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The final, published version in the Journal of Applied Accounting Research, 21 (1), pp. 38-59, 2019 is available at:

https://dx.doi.org/10.1108/JAAR-07-2018-0103

Do analysts understand accruals' persistence? Evidence revisited

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September 2019

Abstract

We revisit the question of whether analysts anticipate accruals' predicted reversals (or persistence) of future earnings. Prior evidence shows that analysts are over optimistic with respect to working capital (WC) accruals which is interpreted as their inability to understand accruals' persistence. Using total accruals (TACC) that in addition to WC accruals cover non-current operating and financing accruals, we show that analysts' forecast errors are uncorrelated with accruals. We show that analysts' optimism with respect to accruals is due to the use of an incomplete accrual measure, which does not necessarily indicate analysts' lack of sophistication. Our results imply that traditional accrual definition should be revised in future studies. The main implication of our finding is that analysts seem to exhibit the necessary sophistication in understanding accruals persistence contrary to suggestions in prior research. Our findings are in line with the idea that any anomalous stock price behaviour related to accruals is not due to analysts' forecasts, i.e., analysts' earnings forecasts and recommendations should not be considered as the originating source of stock price underreaction or overreaction with respect to accruals.

Keywords: accrual persistence, analysts' forecast errors, efficiency

JEL Classification: M41, G10

1. Introduction

We revisit the question of whether sell side security analysts anticipate the persistence of accruals in future earnings[1]. Revisiting this question is important, because prior research finds that accrual components of earnings are less persistent than cash flows and that investors fail to anticipate this property of earnings which results in getting negative returns from buying stock with high accruals (Sloan, 1996). Prior evidence documents that analysts who provide information to investors fail to flag this accruals property (Bradshaw, et al., 2001) and that they are over optimistic about firms with high working capital (WC) accruals. This is generally interpreted as analysts' lack of sophistication in understanding accruals persistence.

A number of more recent studies (Fedyk et al., 2018; Barth et al., 2016) demonstrate that investors' understanding of accruals has improved since Sloan (1996) and that investors no longer appear to naively fixate on earnings. Findings by Barth et al. (2016) reveal that investors can extract accrual information about future firm performance and that each type of accruals has different role in predicting future cash flows and earnings. Fedyk et al., (2018) suggest that investors gradually learn about accruals properties such as persistence and then correct their mispricing. Given the importance of analysts in capital markets as financial intermediaries, and increasing use of analysts' reports by markets, we posit that investors' learning about accrual types' properties and the correction of accrual mispricing is likely to be channelled through a greater use of analysts' forecasts.. Hence, it is important to verify if inferences regarding analysts' forecasts errors with respect to accruals from Bradshaw et al. (2001) correctly reflects the analysts' abilities in this context. We directly investigate whether analysts understand accruals types and characteristics and how this understanding informs their forecasts of earnings. We ask whether analysts' forecasts errors may be explained by analysts' strategic behaviour or whether they may be due to accrual measures which have not been explicitly considered in Bradshaw et al. (2001)'s theory and empirical testing. We build on prior research showing that analysts' forecasts are superior compared to forecasts generated by various earnings expectation models and that analysts are strategic in their forecasts (Fried and Givoly, 1982; Francis and Philbrick, 1993),

[1] Persistence refers to continuity from one period to another.

which is indicative of their high sophistication. Also, a growing evidence in the literature shows that the traditional accrual definition used in the empirical models of analysts' forecast accuracy omits economically important accrual types that are highly relevant for explaining future earnings and returns (e.g., Richardson, Sloan, Soliman, and Tuna, 2005). We argue that analysts are likely to use this important accrual information and that empirical models measuring accruals by means of working capital alone may be incomplete and hence not entirely appropriate and up-to-date to assess the level of analysts' appreciation of accruals. In other words, we suggest that analysts' optimism with respect to accruals found in Bradshaw et al. (2001) may not be due to their lack of sophistication, but rather a result of an incomplete accrual information embedded in forecast accuracy tests. In particular, by omitting non-current operating and financial accruals, analysts' optimism may be a results of a mechanical relation inherent to the model specification in Bradshaw et al. (2001). Given that WC accruals are the least persistent accrual components which are associated with largest mispricing by investors (Richardson et al., 2005) it is perhaps not surprising that WC accruals are strongly associated with analysts' forecasts errors, too (Bradshaw et al. 2001). Our study revises the definition of accruals used in forecasting models by giving consideration to non-current operating and financial accruals, and revisits the issue. This is an important aspect to revisit because analysts' ability to unravel, understand and predict different properties of earnings components (e.g., persistence) is directly linked with the degree of their sophistication. If analysts make significant forecast errors in relation to the predicted persistence of accruals, their forecasts would be misleading with ultimate negative effects on market efficiency given the assumed reliance of investors on analysts, they would appear to lack sophistication which will have adverse effects on their reputation.

Our empirical tests show no correlation between analysts' forecast errors and revised total accruals (TACC). Findings are robust to different samples, periods, model specifications, decile ranked accruals, high accruals, absolute forecast errors, controlling for cash flows and high accounting conservatism. Our findings imply that if analysts are to achieve more accurate forecasts[2], they should be considering

[2] We assume analysts' ultimate objective is to achieve minimum forecast error unless they are not strategically biased. Accuracy is one of key indicators of their performance (analysts who excel in

all rather than *some* accrual components. We interpret this evidence as an indication of analysts' relative sophistication with respect to accruals. In such a context, our findings strongly indicate that if one is to test analysts' ability with respect to anticipating future earnings, all accrual components, i.e., the TACC as defined by Richardson et al. (2005) should be taken into account. We show that using only one component of accruals may lead to misleading inferences regarding analysts' ability to predict accruals. In contrasts to previous studies which use only WC accruals and find that analysts make significant errors in anticipating future earnings and accruals, we use TACC and find no evidence of analysts' forecast errors. Given that TACC is one of the main components of earnings in which WC accruals take a small portion, the correct understanding and anticipation of TACC will matter the most as far as the forecasts accuracy is concerned. Based on this notion, our findings point to the analysts' high information processing abilities which is contrary to prior studies' implications that analysts struggle to correctly anticipate accrual persistency. Moreover, our results imply that if analysts still exhibit errors in future earnings anticipations, this is then likely to be strategically motivated which calls for a future research focused on that particular area of analysts' behaviour rather than building on the arguments that investors and analysts naively fixate on earnings and do not fully appreciate the low persistence of accruals.

We also run forecast error (accuracy) regressions on individual accrual components by decomposing TACC into categories[3]. These tests reveal that analysts' optimism with respect to WC accruals documented by previous research is in fact a result of a mechanical relation given the model's specification, and that it does not indicate analysts' lack of sophistication. If analysts correctly anticipate the persistence of accruals, forecast errors will not be correlated with TACC - which is what we find in the initial tests. However, any individual accrual component deviating from TACC' persistence can correlate either optimistically or pessimistically with forecasts, depending on that particular component's degree of persistence. Our

recommending and finding winning stocks with more accurate estimates are branded as 'all-star' analysts).

[3] Barth et al. (2016) provide evidence that each type of accrual has a different coefficient in forecasting future cash flows, forecasting earnings and in valuation. Each coefficient combines an information weight reflecting the information that accrual type provides and that partitioning accruals increases their ability to forecast future cash flows and earnings and to explain firm value.

findings are in line with this conjunction: forecast errors exhibit optimism with respect to less persistent WC accruals (which have 67% of persistence compared to the 73% persistence of total accruals)[4], but pessimism with respect to highly persistent financial accruals (79% of persistence), while with respect to the non-current operating accruals with a mid-range levels of persistence (at 74% level and closest to the total accruals' persistence), no optimism or pessimism is observed.

An alternative interpretation is that the negative (positive) coefficient[5] on less (more) persistent accrual components in analyst forecast error regressions could be driven by analysts' inability to incorporate different degrees of persistence across various earnings components. Indeed, if our arguments did not hold, i.e., if analysts could not distinguish between different persistence degrees across accrual components, and, say, assigned a random multiple to current earnings to forecast future earnings, then forecast errors would be either negatively or positively correlated with TACC across years, i.e., there would be a significant correlation between forecast error and TACC given that a randomly assigned multiple would not correctly predict future TACC consistently over years. What we observe instead is a consistent zero correlation between forecast errors and TACC across all forecast windows - ranging from the first to the last monthly forecast in every year of observation for the period 1976-2013, which confirms our argument that analysts indeed distinguish between different persistence degrees across accrual components. Our results also hold after we split the sample into two periods, relative to the before and after the application of the Sarbanes and Oxley Act[6] (from 1976 to 2002, and from 2003 to 2013, respectively).

Our paper makes several contributions to the existing knowledge. First, our analysis contributes to the recent strand of literature indicating that market's understanding of accruals has improved (Fedyk et al. 2018; Barth et al., 2016) by investigating

[4] We also test the persistence degree of individual components as in Richardson et al. (2005), reported in the Appendix. These tests show that different components exhibit different persistence degrees with WC accruals being less persistent than financing accruals (67% vs. 79%), and that TACC reflect an average of its components' persistence (73%).

[5] Negative (positive) coefficients in analysts' forecast errors models are indicative of analysts' optimism (pessimism).

[6] Cohen et al. (2008) and Chen and Huang (2013) show that after the Sarbanes and Oxley Act, accrual related earnings management activities has decreased, which could have contributed to analysts understanding of accruals after the Bradshaw et al., (2001) study.

whether and how analysts' understanding of accruals properties and persistence in particular, has improved. While earlier studies, such as Bradshaw et al. (2001) show that analysts are optimistically biased with respect to WC accruals concluding that analysts lack the necessary sophistication in anticipating accruals' persistence, we find that analysts' forecast errors are uncorrelated with TACC, which indicates that prior conclusion with respect to accruals appears to be naïve and somewhat incomplete. Our findings imply that analysts seem to possess the necessary sophistication to understand accrual types and their relative persistence. In addition, our results show that analysts understand well the effect of conservative accounting on accruals' persistence, which further points to their high sophistication.
Second, we show that these earlier studies (Bradshaw et al. 2001) employ an incomplete accrual variable, the WC accruals in testing analysts' forecast accuracy. In particular, by omitting non-current operating and financial accruals, analysts' optimism may be a results of a mechanical relation given the models' specification. With WC accruals being the least persistent accrual type associated with largest mispricing by investors (Richardson et al. 2005) it is not surprising that WC accruals are significantly associated with analysts' forecasts errors. Our study modifies the definition of accruals by including non-current operating and financial accruals and finds no correlation between forecast errors and TACC.

Finally, our findings do not support the argument that analysts' long observed optimism in earnings forecasts may stem from accruals' overestimation. Despite the fact that our sample shows optimistic earnings forecasts of analysts consistent with previous research, we find no correlation with such optimism and accruals. We recognize, however, that analysts' correct anticipation of accruals' persistence does not mean that their earnings forecasts are entirely free of bias. Analysts can make forecast errors for various reasons including strategic biases. For instance, our tests show pessimistic forecast errors with respect to cash flows, which is in line with similar findings in prior research (Drake and Myers, 2011). Hence, we suggest that future research should examine this correlation in greater depth as cash flows components have the highest level of persistence, and hence should be predicted most accurately. If analysts correctly anticipate accruals, which are less persistent than cash flows, but make significant errors in predicting cash flows, then this would suggest further investigation.

One of the major implications of this paper is that it does not warrant analysts' lack of sophistication argument with respect to accruals' persistence. Discriminating between lack of sophistication and high sophistication argument is important for both academics and practitioners as users of analysts' reports. If analysts fail to accurately incorporate accrual information, the forecasts are biased, suboptimal and inefficient. If on the other hand, forecasts are efficient they contribute to market efficiency. Our findings support the latter. Hence, we suggest that future research focuses more on analysts' incentives and model specification issues if forecasts are found to exhibit systematic biases as it is highly possible that systematic forecast errors may be consistent with analysts' economic incentives. We acknowledge that the role and the reputation of analysts as surrogates of market expectations has been questioned in light of the Bradshaw et al.'s (2001) findings while at the same time the use of analysts' reports by institutional investors and money managers in their decisions making process has been growing. Our findings help to resolve this tension by pointing to the analysts' high information processing skills which to a certain extent justifies investors' growing use of analyst reports.

Another implication is that analysts seem to utilise all relevant accrual information in their forecasts, hence traditional accrual definition should be revised in future studies.

The remainder of the paper is organised as follow. The next section provides additional background and develops hypotheses. Section 3 describes the data, Section 4 explains research design and presents the results and Section 5 Section 6 concludes.

2. Theoretical background and hypotheses

2.1. Background

Prior evidence shows that earnings persist and mean reverse (gradually decline in time), i.e., $E_{t+1}=\beta E_t+e_{t+1}$ where $0<\beta<1$, with accrual components in earnings mean reverse quicker than cash flows, $E_{t+1}=\beta(ACC_t+CF_t)+e_{t+1}$ where $0<\beta_{ACC}<\beta_{CF}<1$, but that investors do not seem to anticipate such property of earnings. Firms with high accruals are likely to experience lower earnings in future, and investors who buy firms with high accruals suffer from negative future returns (e.g., Sloan, 1996)[7]. This finding is important for analysts because they provide information to investors, and possibly affect their investment decisions.(Mendenhall, 1991). Therefore, a number of prior studies investigates how analysts incorporate accruals in their forecasts and find that they tend to be optimistic about WC accruals (e.g., Bradshaw et al. 2001; Thomas and Zhang, 2002; Collins et al. 2003; Hanlon, 2005; Mashruwala et al. 2006; Drake and Myers, 2011). This result is mainly interpreted as analysts' failure to anticipate the subsequent earnings declines associated with high accruals consistent with the evidence in Sloan (1996). However, this interpretation is not in line with the inferences by the strand of the literature which suggests analysts' superior ability over mechanical earnings generating models (see Brown and Rozeff, 1978; Fried and Givoly, 1982; Brown et al. 1987; Elgers and Murray, 1992) and analysts' strategic behaviour in forecasting in that analysts' optimism may be rational and originating in the loss functions underpinning their decisions (e.g., Gu and Wu, 2003; Basu and Markov, 2004)[8]. It is also important to note that prior studies on the relation between forecast accuracy and earnings components use WC in their forecast accuracy models assuming that accruals related to a number of special items (restructuring, impairments, equity method losses, etc.) are nonrecurring and investors are more likely to anticipate their nature themselves without relying on analysts information (e.g., Bradshaw et al. 2001). However, the evidence in Doyle et al. (2003) shows that such "special" accruals are far from nonrecurring, and firms with relatively large omissions of such items in their pro forma earnings experience lower returns. Richardson et al. (2005) further show that the traditional accrual definition based on WC excludes important accruals and results in noisy measures of accruals and cash flows which leads to significant mispricing[9]. In sum, these findings altogether offer a challenge to the

[7] Coined as 'Accrual Anomaly', the phenomenon is explained by Sloan (1996) as investors' fixation on reported earnings.

[8] Prior research finds that analysts issue optimistic forecasts to curry favour with managers in order to obtain better access to private information, to attract more investors and to boost investment banking fees (Francis and Philbrick 1993, Lin and McNichols, 1998; Richardson et al. 2004; Cowen et al. Groysberg, and Healy, 2006; Raedy et al. 2006). Analysts can also exhibit self-selection bias, i.e., they follow firms if they hold favourable views about them and censure negative views due to conflict of interest (see McNichols and O'Brien 1997; Michaely and Womack, 1999), which may lead to optimism on average.

[9] Richardson et al. (2005) show that security mispricing is driven by measurement errors, and noncurrent operating and financial accruals may also exhibit significant measurement errors. For instance, great subjectivity involves in the evaluation of noncurrent operating accruals. Changes in

lack of analysts' sophistication argument and encourage us to revisit this issue by giving consideration to an accrual metric that covers all relevant information available to analysts.

2.2. Hypotheses

We argue that analysts' optimism about WC accruals documented by prior research might not be due to their lack of sophistication but rather a result of an incomplete accrual information. Hence, we give consideration to TACC measure as proposed by Richardson et al. (2005) which includes non-current operating and financial accruals in addition to WC accruals. We assume that this broader measure provides more powerful tests of analysts' sophistication regarding accruals as it covers all relevant accrual information available to analysts. If analysts lack the necessary sophistication to understand accruals' persistence, earnings forecast errors should be correlated with this accrual measure that covers full accrual information. In that case, the association between forecast errors and TACC should be negative due to a quick mean reverting nature of accruals. Hence, our first hypothesis is as follows.

H1: Analysts' forecast errors are negatively correlated with total accruals.

On the other hand, if analysts fully understand accruals' persistence, there should be no association between the forecast errors and TACC. Then, as an alternative to *H1*, we should observe:

H1A: Analysts' forecasts errors are not correlated with total accruals

Bradshaw et al. (2001) show that analysts are optimistically biased with respect to WC accruals, and this has led to a conclusion that analysts lack the necessary sophistication in anticipating accruals' persistence. However, Richardson et al. (2005) show that accrual studies have so far omitted economically important accrual categories that are highly relevant for explaining future returns and

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intangibles, capitalised interest expenses, write downs, depreciation, etc., may restrict investors anticipating future economic benefits related to these items. There is also error margin in the evaluation of financial accruals despite their assumed high reliability. There can be high transitions between operating and financing activities (e.g., an interest expense charged as an asset), estimation errors related to financial items/instruments, under/over statement of financial liabilities/assets, concealing unwise borrowing and investment decisions, etc.

earnings. Richardson et al. (2005) disaggregate TACC into components, and rate each accrual category according to its reliability determined by the degree of measurement error that the category is assumed to involve. They find that less reliable accruals result in lower earnings persistence, and that this leads to optimism in security pricing.[10] They also find that TACC exhibit an average persistence degree of its components, while WC accruals show the lowest persistence, financial activity accruals show the highest persistence, and non-current operating accruals show the middle persistence of both[11]. Given that accruals persistence seems to be negatively related to optimism in security pricing, it is reasonable to expect that low persistency accruals are related with optimistic forecast errors, that high persistency accruals are associated with pessimistic forecast errors, while optimism/pessimism disappears with respect to accruals with medium persistence (TACC imply medium level of persistence since they include components across all persistence levels)[12]. In other words, the correlation between forecast errors (optimistic and pessimistic) and accruals will be (i) stronger for less and more persistent accrual components since their persistence significantly deviates from the TACC' persistence, and (ii) weaker or insignificant for accrual components whose persistence is similar or closer to the TACC' persistence. In other words, analysts' optimism found in previous studies with respect to WC accruals is not due to their lack of sophistication, but rather due to the use of the individual accrual component generating this mechanical relation. We therefore hypothesise that:

> *H2*: Analysts' forecast errors are optimistically (pessimistically) correlated with less (more) persistent accruals, while for the accruals with the mid-level persistence, this correlation is insignificant.

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[10] Further studies confirm Richardson et al.'s findings (e.g., Das et al. 1998, Ke and Yu, 2006; Bradshaw et al. 2016).

[11] WC accruals are subject to more measurement errors - they contain subjective estimates like allowances for bad debts and inventory – whilst financial accruals are mainly measured with greater confidence.

[12] Note that analysts forecasts accuracy tests have forecast errors as dependent variable (where forecast error = forecasted earnings - actual earnings, and where earnings = TACC + cash flows), and WC accruals as the key independent variable. The inclusion of WC accruals alone and omission of other accrual components may result in an incomplete model specification and a biased result.

3. Data and sample selection

In the data selection process, we follow Bradshaw et al. (2001) and Richardson et al. (2005). We use non-financial US firms for the period between 1976 and 2013. Financial statement data is obtained from Compustat. Analysts forecast data is from the IBES and returns from CRSP. We use IBES EPS in our tests. Reported EPS is entered into IBES database on the same basis as analyst forecast by and large corresponding to earnings that represents core business as opposed to net income[13]. Hence, IBES EPS is considered to be the closest match with analyst forecast (see, Ramnath et al. 2008; Brown, 2007). However, we have also used Fully Reported GPS instead of Actual IBES EPS in the robustness tests[14].

Bradshaw et al. (2001) use decile ranked accruals focusing on high/low magnitude following Sloan (1996). Kraft et al. (2006) show that it may not be the accruals' magnitude driving stock mispricing, and Xie (2001) shows that investors overprice mainly the portion of abnormal accruals stemming from managerial discretion adding measurement errors to accruals. Combining these findings with Richardson et al. (2005), who show that security mispricing is driven by persistence rather than magnitude[15], we decide to use actual values in our tests. Since the persistence depends on measurement error, we consider it more appropriate to use actual values. We also perform tests with decile ranks of accrual portfolios.

We use total accrual definition as in Richardson et al. (2005):

$$TACC = \Delta WC + \Delta NCO + \Delta FIN \qquad (1)$$

where *TACC* is further decomposed into its underlying components[16]

$$TACC = \underbrace{\Delta COA - \Delta COL}_{\Delta WC} + \underbrace{\Delta NCOA - \Delta NCOL}_{\Delta NCO} + \underbrace{\Delta STI + \Delta LTI - \Delta FINL}_{\Delta FIN} \quad (2)$$

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[14] In the Internet Appendix.

[15] High magnitude does not always translate into more forecast errors. On the contrary, low magnitude but low persistence (e.g., WC accrual) can cause greater forecast bias.

[16] All variables are defined in the Appendix.

We perform our tests across 12 months starting from the initial analysts' forecasts, which are generally issued in the first month after the prior period earnings announcement. Our final sample contains 48,142 firm-year observations per month.

3.1. Descriptive statistics and correlations

Table 1 Panel A reports descriptive statistics for *ROA*, *TACC*, *ΔWC*, *ΔNCO* and *ΔFIN* based accruals. It also includes descriptive statistics for conservatism proxies, *Hidden_reserves* and *C_Score*. Mean *TACC* is 0.051 or roughly 5% of total assets. Means of *ΔWC* and *ΔNCO* are positive while mean *ΔFIN* is negative, which is indicative of an average firm increasing its non-current operations, and financing this increase by net debt[17]. Panel B reveals that all accrual components are positively correlated with *ROA*, with *ΔWC* having the highest correlation. The positive correlation between *ΔWC* and *ΔNCO* suggests that they grow together. Both *ΔWC* and *ΔNCO* are negatively correlated with *ΔFIN,* in line with the suggestion that growth in operating activities is largely financed by debt.

Table 2 reports the descriptive statistics and pairwise correlations for the extended accrual decomposition. Panel A shows that mean values of all accrual components are positive with *ΔNCOA* having the highest mean while *ΔLTI* the lowest suggesting that *NCOA* constitute the major part of accruals. Standard deviations show that much of the variation in WC accruals is attributed to *ΔCOA*. Similar pattern is found with respect to *ΔNCOA* implying that the asset side of operating of accruals is more likely to be subject to measurement error. In contrast, much of the variation in *ΔFIN* can be attributable to *ΔFINL*. These observations suggest that the variation in operating accruals are driven by assets, while the variation in financial activity accruals are driven by liabilities. Panel B shows strong correlation among accrual components. In particular, the positive correlation between *ΔCOA* and *ΔCOL* suggests that a growing (shrinking) business generally results in an increase (decrease) in both current operating assets and liabilities. There is also a positive

[17] The mean values reported in Table 1 Panel A are comparable to the corresponding mean values from Richardson et al. (2005). In particular, the mean TACC (ΔWC) in our paper is 0.051 (0.015) whilst it is 0.052 (0.022) in Richardson et al. (2005). We thank an anonymous reviewer for this point.

correlation between *ΔCOA* and *ΔFINL* suggesting that current operations are not only funded by operating liabilities, but also by financial debt. Moreover, *ΔNCOA* is positively correlated with all liability accruals[18]

Table 3 reports negative means of forecast errors consistent with the prior evidence that analysts are optimistic on average. It also shows that mean errors (and standard deviations) are gradually disappearing as the earnings announcement date approaches. (while initial earnings forecast error is 1.6% of the share price, the last month forecast error is only 0.3% of the price). This trend is expected, since the arrival of new information (e.g., quarterly earnings announcements) prompts analysts to revise their forecasts and forecast errors decrease.

Table 4 Panels A and B show that forecast errors are not correlated with TACC, but optimistically (pessimistically) correlated with operating (financial) accruals. Similar pattern is observed for the extended accrual components providing an initial support to *H1A* and *H2.*

4. Empirical Analysis

4.1. Forecast error regressions on TACC

To test *H1 (H1A),* we use forecast error model by Bradshaw et al. (2001) employing TACC and extend the model by breaking TACC into components. The regressions are run for 12 consecutive months and also incorporate cash flows (*CF*) following Drake and Myers (2011), who argue that accruals and cash flows are the primary components of earnings and that they are highly correlated.

$$Ferror_{s,it+1} = \beta_0 + \beta_1 TACC_{it} + \beta_2 CF_{it} + \varepsilon_{it+1} \qquad (3)$$

[18] Note that the liability component of accruals is substracted from the asset component to arrive at net accruals. Hence, a positive relation between asset and liability implies they are likely to offset each other's effects on net accruals.

While *H1* requires a negative coefficient on *TACC*, the alternative hypothesis *H1A* requires insignificant coefficient on *TACC.*

Table 5 Panels A and B (without and with cash flows) present the results for Equation (3). Both panels confirm *H1A:* analysts' forecasts errors are not correlated with current *TACC.* The coefficients on *TACC* are statistically and economically zero across all 12 months. .[19] To address the possibility that our results may differ between periods before and after the implementation of the Sarbanes-Oxley Act due to a lower accrual based earnings management in the post-SOX period (Chen and Huang, 2013) we split the sample period into two sub periods: from 1976 to 2002 and from 2003 to 2013[20]. The results (untabulated) confirm that the original results hold and that there is no difference between pre- and post-SOC years.

4.2. Forecast error regressions on individual accrual components

To test *H2*, we regress forecast errors on individual accrual components (as initial and extended accrual decomposition) by fitting the following models:

$$Ferror_{s,it+1} = \beta_0 + \beta_1 \Delta WC_{it} + \beta_2 \Delta NCO_{it} + \beta_3 \Delta FIN_{it} + \beta_4 CF_{it} + \varepsilon_{it+1} \quad (4)$$

$$Ferror_{s,it+1} = \beta_0 + \beta_1 \Delta COL_{it} + \beta_2 \Delta COA_{it} + \beta_3 \Delta NCOL_{it} + \beta_4 \Delta NCOA_{it}$$

$$+\beta_5 \Delta LTI_{it} + \beta_6 \Delta FINL_{it} + \beta_7 \Delta STI_{it} + \beta_8 CF_{it} + \varepsilon_{it+1} \quad (5)$$

A negative (positive) sign on coefficients indicates forecast optimism (pessimism)[21]. Before running regressions (4) and (5), we also run persistence tests for individual accrual components following Richardson et al (2005). Reported in Appendix Panels A, B and C, tests show that *CF* has the highest persistent among earnings components with 80%, while *ΔFIN* with 79%, *ΔNCO* with 74%, *TACC*

[19] Note that panel B shows pessimistic errors with CF, which has the highest persistence among earnings components and thus should be easier to predict relative to TACC. Bilinski (2014) shows that accuracy of CF estimates depends on the accuracy of accrual estimates, i.e., if analysts are accurate in estimating accruals, they should also be accurate in estimating CF. Hence, we avoid interpreting this observation as analysts' lack of sophistication given that they seem to be accurate in predicting TACC.

[20] We thank an anonymous referee for this constructive suggestion.

[21] Analyst earnings forecasts have historically been optimistically biased leading to negative forecast errors on average (as calculated forecast minus actual). Hence, our tests are restricted to predicting a negative relation between less persistent accruals and forecast errors as in Bradshaw et al. (2001).

with 73%, and *ΔWC* with 67% which confirms that different accrual components have different persistence characteristics, and *TACC* reflecting an average of its components' persistence.

If the H2 holds, then analysts' forecast errors will be optimistically (pessimistically) correlated with low (high) persistent accruals, while for the accruals with the middle persistence levels, the correlation is insignificant, *H2*[22]. If the lack of sophistication argument holds, the correlation between forecast errors and accruals becomes stronger (weaker) as the persistence of an accrual component decreases (increases), i.e., $\beta_{1\Delta WC}<\beta_{2\Delta NCO}<\beta_{3\Delta FIN}<0$). We acknowledge that the confirmation of *H2* will only support the argument that analysts fully understand accruals' persistence if also *H1A* holds, i.e., if there is no correlation between forecast errors and *TACC*.

Table 6 reports the results for Equations (4) and (5) in Panels A and B. Confirming *H2*, both panels show that forecast errors are optimistically correlated with low persistence accruals, but pessimistically correlated with high persistence accruals across the 12 months, while the accruals of the medium persistence do not show any association with errors (e.g., $\beta_{1\Delta WC}$=-0.039, $\beta_{2\Delta NCO}$=0, $\beta_{3\Delta FIN}$ >=0.017 for month 1). Moreover, the coefficient magnitudes in Panels A and B of Table 6 line up closely with the relative persistence rankings reported in the Appendix A Panels B and C (e.g., persistence degrees respectively are *ΔCOL*=62.9% (0.803-0.177), *ΔCOA*=66.8%, *ΔNCOL*=70.6%, *ΔNCOA*=72.6%, *ΔLTI*=74.4%, *ΔFINL*=75.1%, and *ΔSTI*=76.9%, and their coefficients in forecast errors tests are *ΔCOL*=-0.062, *ΔCOA*=-0.037, *ΔNCOL*=-0.031, *ΔNCOA*=-0.002, *ΔLTI*=0.006, *ΔFINL*=0.024, and *ΔSTI*=0.010. *F-tests* confirm that the coefficients are different from each other.

In sum, both tests reported in Tables 5 and 6 confirm *H1A* and *H2.* The correlation between forecast errors and accruals becomes stronger (weaker) as the persistence of an accrual component decreases (increases), and forecast errors are optimistically (pessimistically) correlated with low (high) persistent accruals, while for the accruals with medium persistence the correlation is insignificant. We interpret these findings as analysts correctly anticipating accruals' persistence. We perform a bank of additional sensitivity analyses (reported in Internet Appendix) which confirm that our results are robust to different samples, periods, model specifications, absolute forecast errors, and to controlling for cash flows and high accounting conservatism.

6. Conclusion

Prior evidence documents that analysts who provide information to investors fail to fully understand accruals' varying persistence levels and as result produce optimistic forecasts of earnings for firms with relatively high WC accruals (Bradshaw, Richardson, and Sloan, 2001). However, growing evidence suggests that the traditional accrual definition used in the empirical models of forecast accuracy omits economically important accruals that are highly relevant for explaining future earnings and returns.

In this paper, we argue that analysts are likely to use this important accrual information and that empirical models measuring accruals by means of WC alone may be incomplete and hence not entirely appropriate and up-to-date to assess the level of analysts' appreciation of accruals. We suggest that that analysts' optimism found in Bradshaw et al. (2001) may not be due to their lack of sophistication, but rather a result of an incomplete accrual information embedded in forecast accuracy tests. We address this issue and give consideration to non-current operating and financial accruals in forecasting models. We find no correlation between analysts' forecast errors and revised TACC. Our findings imply that if analysts are to achieve more accurate forecasts, they should be considering all rather than some accrual components. We believe that our study provides useful implication for future research by documenting that analysts appear to utilise all relevant accrual information in their forecasts and traditional accrual definition should be modified in future accrual studies.

Our findings have potentially important implications for both academics and practitioners as users of analysts' reports in that that it rules out the lack of analysts' sophistication argument. This is important because if analysts fail to accurately incorporate accrual information, the forecasts are biased and inefficient. Our results support the opposite and imply analysts' high information processing skills which helps to explain a trend in the growing use of analysts' reports by investors.

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Appendix

Variable definitions

Ferror	$Ferror_{s,t+1} = [Actual\ EPS_{t+1} – Forecast\ EPS_{s,t+1}]/P_t$ Analysts' earnings forecast errors computed as actual IBES EPS for year t+1 minus analysts' consensus (median) forecast EPS from IBES in month *s* $(s=1, 2, 3, ...12)$ scaled by price from CRSP in the first month that year t earnings is announced.
ROA	Earnings. Operating income after depreciation deflated by average assets
TACC	Total accruals is the change in non-cash assets - change in liabilities deflated by average assets
CF	Cash flows from operating activities deflated by average assets.
ΔOPAC	Operating accruals: change in non-cash working capital (ΔWC_t) plus change in net non-current operating assets (ΔNCO_t), deflated by average assets.
ΔWC	Working capital accruals is the change in net working capital = $WC_t - WC_{t-1}$. *WC* is current operating assets (*COA*) less operating liabilities (*COL*). *COA*=current assets - cash and short term investments, and *COL*=current liabilities - short term debt.
ΔNCO	Non-current operating accruals is the change in net non-current operating assets = $NCO_t - NCO_{t-1}$. *NCO* is = non-current operating assets (*NCOA*) - non-current op.liabilities (*NCOL*). *NCOA*=total assets - current assets - investments and advances , and *NCOL*=total liability - current liabilities - short term debt - long term debt
ΔFIN	Financing accruals is the change in net financial assets = $FIN_t - FIN_{t-1}$. *FIN*=financial assets (*FINA*) - financial liabilities (*FINL*). *FINA*=short term investments (STI) + long term investments (LTI) (Compustat Item IVAO, #32). *FINL*= long term debt + short term debt + preferred stock
Returns	Size adjusted returns are calculated as the sum of 12-month buy and hold stock returns from CRSP (accumulation starts in the fourth month after the fiscal year end) minus the corresponding value-weighted average returns for all firms in the same size-matched decile. To form size deciles, market values are ranked annually, and assigned in equal numbers to ten portfolios.
E/P	Earnings to price ratio calculated as operating income after depreciation at time *t* deflated by market value at time *t-1*.

Size	Natural log of market value of equity. Market value is calculated as the share price multiplied by common shares outstanding
B/P	Book value of equity divided by market value of equity. Book value of equity = Common ordinary equity + Preferred treasury stock Current Assets + Preferred dividends in arrears
Beta	Estimated 60 month rolling regressions using the market model $(Ret_{it} - R_f) = \alpha + \beta_i(Ret_{mt} - R_f) + \epsilon_{it}$ *Ret* is the CRSP monthly buy and hold returns for 12 month for stock *i* at time *t*, R_f is risk the free rate, $(Ret_{mt} - R_f)$ is the equity risk premium of the market portfolio. R_f is obtained from the US Federal Reserve, H15 report as the 10-year US Treasury bond rate for the relevant year. Ret_{mt} is the CRSP monthly value weighted return on a market portfolio cumulated over 12 months.

C_Score Firm specific conditional conservatism proxy varying across years developed using the following Khan and Watts (2009) model based on Basu (1997) asymmetric timelines of earnings measure;

$$X_{it} = \beta_1 + \beta_2 D_i + \beta_3 R_i \left(\mu_1 + \mu_2 Size_i + \mu_3 \frac{M}{B}_i + \mu_4 lev_i D_i\right) + \beta_4 D_i R_i \left(\gamma_1 + \gamma_2 Size_i + \gamma_3 \frac{M}{B}_i + \gamma_4 lev_i\right) + \delta_1 Size_i + \delta_2 \frac{M}{B}_i + \delta_3 Lev_i + \delta_4 D_i Size_i + \delta_5 D_i \frac{M}{B}_i + \delta_6 D_i Lev_i + e_{it}$$

The parameters are estimated annually, *C_Score* is calculated as

$$C\_Score_{it} \equiv \beta_4 = \gamma_1 + \gamma_2 Size_{it} + \gamma_3 {}^{M_{it}}/_{B_{it}} + \gamma_4 lev_{it}$$

Where X is earnings before extraordinary items deflated by market value (MV) at time *t-1*, MV is calculated as the share price multiplied by common shares outstanding. *R* denotes annual buy and hold return inclusive of dividends and other distributions, accumulation period starts in the fourth month after the fiscal year end *t-1* and continues for the next 12 months. *D* is set to 1 if *R<0* and zero otherwise. The coefficient β_4 measures the incremental timeliness for bad news over good news, or conservatism. *E/P* is income at time *t* deflated by market value at time *t-1*. *Size* is the natural log of market value at time *t*, *leverage* is measured as long term debt plus short term debt divided by the market value at time *t*. *M/B* is calculated as market value at time *t* divided by the book value of equity at time *t.* All firm years with missing data, negative total assets and book values are eliminated in estimation. Firms with share price less than $1 are eliminated

Hid_Res Hidden reserves to proxy unconditional accounting conservatism by Penman and Zhang, (2002; 2016) deflated by average assets

$$Hidden\_Reserves_t = R\&Dres_t + ADVres_t + LIFOres_t$$

R&Dres is unamortised balance of R&D expenditures that would have appeared on balance sheet if it had been capitalised and amortised at a straightline rate of 20%, assuming a uniform distribution.

$$R\&Dres_{it} = 0.9R\&D_{it} + 0.7R\&D_{it-1} + 0.5R\&D_{it-2} + 0.3R\&D_{it-3} + 0.1R\&D_{it-4}$$

ADVres is advertisement reserve calculated using advertisement expenditures assuming a useful life of two years, and providing more benefits when first initiated

$$ADres_{it} = ADV_{it} + 1/3ADV_{it-1}$$

LIFOres is LIFO reserves reported in the inventory footnotes in financial reports.

PANEL A: Persistence of accruals (-TACC)

$ROA_{it+1} = \rho_0 + \rho_1 ROA_{it} + \rho_2 TACC_{it} + \vartheta_{it+1}$

	intercept	*ROA*	*TACC*	R^2
mean coef.	0.008	0.797 ***	-0.068 ***	0.632
t-stat		*99.11*	*-16.15*	

PANEL B: Persistence of accruals (initial decomposition)

$ROA_{it+1} = \rho_0 + \rho_1 ROA_{it} + \rho_2 \Delta WC_{it} + \rho_3 \Delta NCO_{it} + \rho_4 \Delta FIN_{it} + \vartheta_{it+1}$

	intercept	*ROA*	*ΔWC*	*ΔNCO*	*ΔFIN*	R^2
mean coef.	0.007	0.791 ***	-0.122 ***			0.631
pvalue			*-16.09*			
mean coef.	0.008	0.782 ***		-0.051 ***		0.625
t-stat				*-10.79*		
mean coef.	0.005	0.777 ***			0.002	0.629
t-stat					*0.26*	
mean coef.	*0.009*	*0.804* ***	*-0.137* ***	*-0.065* ***	-0.045 ***	0.634
t-stat			-19.59	-12.32	-11.78	
Persistence order		*highest*	*low*	*medium*	*high*	

PANEL B: Persistence of accruals (extended decomposition)

$$ROA_{it+1} = \rho_0 + \rho_1 ROA_{it} + \rho_2 \Delta COL_{it} + \rho_3 \Delta COA_{it} + \rho_4 \Delta NCOL_{it} + \rho_5 \Delta NCOA_{it} + \rho_6 \Delta LTI_{it} + \rho_7 \Delta FINL_{it} + \rho_8 \Delta STI_{it} + \vartheta_{it+1}$$

	intercept	*ROA*	*(-)ΔCOL*	*ΔCOA*	*(-)ΔNCOL*	*ΔNCOA*	*ΔLTI*	*(-)ΔFINL*	*ΔSTI*	R^2
Predicted reliability [a]			High	Low	Medium	Low	Medium	High	High	
mean coef.	0.005	0.776 ***	-0.035 ***							0.62
t-stat			*-4.03*							
mean coef.	0.008	0.786 ***		-0.065 ***						0.63
t-stat				*-11.3*						
mean coef.	0.005	0.777 ***			-0.044 ***					0.62
t-stat					*-4.52*					
mean coef.	0.007	0.782 ***				-0.047 ***				0.62
t-stat						*-10.17*				
mean coef.	0.006	0.78 ***					-0.037 ***			0.63
t-stat							*-4.45*			
mean coef.	0.005	0.776 ***						0.010 ***		0.62
t-stat								*2.00*		
mean coef.	0.006	0.775 ***							-0.026 ***	0.62
t-stat									*-5.53*	
mean coef.	0.008	0.803 ***	-0.177 ***	-0.132 ***	-0.097 ***	-0.077 ***	-0.059 ***	-0.052 ***	-0.034 ***	0.63
t-stat			*-18.40*	*-19.11*	*-8.38*	*-14.21*	*-6.65*	*-9.46*	*-6.77*	
Persistence Order		*8 Highest*	*1 Low*	*2*	*3*	*4*	*5*	*6*	*7 high*	

ROA $_{t+1}$ denotes earnings and *ROA* $_t$ denotes cash flows by the model construction. Other variables represent accrual components of earnings. See Appendix for models ROA (1), (2) and (3). Standard errors are clustered by firm and year using the Petersen (2009) approach. The sample consists of 142,821 firm-year observations for 1976-2013, all earnings and accrual variables are deflated by average assets and winsorised to +1 and -1. See Appendix for variable definitions. *** denotes the statistical significance at 1% level

Table 1

Descriptive statistics and correlations for ROA, accruals, conservatism

PANEL A: Descriptive statistics

	mean	std.dev.	25%	median	75%
ROA_{t+1}	0.045	0.214	0.007	0.08	0.14
ROA_t	0.043	0.186	0.002	0.076	0.136
$TACC_t$	0.051	0.195	-0.021	0.037	0.109
$\Delta OPAC_t$	0.063	0.195	-0.027	0.041	0.135
ΔFIN_t	-0.012	0.176	-0.071	-0.002	0.048
ΔWC_t	0.015	0.106	-0.024	0.008	0.052
ΔNCO_t	0.048	0.159	-0.015	0.021	0.084
C_Score_t	0.013	0.115	-0.052	0.012	0.081
$Hidden\_Reserves_t$	0.163	0.190	0.035	0.098	0.218

PANEL B: Correlation matrix—Pearson (above diagonal) and Spearman (below diagonal)

	ROA_{t+1}	ROA_t	$TACC_t$	$\Delta OPAC_t$	ΔFIN_t	ΔWC_t	ΔNCO_t	C_S_t	H_R_t
ROA_{t+1}	-	0.75 ***	0.13 ***	0.09 ***	0.05 ***	0.01 ***	0.04 ***	-0.24 ***	-0.16 ***
ROA_t	0.79 ***	-	0.22 ***	0.18 ***	0.05 ***	0.20 ***	0.08 ***	-0.27 ***	-0.17 ***
$TACC_t$	0.23 ***	0.38 ***	-	0.69 ***	0.45 ***	0.40 ***	0.47 ***	-0.10 ***	-0.02 ***
$\Delta OPAC_t$	0.13 ***	0.27 ***	0.60 ***	-	-0.45 ***	0.60 ***	0.84 ***	-0.08 ***	-0.06 ***
ΔFIN_t	0.09 ***	0.08 ***	0.29 ***	-0.47 ***	-	-0.22 ***	-0.41 ***	-0.02 ***	0.04 ***
ΔWC_t	0.12 ***	0.23 ***	0.41 ***	0.63 ***	-0.27 ***	-	0.07 ***	-0.01 ***	-0.02 ***
ΔNCO_t	0.11 ***	0.22 ***	0.47 ***	0.80 ***	0.41 ***	0.16 ***	-	-0.12	-0.07 ***
C_Score_t	-0.02 ***	-0.02 ***	-0.08 ***	-0.06 ***	-0.01 ***	-0.01 ***	-0.06	-	0.05
H_Rt	-0.39 ***	-0.43 ***	-0.05 ***	-0.08 ***	0.03 ***	-0.05 ***	-0.07 ***	0.00	-

Earnings/accruals sample consists of 142,821 firm-year observations, while *Hidden_Reserves* (H_R) and *C_Score* (C_S) samples consist of 98,196 and 96,324 firm-year observations respectively for 1976-2013. All earnings and accrual variables are deflated by average assets and winsorised to +1 and -1, while *C_Score* and *Hidden_Reserves* are winsorised to %1 and %99. See Appendix for variable definitions. *** denotes the statistical significance at 1% level

Table 2

Descriptive statistics and correlations for extended accrual decomposition

PANEL A: Descriptive statistics

	mean	std.dev.	25%	median	75%
ΔCOA_t	0.040	0.132	-0.01	0.022	0.081
ΔCOL_t	0.025	0.09	-0.009	0.015	0.051
$\Delta NCOA_t$	0.055	0.163	-0.012	0.025	0.091
$\Delta NCOL_t$	0.006	0.049	-0.001	0.001	0.011
ΔSTI_t	0.007	0.105	0	0	0
ΔLTI_t	0.002	0.047	0	0	0
$\Delta FINL_t$	0.021	0.141	-0.023	0	0.051

PANEL B: Correlation matrix—Pearson (above diagonal) and Spearman (below diagonal)

	ROA_{t+1}	ROA_t	ΔCOA_t	ΔCOL_t	$\Delta NCOA_t$	$\Delta NCOL_t$	ΔSTI_t	ΔLTI_t	$\Delta FINL_t$
ROA_{t+1}	-	0.75 ***	0.11 ***	0.04 ***	0.05 ***	0.02 ***	0.03 ***	0.02 ***	-0.03 ***
ROA_t	0.79 ***	-	0.16 ***	0.00	0.09 ***	0.01 ***	0.04 ***	0.02 ***	-0.02 ***
ΔCOA_t	0.20 ***	0.31 ***	-	0.60 ***	0.29 ***	0.08 ***	0.01	0.01 ***	0.33 ***
ΔCOL_t	0.15 ***	0.18 ***	0.57 ***	-	0.31 ***	0.07 ***	0.09 ***	0.03 ***	0.20 ***
$\Delta NCOA_t$	0.14 ***	0.25 ***	0.38 ***	0.35 ***	-	0.23 ***	-0.01	-0.01 ***	0.51 ***
$\Delta NCOL_t$	0.15 ***	0.19 ***	0.14 ***	0.11 ***	0.31 ***	-	0.01 ***	0.06 ***	0.03 ***
ΔSTI_t	0.07 ***	0.09 ***	-0.02 ***	0.08 ***	-0.02 ***	0.02 ***	-	-0.02 ***	0.03 ***
ΔLTI_t	0.02 ***	0.04 ***	0.03 ***	0.04 ***	0.02 ***	0.06 ***	0.00	-	0.08 ***
$\Delta FINL_t$	-0.04 ***	-0.04	0.32 ***	0.17 ***	0.05 ***	0.11 ***	-0.02 ***	0.05 ***	-

The sample consists of 142,821 firm-year observations for 1976-2013. Variables are deflated by average assets and winsorised to +1 and -1. See Appendix for variable definitions. *** denotes the statistical significance at 1% level

Table 3

Descriptive statistics for earnings forecast errors

	mean	std.dev.	25%	median	75%
M1Ferror	-0.016	0.049	-0.020	-0.002	0.003
M2Ferror	-0.015	0.048	-0.018	-0.002	0.003
M3Ferror	-0.013	0.056	-0.016	-0.001	0.003
M4Ferror	-0.012	0.055	-0.014	-0.001	0.003
M5Ferror	-0.011	0.054	-0.013	-0.001	0.003
M6Ferror	-0.009	0.038	-0.010	-0.001	0.003
M7Ferror	-0.008	0.039	-0.008	0.000	0.002
M8Ferror	-0.007	0.037	-0.007	0.000	0.002
M9Ferror	-0.005	0.038	-0.005	0.000	0.002
M10Ferror	-0.004	0.040	-0.003	0.000	0.002
M11Ferror	-0.004	0.040	-0.002	0.000	0.002
M12Ferror	-0.003	0.033	-0.002	0.000	0.002

m1, m2, ...m12 denote months, *Ferror* denotes analysts' earnings forecast error. The number of firm-year observations are 48,142 across 12 months for 1976-2013. See appendix for variable definitions.

Table 4

Correlations between analysts forecast errors, accruals and conservatism across 12 months

PANEL A: Pearson correlations: intial accrual decomposition and average forecast errors

	$TACC_t$	$\Delta OPAC_t$	ΔFIN_t	ΔWC_t	ΔNCO_t	C_Score_t	H_Reserv_t
$M1Ferror_{t+1}$	0.01	-0.06 ***	0.07 ***	-0.07 ***	-0.03 ***	-0.11 ***	0.00
$M2Ferror_{t+1}$	0.00	-0.06 ***	0.07 ***	0.07 ***	-0.04 ***	-0.09 ***	0.01
$M3Ferror_{t+1}$	0.00	-0.05 ***	0.05 ***	-0.05 ***	-0.03 ***	-0.09 ***	0.02
$M4Ferror_{t+1}$	0.00	-0.05 ***	0.05 ***	-0.05 ***	-0.03 ***	-0.09 ***	0.02 ***
$M5Ferror_{t+1}$	0.00	-0.05 ***	0.05 ***	-0.04 ***	-0.03 ***	-0.08 ***	0.03 ***
$M6Ferror_{t+1}$	0.00	-0.06 ***	0.06 ***	-0.06 ***	-0.03 ***	-0.08 ***	0.03 ***
$M7Ferror_{t+1}$	0.00	-0.06 ***	0.05 ***	-0.05 ***	-0.04 ***	-0.08 ***	0.03 ***
$M8Ferror_{t+1}$	0	-0.05 ***	0.05 ***	-0.05 ***	-0.03 ***	-0.06 ***	0.03 ***
$M9Ferror_{t+1}$	0.01	-0.04 ***	0.05 ***	-0.04 ***	-0.02 ***	-0.06 ***	0.03 ***
$M10Ferror_{t+1}$	0	-0.04 ***	0.04 ***	-0.03 ***	-0.03 ***	-0.05 ***	0.02 ***
$M11Ferror_{t+1}$	0	-0.04 ***	0.04 ***	-0.03 ***	-0.03 ***	-0.05 ***	0.03 ***
$M12Ferror_{t+1}$	0.00	-0.03 ***	0.03 ***	-0.03 ***	-0.02 ***	-0.05 ***	0.02 ***

PANEL B: Pearson correlations: extended accrual decomposition and average forecast errors

	ΔCOA_t	ΔCOL_t	$\Delta NCOA_t$	$\Delta NCOL_t$	ΔSTI_t	ΔLTI_t	$\Delta FINL_t$
$M1Ferror_{t+1}$	-0.04 ***	-0.03 ***	-0.03 ***	-0.02 ***	0.03 ***	0.01	0.07 ***
$M2Ferror_{t+1}$	-0.04 ***	-0.03 ***	-0.03 ***	-0.03 ***	0.03 ***	0.01	0.07 ***
$M3Ferror_{t+1}$	-0.03 ***	-0.01 ***	-0.03 ***	-0.01 ***	0.02 ***	0.01	0.05 ***
$M4Ferror_{t+1}$	-0.03 ***	-0.01 ***	-0.03 ***	-0.03 ***	-0.02 ***	0.01	0.05 ***
$M5Ferror_{t+1}$	-0.03 ***	-0.01 ***	-0.02 ***	-0.03 ***	-0.02 ***	0.00	0.05 ***
$M6Ferror_{t+1}$	-0.04 ***	-0.01 ***	-0.03 ***	-0.02 ***	-0.02 ***	0.00	0.06 ***
$M7Ferror_{t+1}$	-0.03 ***	-0.02 ***	-0.02 ***	-0.05 ***	0.02 ***	0.01	0.05 ***
$M8Ferror_{t+1}$	-0.03 ***	-0.02 ***	-0.02 ***	-0.05 ***	0.02 ***	0.00	0.05 ***
$M9Ferror_{t+1}$	-0.03 ***	-0.01	-0.02 ***	-0.02 ***	0.02 ***	0.01	0.04 ***
$M10Ferror_{t+1}$	-0.02 ***	-0.01 ***	-0.01 ***	-0.05 ***	0.02 ***	0.01	0.04 ***
$M11Ferror_{t+1}$	-0.01 ***	-0.02 ***	-0.01 ***	-0.05 ***	0.02 ***	0.00	0.03 ***
$M12Ferror_{t+1}$	-0.01 ***	-0.02 ***	-0.01	-0.04 ***	0.01 ***	0.00	0.03 ***

m1, m2, ...m12 denote months, *Ferror* denotes analysts' earnings forecast error. The number of firm-year observations are 48,142 across 12 months for 1976-2013 for which consensus analsyt earning forecasts and actual earnings are available on the IBES summary file. Accrual variables are winsorised to +1 and -1, while forecast errors are winsorised to 1% and 99%. See Appendix fr variable defnition. *** denotes the statistical significance at 1% level

Table 5

Regressions for forecast errors on TACC and cash flows over 12 months

PANEL A: Forecast errors and total accruals

$$Ferror_{s,it+1} = \beta_0 + \beta_1 TACC_{it} + \varepsilon_{it+1}$$

Month	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
Intercept (coef.)	-0.017 ***	-0.015 ***	-0.013 ***	-0.012 ***	-0.01 ***	-0.009 ***	-0.008 ***	-0.007 ***	-0.005 ***	-0.004 ***	-0.003 ***	-0.003 ***
TACC (coef.)	0.002	0	0	0	0	0	0	0	0.001	0	0	0
t-stat	*0.94*	*0.39*	*-0.05*	*-0.1*	*-0.22*	*0.15*	*-0.07*	*0.08*	*0.67*	*0.15*	*0.15*	*0.2*

PANEL B: Forecast errors, total accruals and cash flows

$$Ferror_{s,it+1} = \beta_0 + \beta_1 CASHF_{it} + \beta_2 TACC_{it} + \varepsilon_{it+1}$$

Month	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
Intercept (coef.)	-0.018 ***	-0.016 ***	-0.013 ***	-0.013 ***	-0.011 ***	-0.009 ***	-0.008 ***	-0.007 ***	-0.005 ***	-0.004 ***	-0.004 ***	-0.003 ***
TACC (coef.)	0	-0.002	-0.03	0.003	-0.003	0.002	-0.002	-0.002	0	-0/001	0	0
t-stat	*0.19*	*0.72*	*-1.17*	*-0.88*	*-0.90*	*-0.71*	*-0.70*	*-0.48*	*0.67*	*-0.42*	*-0.32*	*-0.35*
CF(coef.)	0.043 ***	0.037 ***	0.032 ***	0.029	0.026 ***	0.022 ***	0.021 ***	0.017 ***	0.014 ***	0.013 ***	0.012 ***	0.11 ***
t-stat	*8.85*	*8.75*	*7.45*	*8.05*	*8.00*	*6.97*	*7.41*	*6.92*	*6.46*	*6.43*	*6.30*	*6*
$\%R^2$	1.63	1.27	0.65	0.53	0.45	0.72	0.59	0.43	0.27	0.19	0.17	0.22

m1, m2, ...m12 denote months, *Ferror* denotes analysts' earnings forecast error. The number of firm-year observations are 48,142 from 1976 to 2013 for which consensus analsyt earning forecasts and actual earnings are available on the IBES summary statistics file. Standard errors are clustered by firm and year using the Petersen (2009) approach. See Appendix for variable definitions. *** denotes the statistical significance at 1% level

Table 6

Forecast errors and accrual components over 12 months

PANEL A: Forecast errors and accruals (initial accrual decomposition)

$$Ferror_{s,it+1} = \beta_0 + \beta_1 \Delta WC_{it} + \beta_2 \Delta NCO_{it} + \beta_3 \Delta FIN_{it} + \beta_4 CF_{it} + \varepsilon_{it+1}$$

		m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
Intercept (coef.)		-0.015 ***	-0.014 ***	-0.12 ***	-0.011 ***	-0.01 ***	-0.008 ***	-0.007 ***	-0.006 ***	-0.005 ***	-0.004 ***	-0.003 ***	-0.003 ***
	Persistence Order [(d)]												
ΔWC (coef.)	*1 Low*	-0.039 ***	-0.038 ***	-0.033 ***	-0.027 ***	-0.025 ***	-0.026 ***	-0.023 ***	-0.019 ***	-0.015 ***	-0.013 ***	-0.011 ***	-0.010 ***
t-stat		*-8.63*	*-8.85*	*-5.98*	*-6.19*	*-6.27*	*-9.12*	*-8.52*	*-7.11*	*-6.73*	*-5.25*	*-3.82*	*-4.46*
ΔNCO (coef.	*2*	-0.001	-0.003	-0.005	-0.007	-0.007	-0.003	-0.005	-0.004	-0.001	-0.003	-0.003	-0.003
t-stat		*-0.33*	*-1.00*	*-1.22*	*-1.06*	*-1.13*	*-0.99*	*-0.97*	*-0.78*	*-0.47*	*-0.86*	*-0.81*	*-0.74*
ΔFIN (coef.)	*3*	0.017 ***	0.015 ***	0.012 ***	0.011 ***	0.01 ***	0.01 ***	0.009 ***	0.008 ***	0.007 ***	0.005 ***	0.005 ***	0.005 ***
t-stat		*5.46*	*5.03*	*4.38*	*3.82*	*3.76*	*4.15*	*3.84*	*3.96*	*4.27*	*4.00*	*3.56*	*3.88*
CF (coef.)	*4 High*	0.042 ***	0.035 ***	0.030 ***	0.027 ***	0.025 ***	0.021 ***	0.020 ***	0.016 ***	0.013 ***	0.012 ***	0.011 ***	0.010 ***
t-stat		*8.58*	*8.57*	*7.10*	*7.70*	*7.77*	*6.85*	*7.48*	*6.99*	*6.39*	*6.63*	*6.58*	*6.29*

PANEL B: Forecast errors and accruals (extended accrual decomposition)

$$Ferror_{s,it+1} = \beta_0 + \beta_1 \Delta COL_{it} + \beta_2 \Delta COA_{it} + \beta_3 \Delta NCOL_{it} + \beta_4 \Delta NCOA_{it} + \beta_5 \Delta LTI_{it} + \beta_6 \Delta FINL_{it} + \beta_7 \Delta STI_{it} + \beta_8 CF_{it} + \varepsilon_{it+1}$$

		m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
Intercept (coef.)		-0.016 ***	-0.014 ***	0.012 ***	-0.011 ***	0.010 ***	-0.009 ***	-0.008 ***	-0.008 ***	-0.005 ***	-0.004 ***	-0.004 ***	-0.003 ***
	Persistence Order												
(-)ΔCOL (coe	*1 Low*	-0.062 ***	-0.034 ***	-0.030 ***	-0.024 ***	-0.023 ***	-0.024 ***	-0.021 ***	-0.017 ***	-0.013 ***	-0.011 ***	-0.009 ***	-0.008 ***
t-stat		-7.26	-7.44	-5.47	-5.47	-5.56	-7.85	-7.37	-6.39	-6.04	-4.87	-3.58	-4.03
ΔCOA (coef.	*2*	-0.037 ***	-0.034 ***	-0.030 ***	-0.024 ***	-0.023 ***	-0.024 ***	-0.021 ***	-0.017 ***	-0.013 ***	-0.011 ***	-0.009 ***	-0.008 ***
t-stat		*-7.26*	*-7.44*	*-5.47*	*-5.47*	*-5.56*	*-7.85*	*-7.37*	*-6.39*	*-6.04*	*-4.87*	*-3.58*	*-4.03*
(-)ΔNCOL (c	*3*	-0.031 ***	-0.038 ***	-0.031 ***	-0.036 ***	-0.025 **	-0.027 ***	-0.006	-0.005	-0.009 ***	-0.005	-0.004	-0.004
t-stat		*-4.02*	*-3.21*	*-3.78*	*-2.27*	*-1.96*	*-3.94*	*-1.59*	*-1.57*	*-2.97*	*-1.32*	*-1.28*	*-1.19*
ΔNCOA (coef	*4*	-0.002	-0.004	-0.005	-0.006	-0.006	-0.002	-0.004	-0.003	0	-0.003	-0.003	-0.002
t-stat		*-0.71*	*-1.22*	*-1.32*	*-1.03*	*-0.99*	*-0.69*	*-0.79*	*-0.66*	*-0.11*	*-0.69*	*-0.73*	*-0.62*
ΔLTI (coef.)	*5*	0.006	0.006	0.006	0.005	0.004	0.003	0.001	0.003	0.002	0.001	0.001	0.001
t-stat		*1.33*	*1.21*	*1.13*	*1.17*	*0.92*	*0.91*	*0.88*	*0.33*	*1.01*	*0.96*	*0.56*	*0.48*
(-)ΔFINL (co	*6*	0.024 ***	0.022 ***	0.019 ***	0.017 ***	0.016 ***	0.015 ***	0.012 ***	0.012 ***	0.009 ***	0.009 ***	0.008 ***	0.007 ***
t-stat		*5.95*	*5.65*	*4.68*	*4.69*	*4.94*	*4.74*	*4,98*	*4.75*	*3.89*	*4.26*	*3.85*	*3.91*
ΔSTI (coef.)	*7*	0.010 ***	0.008 ***	0.007 ***	0.007 ***	0.006 ***	0.006 ***	0.006 ***	0.006 ***	0.006 ***	0.004 ***	0.004 ***	0.004 ***
t-stat		*4.23*	*3.59*	*3.15*	*2.32*	*2.37*	*2.75*	*2.87*	*3.51*	*4.21*	*3.47*	*2.92*	*3.45*
CF (coef.)	*8 High*	0.041 ***	0.035 ***	0.030 ***	0.029 ***	0.024 ***	0.020 ***	0.020 ***	0.016 ***	0.012 ***	0.011 ***	0.010 ***	0.010 ***
t-stat		*8.71*	*8.65*	*7.15*	*7.67*	*7.79*	*6.84*	*7.21*	*6.82*	*5.60*	*6.68*	*6.54*	*5.92*

m1, m2, ...m12 denote months, *Ferror* denotes analysts' earnings forecast error. Persistence order of earnings components is obtained from the multivariate persistence regressions provided in Appendix(Panels A-C). The number of firm-year observations are 48,142 for 1976-2013 for which consensus analsyt earning forecasts and actual earnings are available on IBES summary statistics file. Standard errors are clustered by firm and year using Petersen (2009). Untabulated *F-tests* reveal that coefficients are different from each other in the first 3-4 months. See Appendix for variable definitions. *** denotes the statistical significance at 1% level