seasonality.
$\text{ABSEQ}_{\text{EARN}}$	The absolute value of prediction error of *Earnings* model using the coefficients from seasonal method regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_{t-3}} - \left(\hat{\alpha}_2 + \hat{\beta}_{21} \frac{Earning_t}{Total\ assets_{t-3}}\right)\right\rvert$, where $\hat{\alpha}_2$ and $\hat{\beta}_{21}$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-4}}$ on $\frac{Earnings_{t-4}}{Total\ assets_{t-4}}$ using 32 past observations. No variables in the regression are adjusted for seasonality.
$\text{ABSEQ}_{\text{COMPONENTS}}$	The absolute value of prediction error of *Components* model using the coefficients from seasonal method regressions, $\left\lvert \frac{Earnings_{t+1}}{Total\ assets_{t-3}} - \left(\hat{\alpha}_3 + \hat{\beta}_{31} \frac{CFO_{t-3}}{Total\ assets_{t-3}} + \hat{\beta}_{32} \frac{\Delta AR_{t-3}}{Total\ assets_{t-3}} + \hat{\beta}_{33} \frac{\Delta AP_{t-3}}{Total\ assets_{t-3}} + \hat{\beta}_{34} \frac{\Delta Inv_{t-3}}{Total\ assets_{t-3}} + \hat{\beta}_{35} \frac{\text{DEPAMOR}_{t-3}}{Total\ assets_{t-3}} + \hat{\beta}_{36} \frac{\text{Other}_{t-3}}{Total\ assets_{t-3}}\right)\right\rvert$, where $\hat{\alpha}_3, \hat{\beta}_{31}, \hat{\beta}_{32}, \hat{\beta}_{33}, \hat{\beta}_{34}, \hat{\beta}_{35}$ and, $\hat{\beta}_{36}$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-4}}$ on

	$\frac{CFO_{t-4}}{Total\ assets_{t-4}}, \frac{\Delta AR_{t-4}}{Total\ assets_{t-4}}, \frac{\Delta AP_{t-4}}{Total\ assets_{t-4}}, \frac{\Delta Inv_{t-4}}{Total\ assets_{t-4}}, \frac{\text{DEPAMOR}_{t-4}}{Total\ assets_{t-4}}, \frac{\text{Other}_{t-}}{Total\ asse}$, using 32 past observations. Earnings and CFO are defined in ABSEQ$_{\text{CFO}}$. AR is accounts receivable (data item RECTQ), AP is accounts payable (data item APQ), Inv is inventory (data item INVTQ), DEPAMOR (data item DPCY) is depreciation and amortization, and $Other = \text{ACC} - (\Delta AR_{t-1} + \Delta AP_{t-1} + \Delta Inv_{t-1} + \text{DEPAMOR}_{t-1})$. None of the variables in the regression are adjusted for seasonality.
ABSEEPS $_{\text{CFO}}$	The absolute value of per-share basis prediction error of the *CFO-only* model, $\left\lvert \frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{PREDICT_{CFO} \times Total\ assets_t}{SHARES_t} \right\rvert$, where $PREDICT_{CFO} = \hat{\alpha}_1 + \hat{\beta}_{11} \frac{CFO_t}{Total\ assets_t}$. $\hat{\alpha}_1$ and SHARE is common shares used to calculate basic earnings per share (CSHPRQ). $\hat{\alpha}_1$ 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 32 past observations. Earnings are defined as data item NIQ (earnings) less XIDOQ (extraordinary items and discontinued operations, income statement), and CFO is data item OANCFY (operating activities – net cash flows) less XIDOCY (extraordinary items and discontinued operations, statement of cash flows) in CompuStat Quarterly. Earnings and CFO in the regression are treated for seasonality using the X11 procedure.
ABSEEPS $_{\text{CFO ACC}}$	The absolute value of per-share basis prediction error of the *CFO & ACC* model, $\left\lvert \frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{PREDICT_{CFO\ ACC} \times Total\ assets_t}{SHARES_t} \right\rvert$, where $PREDICT_{CFO\ ACC} = \hat{\alpha} + \hat{\beta}_1 \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_2 \frac{ACC_t}{Total\ assets_t}$ and SHARE is common shares used to calculate basic earnings per share (CSHPRQ). $\hat{\alpha}$, $\hat{\beta}_1$ 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 32 past observations. Earnings and CFO are defined in ABSEEPS$_{\text{CFO}}$. ACC is defined as earnings less CFO. Earnings and CFO in the regression are treated for seasonality using the X11 procedure.
ABSEEPS $_{\text{EARN}}$	The absolute value of per-share basis prediction error of the *Earnings* model, $\left\lvert \frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{PREDICT_{EARN} \times Total\ assets_t}{SHARES_t} \right\rvert$, where $PREDICT_{EARN} = \hat{\alpha}_2 + \hat{\beta}_{21} \frac{Earning_t}{Total\ assets_t}$ and SHARE is common shares used to calculate basic earnings per share (CSHPRQ); $\hat{\alpha}_2$ 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 32 past observations. Variables in the regression are treated for seasonality using X11 procedure. Earnings are defined in ABSEEPS$_{\text{CFO}}$.
ABSEEPS $_{\text{COMPONENTS}}$	The absolute value of per-share basis prediction error of the *Components* model, $\left\lvert \frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{PREDICT_{COMPONENTS} \times Total\ assets_t}{SHARES_t} \right\rvert$, where $PREDICT_{COMPONENTS} = \hat{\alpha}_3 + \hat{\beta}_{31} \frac{CFO_t}{Total\ assets_t} + \hat{\beta}_{32} \frac{\Delta AR_t}{Total\ assets_t} + \hat{\beta}_{33} \frac{\Delta AP_t}{Total\ assets_t} + \hat{\beta}_{34} \frac{\Delta Inv_t}{Total\ assets_t} + \hat{\beta}_{35} \frac{\text{DEPAMOR}_t}{Total\ assets_t} + \hat{\beta}_{36} \frac{\text{Other}_t}{Total\ assets_t}$ and SHARE is common shares used to calculate basic earnings per share (CSHPRQ).

	$\hat{\alpha}_3, \hat{\beta}_{31}, \hat{\beta}_{32}, \hat{\beta}_{33}, \hat{\beta}_{34}, \hat{\beta}_{35}$ and, $\hat{\beta}_{36}$ are estimated in a firm-specific regression of $\frac{Earnings_t}{Total\ assets_{t-1}}$ on $\frac{CFO_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta AR_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta AP_{t-1}}{Total\ assets_{t-1}}, \frac{\Delta Inv_{t-1}}{Total\ assets_{t-1}}, \frac{\mathrm{DEPAMOR}_{t-1}}{Total\ assets_{t-1}}, \frac{\mathrm{Other}_{t-}}{Total\ asse}$, using 32 past observations. Earnings and CFO are defined in $\mathrm{ABSEEPS_{CFO}}$. AR is accounts receivable (data item RECTQ), AP is accounts payable (data item APQ), Inv is inventory (data item INVTQ), DEPAMOR (data item DPCY) is depreciation and amortization, and $Other = \mathrm{ACC} - (\Delta AR_{t-1} + \Delta AP_{t-1} + \Delta Inv_{t-1} + \mathrm{DEPAMOR}_{t-1})$. Earnings and CFO in the regression are treated for seasonality using the X11 procedure.
$\mathrm{ABSEEPS_{RW}}$	The absolute value of per-share basis prediction error of the Random Walk model, $\left\lvert\frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{Earnings_t}{SHARES_t}\right\rvert$, where earnings are defined as data item NIQ (earnings) – XIDOQ (extraordinary items and discontinued operations, income statement) and SHARE is common shares used to calculate basic earnings per share (CSHPRQ)
ABSEEPS SEASONAL RW	The absolute value of per-share prediction error of the Seasonal Random Walk model, $\left\lvert\frac{Earnings_{t+1}}{SHARES_{t+1}} - \frac{Earnings_{t-3}}{SHARES_{t-3}}\right\rvert$, where earnings are defined as data item NIQ (earnings) – XIDOQ (extraordinary items and discontinued operations) and SHARE is common shares used to calculate basic earnings per share (CSHPRQ)
AFE	Analysts' forecast error, 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*, $\lvert \text{Actual EPS}_{t+1} - \text{FORECAST}_{\text{FIRST}, t+1} \rvert$,
LOSS	An indicator variable that equals one if Earnings in quarter $t < 0$ and 0 otherwise
MKTCAP	Market capitalization, measured at the end of fiscal quarter *t* (quarterly close price, PRCCQ times the common share outstanding at the end of quarter *t*, CSHOQ)
TA	Total assets, measured at the end of fiscal quarter *t*
ROA	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.
BTM	Book-to-market ratio: book value (equity) divided by market capitalization at the end of the fiscal quarter *t*.
LEV	Total debt divided by total assets at the end of the fiscal quarter *t*.
ABSDISCACC	The absolute value of discretionary accruals at t, based on the modified Jones (1991) model
ABSRM	The absolute value of the RM proxy at fiscal end t, as suggested in Cohen et al. (2008)
VOLEARN	The standard deviation of Earnings divided by average of the total assets_{t-1} and total assets_t in the past 16 quarters. Earnings are adjusted for the seasonality using the X11 procedure.
VOLCFO	The standard deviation of CFO divided by the average of total assets_{t-1} and total assets_t in the past 16 quarters. CFO is adjusted for seasonality using the X11 procedure.