The Effect of Conditional Accounting Conservatism on the Predictive Ability of Accrual Components with Respect to Future Cash Flows

Wei Chen
School of Business, University of Connecticut
wei.2.chen@uconn.edu

Daniel W. Collins
Tippie College of Business, University of Iowa
daniel-collins@uiowa.edu

Sam Melessa
College of Business, University of Nebraska–Lincoln
smelessa2@unl.edu

March 2024

Abstract: We investigate the impact of conditional conservatism (timely loss recognition) on the ability of accruals and its components to predict future cash flows. Prior studies claim that conditional conservatism detracts from the valuation role of earnings. We argue that if timely loss recognition improves contracting efficiency by providing early warnings of declines in future cash flows, then these accruals should provide better predictions of future cash flows for valuation purposes. Consistent with this conjecture, we find a positive association between timely loss recognition and the ability of accrual components to predict future cash flows in bad news periods. Moreover, we find the effect is concentrated in income-reducing asset accruals that are more likely to reflect timely loss recognition (e.g., impairments and write-downs) than are liability accruals. We conduct additional analyses to strengthen the validity of our results. Our findings stand in contrast to claims that conditional conservatism impairs the valuation role of earnings.

Keywords: conditional conservatism; timely loss recognition; accruals; cash flow predictability.

The Effect of Conditional Accounting Conservatism on the Predictive Ability of Accrual Components with Respect to Future Cash Flows

1. Introduction

Prior research suggests that the existence of conditional conservatism or "the accountant's tendency to require a higher degree of verification to recognize good news as gains than to recognize bad news as losses" (Basu 1997, p. 7) is driven, in part, by the contracting demands of various parties that transact with the firm (e.g., Basu 1997; Holthausen and Watts 2001; Watts 2003a, 2003b). The idea advanced in this literature is that conditional conservatism facilitates efficient contracting through the timely recognition of economic losses. For example, Nikolaev (2010) argues that the timely recognition of economic losses in financial statements makes debt covenants more binding in times of distress and limits managers' opportunistic behavior. Hence, timely loss recognition enhances the debt contracting role of accounting information.

In contrast to the claimed contracting benefits of conservatism, some have claimed that conditional conservative accounting detracts from earnings' valuation role.[1] For example, Holthausen and Watts (2001) argue that evidence of the increase in timely loss recognition over time suggests a lessened emphasis by standard setters on the valuation role of earnings. Similarly, Heflin et al. (2015) contend that "...conditional conservatism reduces the usefulness of GAAP earnings for valuation by investors." Patatoukas and Thomas (2016) state that "Empirical research has largely assumed that the level of conditional conservatism provides no value-relevant information." Barth et al. (2020) argue that greater conditional conservatism is associated with slower resolution of investor disagreement and heighted uncertainty at earnings announcements, suggesting that greater conditional conservatism detracts from earnings' valuation role.

[1] We note that several studies suggest the contracting and valuation roles of accounting are complementary. For example, Bushman, Engel, and Smith (2006) and Banker, Huang, and Natarajan (2009) both find a positive relation between the value relevance of earnings and the use of earnings in compensation contracts.

More specifically, there are two main arguments for how conditional conservatism could detract from the valuation role of earnings. The first argument focuses on the degree of verification required to recognize good news in earnings. This argument asserts that ceteris paribus, a higher verification threshold for good news produces earnings information that is less timely and therefore less efficient and less value relevant (e.g., Watts 2003a; Guay 2006; Guay and Verrecchia 2006; Kothari et al. 2010). In contrast, the second argument focuses on the degree of verification required for the recognition of bad news and contends that, ceteris paribus, a lower verification threshold for recognizing bad news generates more transitory accruals that are noisier and less reliable (e.g., Guay and Verrecchia 2006; Bandyopandhyay et al. 2010; Kothari et al. 2010; Heflin et al. 2015). Prior studies refer to two types of accounting information about future cash flows: easy-to-verify information and difficult-to-verify information (e.g., Ball 2001; Watts 2003a, 2003b; Guay and Verrecchia 2006). These studies argue that timely loss recognition applies primarily to the accounting treatment of difficult-to-verify information. Thus, applying the lower verification threshold associated with timely loss recognition to difficult-to-verify information is likely to produce accruals with greater measurement error in bad news periods. For example, Bandyopandhyay et al. (2010) argue that "estimating future anticipated losses (conservative accounting) might impart measurement error and bias into accounting accruals arising from uncertainty about the amount of accruals that will be recognized in earnings."[2]

The second argument suggests that despite the timelier recognition of bad news, the quality of accruals is reduced due to difficulties in estimating the effects of bad news on accruals as well as strategic earnings management that accompanies the discretion inherent in the estimation of negative accruals such as asset write-downs and impairments (e.g., Kothari et al. 2010; Heflin et

[2] A third argument suggests that it is the actual *asymmetry* in verification thresholds that impairs the usefulness of earnings for valuation purposes (e.g., Barth et al. 2020).

al. 2015). In this study, we focus on the second argument and examine whether timely loss recognition impairs the valuation role of earnings in bad news periods.

In their review of the accounting literature related to corporate governance and debt contracting, Armstrong, Guay, and Weber (2010) assert that under the view that conservative accounting is a commitment to timely loss recognition, as opposed to an "asymmetric accounting practice for recognizing good news more slowly than bad news," the benefits of conservative reporting could potentially be realized not only in numerous contracting settings but also in valuation settings, and they call for additional research on this topic. Specifically, Armstrong et al. (2010) note that "the potential for conservative accounting to assist investors in valuation is an interesting area for future research, given the common perception (or, possibly, misperception) that although conservative accounting may assist firms in contracting and governance settings, such benefits come at the expense of accounting's role in valuation."[3] Following Armstrong et al. (2010), we take the view that accounting conservatism represents a commitment to timely loss recognition. Our study answers their call for additional research by investigating whether timely loss recognition enhances or detracts from the predictive usefulness of accruals and its components with respect to future cash flows in bad news periods.[4]

We examine the relation between timely loss recognition and the predictive ability of accruals with respect to future cash flows because prior research suggests that one way the value relevance of earnings can be measured is through the ability of earnings and its components to predict future cash flows (e.g., Dechow 1994; Finger 1994; Francis and Schipper 1999). In addition,

[3] Note that this call for additional research was published well after Ball and Shivakumar (2006), which is most closely related to our study. We discuss in detail the differences between our study and related studies including Ball and Shivakumar (2006) in Section 2.
[4] Patatoukas and Thomas (2016) also call for additional research that considers the possibility that conservative reporting provides benefits in valuation settings.

Barth et al. (2001) argue that predicting future cash flows is a fundamental element of the equity valuation process, and the FASB states that a primary objective of financial reporting is to provide information useful to market participants in assessing the amount and timing of future cash flows (see SFAC No. 8).

We predict that greater conditional conservatism resulting from more timely loss recognition will be accompanied by a greater ability of accruals to predict future cash flows in bad news periods. Our prediction builds on the reasoning that if timely loss recognition improves contracting efficiency by providing early warnings of declines in future cash flows from assets in place, then timely loss recognition should also improve the ability of earnings (through accruals) to predict future cash flows. Contrary to widely held beliefs, our evidence suggests that timely loss recognition that enhances the contracting role of accounting also enhances the valuation role of accounting by producing accruals that better predict future cash flows in bad news periods.

Specifically, we test our prediction by examining the relation between timely loss recognition and the incremental ability of accruals relative to cash flows to predict future cash flows, where timely loss recognition and the predictive ability of accruals are measured for different industry-leverage groups. We conduct our analyses on industry-leverage groups for two reasons. First, prior research suggests that the predictive ability of accruals with respect to future cash flows varies by industry (e.g., Dechow et al. 1998; Barth et al. 2001). Thus, it is important to recognize industry differences in the mapping from accruals to future cash flows. Second, we create groups of firms ranked on leverage because prior research provides consistent evidence that timely loss recognition varies with firm leverage (e.g., Watts 2003a; Zhang 2008; Khan and Watts 2009; Nikolaev 2010). Accordingly, we form industry-leverage groups by sorting firm-years into leverage deciles within the industry classifications used in Barth et al. (2001). Then, for each industry-leverage group, we estimate the level of timely loss recognition and the predictive ability of accruals with respect to future cash flows.

To estimate timely loss recognition, we employ the accruals-based adjustment to the Basu (1997) model proposed by Collins et al. (2014). We also remove the expected components of accruals and returns as recommend by Ball et al. (2013). To assess the incremental predictive ability of current period accruals over current period cash flows to predict future cash flows, we adopt the cash flow prediction model developed by Barth et al. (2001) and the R^2 decomposition approach developed by Theil (1971), which has been used in prior accounting studies (e.g., Collins et al. 1997; Kim and Kross 2005; Bandyopadhyay et al. 2010).

Consistent with our predictions, we find that industry-leverage groups that exhibit more timely loss recognition exhibit greater predictive ability of accruals with respect to future cash flows in bad news periods. Given that expected future earnings are often used in valuation, we also examine the relation between timely loss recognition and the ability of accruals to predict future earnings. Again, we document a positive association between timely loss recognition and the predictive ability of accruals with respect to future earnings in bad news periods. These results suggest more timely recognition of economic losses *improves* the ability of accruals to predict both future cash flows and future earnings, thus enhancing the valuation role of accounting numbers. We conduct numerous robustness tests to strengthen the validity of our results. For example, we show that our results are not driven by the confounding effects of cost stickiness and business curtailments on our measure of timely loss recognition (Banker et al. 2016; Lawrence et al. 2017). We also implement placebo tests similar to those in Patatoukas and Thomas (2011) and find results that further mitigate concerns about potential bias in the measure of timely loss recognition.

One concern with using industry-leverage groupings in our analyses is that firms with greater leverage may have more predictable cash flows, which facilitates raising debt capital (hence, higher leverage). To mitigate the concern that leverage is driving our main findings with respect to predictive ability, we conduct tests on industry-information asymmetry and industry-investment cycle portfolios. Studies by LaFond and Watts (2008) and Khan and Watts (2009) provide the rationale for information asymmetry and investment cycle being positively related to timely loss recognition. Unlike leverage, however, the advantage of using information asymmetry and investment cycle to form groups is that both variables are likely to be *negatively* related to the predictive ability of accruals with respect to future cash flows (e.g., Dechow et al. 1998; Healy and Palepu 2001; Nallareddy et al. 2020). Following the same procedure used with the industry-leverage groupings, we find both alternative partitioning schemes yield a significant positive relation between timely loss recognition and the ability of accruals to predict future cash flows.

This study seeks to provide clear evidence on a currently unresolved question as to whether timely loss recognition enhances or deters the valuation role of earnings (through accruals). Specifically, our study contributes to the literature on timely loss recognition (conditional conservatism) by demonstrating that firms that exhibit greater timely loss recognition also exhibit greater predictive ability of accruals with respect to future cash flows (earnings) in bad news periods. Thus, our results suggest that conditional conservative reporting actually enhances the valuation role of earnings rather than detracting from this role as some have claimed (e.g., Gjesdal 1981; Holthausen and Watts 2001; Heflin et al. 2015). Ball and Shivakumar (2006), Kim and Kross (2005), and Bandyopadhyay et al. (2010) find results that suggest there may be a positive association between conditional conservatism and the ability of earnings and earnings components to predict future cash flows. However, for reasons we elaborate in section 2, one cannot conclude from these studies whether timely loss recognition as reflected in the accrual component of earnings is what drives the increased predictive ability with respect future cash flows (earnings).

Our findings also have implications for accounting regulators. The FASB in SFAC No. 8 (2010) removed conservatism as an important qualitative characteristic of accounting and has gone on record as favoring more "neutral" accounting practices. The IASB, however, includes in its Conceptual Framework the idea of "prudence" defined as the exercise of caution when making judgements under conditions of uncertainty, as a desirable qualitative characteristic of accounting. Although the exercise of prudence does not necessarily imply a need for asymmetry in the recognition of good news and bad news, asymmetric recognition requirements may be used in cases when they yield information that faithfully represents what it purports to represent.[5] Accurate assessments of the costs and benefits of timely loss recognition require an understanding of the implications of conditional conservatism on the valuation role of earnings. Our results provide evidence on the valuation benefits of conservative reporting.

The remainder of the paper is organized as follows. In the next section, we discuss the motivation for our study and develop our hypothesis. Section 3 outlines the research design and Section 4 presents the sample and empirical results. Section 5 describes additional analyses. Section 6 concludes and discusses the implications of our findings.

2. Motivation and Hypothesis Development

Accounting information not only plays an important role in the various contracting settings of the firm, but it is also useful to investors making valuation and investment decisions. A large literature supports the notion that accounting information is useful in valuation contexts (see Richardson et al. 2010; Kothari 2001 and others for reviews of this literature). The ability to predict

[5] See paragraphs 2.16 and 2.17 of the IASB's *Conceptual Framework for Financial Reporting* as revised in March 2018.

future cash flows is central to the determination of the market value of a firm's equity (e.g., FASB 2010). Several studies have examined the ability of accounting earnings and its cash flow and accrual components to predict future cash flows (e.g., Dechow 1994; Finger 1994; Dechow et al. 1998; Barth et al. 2001). In particular, Barth et al. (2001) build on the Dechow et al. (1998) model and demonstrate that different accrual components reflect different information about future cash flows. Barth et al. (2001) find that disaggregating accruals into major components can significantly improve the predictive ability of accruals with respect to future cash flows.[6]

Other studies have argued that the contracting role of accounting is inconsistent with the valuation role of accounting (e.g., Gjesdal 1981; Holthausen and Watts 2001; Heflin et al. 2015). Timely loss recognition applies primarily to the accounting treatment of difficult-to-verify information (e.g., Ball 2001; Watts 2003a, 2003b; Guay and Verrecchia 2006). Thus, the lower loss-recognition threshold of timely loss recognition increases transitory components in earnings (e.g., Ball and Shivakumar 2005; Heflin et al. 2015), which reduce earnings persistence and thus could decrease the informativeness of earnings and its components (e.g., Collins and Kothari 1989; Tucker and Zarowin 2006). Additionally, management can abuse the lower verification threshold associated with timely loss recognition by recognizing too much bad news via "big bath" accruals (e.g., Kothari et al. 2010). Management can also use the lower verification threshold as an earnings-smoothing device to generate "cookie-jar" reserves (e.g., DeAngelo et al. 1994; Francis et al. 1996; Myers et al. 2007).

If accrual estimates reflecting more timely recognition of losses are noisy, then the noisy accruals could have decreased ability to predict future cash flows. For instance, Ball and

[6] Byzalov and Basu (2016) and Banker et al. (2017) discuss the differences in impairment tests for different assets and provide an explanation for why disaggregating accruals can significantly increase ability of accruals to predict future cash flows.

Shivakumar (2006) document that when market-adjusted abnormal returns are used as the proxy for bad news, the predictive ability of earnings components (accruals and cash flows) for future cash flows is marginally greater in good news years than in bad news years (p.239). Ball and Shivakumar interpret this preliminary result as indicating that, when abnormal returns are the loss proxy, accruals in bad news years are noisier. On the other hand, if timely loss recognition improves contracting efficiency by providing early warnings of declines in future cash flows from assets in place, then timely loss recognition should improve the ability of earnings (through accruals) to predict future cash flows. Thus, whether conditional conservative reporting enhances the predictive ability of accruals with respect to future cash flows remains an open question.

Given that timely loss recognition is triggered by bad news, it is important to distinguish between good news and bad news periods when assessing whether timely loss recognition enhances or detracts from the usefulness of accruals in predicting future cash flows. If timely loss recognition enhances the usefulness of accruals for valuation, then we expect that timely loss recognition will improve the ability of accruals and its components to predict one-period ahead future cash flows in bad news periods. If, on the other hand, the claims in prior studies that greater timely loss recognition detracts from the usefulness of earnings and its components in valuation are correct, then we expect timely loss recognition to be negatively related (or unrelated) with the ability of accruals to predict future cash flows in bad news periods.

Our study is related to Ball and Shivakumar (2006) who use the following two specifications to examine the improved predictive ability (in terms of adjusted R^2) that results from a *piecewise linear* regression versus a *linear* regression in predicting future operating cash flows:

Linear regression: $$CF_{it+1} = \beta_0 + \beta_1 CF_{it-1} + \beta_2 ACC_{it-1} + \beta_3 CF_{it} + \beta_4 ACC_{it} + \varepsilon_{it+1} \quad (1)$$

Piecewise linear regression: $$CF_{it+1} = \alpha_0 + \alpha_1 CF_{it-1} + \alpha_2 ACC_{it-1} + \alpha_3 CF_{it} + \alpha_4 ACC_{it} + \alpha_5 DVAR_{it} + \alpha_6 CF_{it} * DVAR_{it} + \alpha_7 ACC_{it} * DVAR_{it} + \varepsilon_{it+1} \quad (2)$$

where DVAR is an indicator variable for bad news.[7] Ball and Shivakumar (2006) report in their Table 9 that the explanatory power of the piecewise linear regression in equation (2) is substantially larger than that of the linear regression in equation (1). Importantly, Ball and Shivakumar (2006) interpret the results in Table 9 as evidence consistent with conditional conservatism either improving or *impairing* the predictive ability of accruals in bad news periods.[8] Ball and Shivakumar then conduct an untabulated analysis of equation (2) separately for good news years versus bad news years to evaluate whether Table 9 suggests timely loss recognition improves the predictive ability of accruals (which implies greater explanatory power in loss years) or impairs the predictive ability of accruals (which implies lower explanatory power in loss years).

The results of this analysis are mixed. Although equation (2) yields substantially higher adjusted R^2 in bad news years relative to good news years for three of their four loss proxies, the important exception is when market-adjusted abnormal returns are used as the loss proxy. For this loss proxy, Ball and Shivakumar (2006) find the R^2 values are marginally *lower in bad news years* than in good news years (53.2% vs 56.3%). This is a critical finding given that (1) the result is inconsistent with timely loss recognition improving the predictive ability of accruals in bad news years, and (2) abnormal returns are the most widely used and least problematic loss proxy in the literature (e.g., Ryan 2006; Ball, Kothari and Nikolaev 2013).[9] Thus, one cannot rule out the

---

[7] Bad news is measured as either negative cash flows, decreases in cash flows, negative industry adjusted cash flows, or negative market-adjusted abnormal returns.

[8] Ball and Shivakumar (2006, p. 239) state "The significant incremental coefficient on accruals in loss years, although consistent with asymmetrically timely loss recognition, alternatively could indicate that accruals in loss years are noisier. The predictive regression for future cash flows then would have lower explanatory power in loss years."

[9] Ryan (2006) states that the primary drawback with using operating cash flows as a measure of news "is the difficulty of identifying variables that convey news in a fashion remotely as comprehensive as returns while not introducing other model specification problems. For example, while operating cash flows are perhaps the most natural choice in terms of comprehensiveness, they raise a host of issues of their own: they exhibit asymmetric timeliness, are affected by a number of accounting choices (e.g. capital vs. operating leases), are a part of earnings and are correlated with accruals in a highly contextual fashion."

explanation that the differences in predict ability are driven by noisy accruals resulting from the lower verification threshold for recognizing bad news in a more timely fashion.

Moreover, in equation (2), both the accrual and cash flow components of earnings are allowed to vary in good news versus bad news periods, i.e., equation (2) tests the benefits of allowing for piecewise linearity in <u>both</u> cash flows and accruals. Thus, the R^2 analysis Ball and Shivakumar (2006) conduct cannot distinguish whether the increased predictive ability is due to cash flows, accruals, or both. This is critical because an increase in explanatory power generated by modeling a piecewise linear relation between current and future cash flows cannot be attributed to conditional conservatism.[10] Note that cash flows appear to be the primary determinant in the model based on the magnitudes of the reported coefficients and t-statistics.[11]

Our study differs from Kim and Kross (2005) and Bandyopadhyay et al. (2010) in two significant ways. First, Kim and Kross (2005) and Bandyopadhyay (2010) examine the relation between *overall* conservatism (both unconditional and conditional conservatism) and the predictive ability of accruals.[12] Because unconditional conservatism preempts conditional conservatism and measures of overall conservatism tend to correlate negatively with asymmetric timely loss recognition (e.g., Givoly et al. 2007), one cannot interpret a positive relation between

[10] Basu (1997, p. 19) notes: "The increased timeliness of earnings over cash flows for 'bad news" [negative return periods] but not 'good news' is consistent with accounting conservatism being reflected in accruals." Collins et al. (2014) show that earnings asymmetric timeliness captures both accrual and operating cash flow (CFO) asymmetric timeliness. Because recognition of operating cash flows does not reflect differential verification thresholds for recognizing unrealized gains versus losses, CFO asymmetry adds noise or bias to tests of conditional conservatism. Moreover, they show that non-linearity in cash flows is largely a function of firms' life-cycle stage.

[11] In addition, Nallareddy, Sethuraman, and Venkatachalam (2020) find that the cash flow component dominates the accrual component in predicting future cash flows.

[12] In fact, Bandyopadhyay et al. (2010) clearly state that their "paper does not attempt to disentangle the effect of conditional versus unconditional conservatism" (p. 423). The measures of conservatism (e.g., cumulative non-operating accruals) used by Kim and Kross (2005) and Bandyopadhyay et al. (2010) are likely to be driven primarily by unconditional conservatism (e.g., Ryan 2006).

overall conservatism and the predictive ability of accruals as evidence that conditional conservatism improves the predictive ability of accruals.

A second important difference between our study and these two earlier studies is that the accrual measures used by Kim and Kross (2005) and Bandyopadhyay et al. (2010) are measures as year-over-year changes in balance sheet working capital accounts, which are contaminated by measurement error. Hribar and Collins (2002) point out the non-trivial and pervasive errors that occur when using the balance sheet approach to measure accruals (and cash flows) because of mergers and acquisitions and divestitures.[13] These errors can be particularly problematic in studies examining the ability of cash flows and accruals to predict future cash flows and studies estimating conditional conservatism as pointed out by Nallareddy et al. (2020) and Chen et al. (2020).[14] Our study uses accruals and cash flows taken directly from the cash flow statement.

3. Research Design

We conduct our analyses at an industry-leverage group level. The following is an overview of key steps in our design:

Step 1 – Sort firm-year observations into industry-leverage groups.

Step 2 – Estimate the level of timely loss recognition for each industry-leverage group.

Step 3 – Estimate the incremental predictive ability of accruals over cash flows in bad news periods for each industry-leverage group.

Step 4 – Regress the incremental predictive ability of accruals on the level of timely loss recognition across industry-leverage portfolios.

[13] Chen, Collins, Hribar, and Volant (2022) document that the balance sheet approach to measuring accruals and then backing into operating cash flows from the earnings identity equation produces negatively correlated measurement errors in accruals and cash flows. They show that this approach biases the coefficient on accruals upward and the coefficient on cash flows downward when these measures are used as regressors, which can result in nontrivial Type I and Type II errors relative to using accrual and cash flow measures from the statement of cash flows.

[14] Kim and Kross (2005) and Bandyopadhyay et al. (2010) both document that temporal increases in conservatism result in the increasing ability of current earnings to forecast future cash flows. However, Nallareddy et al. (2020) find that the temporal "trends in conservatism ... are less likely to explain the increasing predictive ability of earnings or cash flows (p.15)"

Each of the steps in our research design is important and allows us to draw more direct inferences about whether increased timely loss recognition (as reflected in the accrual components of earnings) contributes to the increased ability of the accrual components of earnings to predict future cash flows and future earnings.

Step 1: Sort firm-year observations into industry-leverage groups

We partition the sample by industry because the ability of accruals to predict future cash flows varies by industry due to differences in business models and operating activities (e.g., Dechow et al. 1998; Barth et al. 2001). Thus, we separate our sample into the 13 industries as defined in Barth et al. (2001).[15] Next, within each industry, we form deciles of firm-years pooled over time based on firm leverage. Prior literature suggests that timely loss recognition varies with firm leverage (e.g., Watts 2003a; Zhang 2008; Khan and Watts 2009; Nikolaev 2010).[16] For instance, Khan and Watts (2009) include leverage as one of the three firm-specific characteristics used to construct a firm-year measure of conditional conservatism (the other two variables are market-to-book and size). Therefore, we partition the observations in each industry based on leverage to create groups of firm-year observations that exhibit variation in timely loss recognition.[17]

[15] Utilities (SIC codes between 4900 and 4999) is one of the 13 industries classified in Barth et al. (2001). We exclude firms in the Utilities industry (a heavily regulated industry) from our analysis.

[16] Agency conflicts between lenders and shareholders drive the demand for timely loss recognition, which allows debt covenants to become binding in times of distress. For example, Ahmed et al. (2002) find that firms facing more severe bondholder-shareholder conflicts over dividend policy tend to adopt more conservative accounting practices. Zhang (2008) finds accounting conservatism benefits lenders through timely signaling of default risk and benefits borrowers through lower initial interest rates.

[17] One concern with this research design is that leverage could affect not only timely loss recognition, but also the predictive ability of accruals with respect to future cash flows. If firms with higher leverage also have accruals that are more predictive of future cash flows in bad news periods, then a positive relation between timely loss recognition and the predictive ability of accruals could be misattributed to timely loss recognition. To address this concern, we also examine the relation between leverage and the predictive ability of accruals in good news periods. Here, we partition good news observations in each industry into high and low leverage groups and find no evidence of a positive relation between leverage and predictive ability (results untabulated). We also conduct analyses by using information asymmetry and investment cycle to partition observations within industries (see section 5).

Step 2: Estimate the level of timely loss recognition for each industry-leverage group

We estimate timely loss recognition for each industry-leverage group using the accruals-based modification to the Basu (1997) model proposed by Collins et al. (2014). Collins et al. document that the operating cash flow component of earnings does not reflect differential verification thresholds for recognizing unrealized gains versus unrealized losses. In addition, Ball et al. (2013) demonstrate that failing to control for expected earnings and expected returns in a Basu-type model can lead to biased estimates of conditional conservatism (timely loss recognition). Thus, we estimate the bad news timeliness with the following specification:

$$ACC^*_{itk} = \beta_{0k} + \beta_{1k}D_{itk} + \beta_{2k}AbRet_{itk} + \beta_{3k}AbRet_{itk} * D_{itk} + \epsilon_{itk} \quad (3)$$

where i, t, and k indicate firm, year, and industry-leverage group respectively. ACC^*_{itk} indicates unexpected accruals, calculated as total operating accruals minus lagged total operating accruals ($ACC_{itk} - ACC_{i,t-1,k}$). We use total operating accruals as the dependent variable because conditional conservatism is manifested through accruals such as asset write-downs, goodwill impairments, and restructuring charges (e.g., Basu 1997; Collins et al. 2014). We use lagged operating accruals as a proxy for expected accruals (see Patatoukas and Thomas 2016) and use 5×5 size and book-to-market portfolio returns as our proxy for expected returns.[18] Abnormal return ($AbRet_{itk}$) is our proxy for news. D_{itk} is a dummy variable equal to one if $AbRet_{itk} < 0$, and zero otherwise. In equation (3), bad news timeliness (BT_k) is measured as the sum of β_{2k} and β_{3k}, which captures the bad news timeliness for industry-leverage group k.

Step 3: Estimate the predictive ability of accruals over cash flows in bad news periods

[18] The 5×5 size and book-to-market reference portfolios are constructed annually, and the portfolio returns are obtained from Ken French's data library. The average return for each portfolio is used as a measure of expected return for the portfolio firms.

Consistent with prior studies (e.g., Collins et al. 1997; Kim and Kross 2005), we use R^2 decomposition (Theil 1971) to estimate the incremental ability of accruals relative to cash flows to explain future cash flows. This is important because it is the accrual component, not the cash flow component, of earnings that reflects timely loss recognition (Basu 1997; Collins et al. 2014), and we examine whether timely loss recognition as reflected in accruals is what drives the increased predictive ability with respect future cash flows.[19] To measure incremental predictive ability, we first regress future (t+1) cash flows on current period (t) cash flows:

$$\bar{R}_{1k}^2: \quad CF_{i,t+1,k} = \beta_{0k} + \beta_{1k} CF_{i,t-1,k} + \beta_{2k} ACC_{i,t-1,k} + \beta_{3k} CF_{itk} + \mu_{itk} \tag{4}$$

We include $CF_{i,t-1,k}$ and $ACC_{i,t-1,k}$ to control for expected cash flows at the beginning of year t (see Ball and Shivakumar 2006). We denote the adjusted R^2 from this equation as $\bar{R}_{1k}^2$.

Next, we augment equation (4) by introducing separate accrual components (taken from the cash flow statement). Barth et al. (2001) show that disaggregating total operating accruals into separate accrual components significantly enhances the ability of accruals to predict future cash flows. This is because the various accrual components contain specific information about, and exhibit different relations with, future cash flows. Thus, disaggregating accruals into its component parts allows for a more complete specification for evaluating accruals' usefulness in predicting future cash flows. We decompose accruals into six components: changes in account receivable (ΔAR), changes in inventory (ΔINV), changes in account payable (ΔAP), depreciation and amortization (DPC), other accruals ($OTHER$), and special items (SI).[20] The predictive ability of this augmented model is given by the $\bar{R}_{2k}^2$ from the following equation:

[19] Another reason that we focus on accruals, rather than earnings, is that factors such as a firm's life-cycle stage can affect cash flow asymmetry (Collins et al. 2014) and life-cycle stage is likely to be related to the ability of earnings components to predict future cash flows (earnings).

[20] Several studies suggest special-item accruals and non-special-item accruals have different predictive abilities with respect to future cash flows (e.g., Burgstahler et al. 2002; Cready et al. 2010; Cready et al. 2012). We adjust the *OTHER* component of accruals (obtained from the cash flows statement) so that it does not include any special-item

$$\bar{R}^2_{2k}: \quad CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AR_{itk} + \beta_{5k}\Delta INV_{itk}$$
$$+\beta_{6k}\Delta AP_{itk} + \beta_{7k}DPC_{itk} + \beta_{8k}OTHER_{itk} + \beta_{4k}SI_{itk} + \mu_{itk} \quad (5)$$

The incremental explanatory power of $\bar{R}^2_{2k}$ over $\bar{R}^2_{1k}$ (i.e., $\bar{R}^2_{2k} - \bar{R}^2_{1k}$) captures the incremental predictive ability of accruals relative to cash flows with respect to future cash flows. Importantly, we use only observations in bad news periods to assess the predictive ability of accruals because we are interested in evaluating the impact of bad news timeliness, which is manifested in bad news (negative abnormal return) periods, on predictive ability.

Step 4: Regress the predictive ability of accruals on the level of timely loss recognition

After estimating the bad news timeliness and incremental predictive ability of accruals for each industry-leverage group, we employ the following specification to estimate the relation between bad news timeliness and the predictive ability of accruals with respect to future cash flows:

$$PA\_ACC_k = \beta_0 + \beta_1 BT_k + \beta_2 FirmAge_k + \beta_3 InvCycle_k + \beta_4 Volatility_k$$
$$+\beta_5 InfoAsym_k + \beta_6 Size_k + \beta_7 MTB_k + \beta_8 Lev_k + Industry\ Fixed\ Effects + e \quad (6)$$

where k indicates the industry-leverage group. PA_ACC_k is the incremental predictive ability of accruals, calculated as $\bar{R}^2_{2k} - \bar{R}^2_{1k}$ from estimating equations (4) and (5); BT_k is the bad news timeliness of accruals, calculated as $\beta_{2k} + \beta_{3k}$ from estimating equation (3).[21] BT_k is our variable of interest. Consistent with the contracting role of accruals enhancing the valuation role of accruals, we expect that the timely loss recognition exhibited by accruals will be positively associated with

accruals. Because we derive special item accruals (*SI*) using Compustat's *SPI* variable, which includes unusual or nonrecurring items presented above taxes, we adjust the special items to an after-tax basis to remove the tax effects of special item accruals from *OTHER*. In doing so, we apply a tax rate of 35% to all firm-years (e.g., Burgstahler et al. 2002), as it is not practical to determine the tax rate for each observation. The tax effects related to non-special-item accruals are captured in the *OTHER* component of accruals. Additionally, because special items can include items such as restructuring costs (e.g., severance pay for terminated employees) and litigation settlements, not all special item components are accruals. However, we follow the research design of Dechow and Ge (2006) who demonstrate that the major components in special items are accruals, and decompose accruals into special-items and non-special-items accruals by treating the Compustat variable (*SPI*) for special items as special-item accruals.

[21] Later, in Table 6, we assess the association between asymmetric timely loss recognition as measured by the β_{3k} coefficient in Eqn (3) and the predictive ability of accruals in bad news versus good news periods.

the incremental ability of accruals to predict future cash flows in bad news periods, i.e. we expect a positive β_1 coefficient on BT_k.

Following prior literature (e.g., Dechow et al. 1998; Barth et al. 2001; Ball et al. 2013; García Lara et al. 2016), we include a set of control variables in equation (6) that prior research has shown to be correlated with the predictive ability of accruals. Each of the control variables is calculated as the average value within each industry-leverage group. For example, $FirmAge$ is the average firm age of all firm-year observations within an industry-leverage group, where the age of a firm in a given year is measured as the duration (in number of years) of the firm's return history on CRSP. See appendix A for the definition of variables. The inclusion of leverage (*Lev*) as a control is critical as it alleviates the concern that the coefficient on BT_k could reflect a relation between leverage and the predictive ability of accruals that is independent of timely loss recognition. We also include industry fixed effects based on the same industries used in creating the industry-leverage groups.

In addition to predicting future cash flows, we also investigate the relation between bad news timeliness and the predictive ability of accruals with respect to *future earnings*. Earnings is a key performance metric used by managers, analysts, shareholders, and debt holders. Prior studies in the value relevance and fundamental analysis literature highlight the importance of forecasting future earnings for valuation purposes.[22] Moreover, survey evidence reveals that managers are willing to sacrifice economic value in exchange for more predictable earnings (Graham et al. 2005). In addition, investors pay close attention to earnings and reward (penalize) firms for reporting earnings that meet (miss) analysts' earnings forecasts (e.g., Degeorge et al. 1999; Brown and

[22] Studies often use earnings, residual earnings, or earnings growth as a primary input to valuation (e.g., Finger 1994; Ohlson 1995; Abarbanell and Bushee 1997; Nissim and Penman 2001; Dichev and Tang 2009; Holthausen and Watts 2001; Richardson et al. 2010).

Caylor 2005). Therefore, we also examine whether timely recognition of economic losses is positively associated with the predictive ability of accruals with respect to future earnings in bad news periods. To do this, we substitute future earnings (E_{t+1}) as the dependent variable in equations (4) and (5) to estimate the incremental ability of accruals to predict future earnings. Similarly, we use equation (6) to investigate the relation between bad news timeliness and the predictive ability of accruals with respect to future earnings.

4. Empirical Analyses

4.1 Sample and descriptive statistics

Our sample consists of firm-years from 1988 to 2017 obtained from the Compustat database. The sample begins in 1988 due to the availability of statement of cash flow data, which allows a direct calculation of accruals and cash flows (see Hribar and Collins 2002). In constructing our sample, we exclude financial institutions (SIC codes between 6000 and 6999) and firms in regulated industries (SIC codes between 4900 and 4999). We also eliminate holding companies, American Depositary Receipts (ADRs), and limited partnership organizations. We impose a minimum price filter, $Price_t > \$1$, to exclude firms with very low stock prices to avoid low denominator scaling problems. Additionally, we eliminate observations with negative shareholders' equity.[23] We also require observations to have non-missing data for variables used in regressions.[24] All continuous variables are truncated at the 2nd and 98th percentiles.[25] We also exclude firm-years that have merger and acquisition or divestiture transactions either in the year in which the prediction variables are measured (year *t*) or the year in which cash flows are being

[23] Our main results are robust to including observations with negative shareholder equity.
[24] We calculate changes in accounts receivable (*RECCH*), changes in inventory (*INVCH*), changes in accounts payable (*APALCH*) from the statement of cash flows. Following Barth et al. (2001), if *RECCH*, *INVCH*, or *APALCH* are missing, then ΔAR, ΔINV, and ΔAP are calculated as the change in accounts receivable (*RECT*), inventory (*INVT*), and accounts payable (*AP*) plus accrued expenses (*XACC*), respectively, using successive balance sheet information.
[25] We truncate the top and bottom 2% of the continuous variables to mitigate the effect of outliers on our results, in particular the out-of-sample analysis in section 5.

predicted (year t+1).[26] These transactions confound the relation between accruals in period t and operating cash flows in period t+1 used in our predictive ability tests because the entities that make up the consolidated totals taken from Compustat are different across adjacent years. Table 1 summarizes our sample selection procedure.

The final sample consists of 28,113 firm-years over the period 1988-2017. Table 2, Panel A summarizes the descriptive statistics. While the mean of *CF* is positive (7.0% of lagged market value of equity), the mean is negative for *ACC* (-5.6%), reflecting the fact that total accruals are dominated by depreciation and amortization accruals. Panel B of Table 2 reports Pearson and Spearman correlations. The correlations between earnings, cash flows, and accrual components are consistent with those reported in Barth et al. (2001). Also, consistent with Dechow and Ge (2006), special items are positively correlated with total accruals. As discussed in section 3, we partition the sample by the industries identified in Barth et al. (2001), and then further partition the firm-years within each industry into deciles based on firm leverage. We require a minimum of 40 bad news observations (negative abnormal returns) for each group.[27] After imposing these restrictions, we obtain 92 industry-leverage groups.[28]

4.2 Empirical results: Bad news timeliness and the predictive ability of accruals

We first report bad news timeliness and the predictive ability of accruals for each industry to provide a sense of variation in the level of timely loss recognition and predictive ability of accruals with respect to future cash flows across industries. Panel A of Table 3 reports the results

[26] We obtain the M&A sample from SDC Platinum. We identify the divestiture sample from three sources: (i) observations marked with divestiture or spinoff in SDC Platinum; (ii) observations with distribution code indicating a divestiture in CRSP (i.e., *distcd* = 3762, 3763, or 3764), and (iii) observations with discontinued operations greater than $500,000.

[27] This requirement results in the exclusion of firms in Agriculture (sic codes 0100-0999) and Mining & Construction (sic codes 1000–1999 excluding 1300–1399).

[28] The presence of zero-leverage firms has led to the uneven distribution of groups. Some groups that include zero-leverage firms are disproportionately large, while others have fewer observations. This imbalance has resulted in a total of 92 industry-leverage groups instead of the anticipated 100.

of estimating equation (3) for firm-year observations in each industry and shows that bad news timeliness [$\beta_{2k} + \beta_{3k}$ in equation (3)] differs considerably across industries. For example, the bad news timeliness varies from -0.007 for the pharmaceuticals industry to 0.084 for the chemicals industry. To demonstrate that bad news timeliness varies with firm leverage, we split the sample into two groups using the median leverage in each industry.[29] Panel B of Table 3 reports the bad news timeliness for firm-year observations with high versus low leverage. As expected, the results indicate that bad news timeliness is higher for the high leverage group compared to the low leverage group (the difference is statistically significant).

Table 4 presents the adjusted R^2 values from estimating the predictive ability of equations (4) and (5). The results show that the predictive ability of accruals varies considerably across industries, likely due to differences in business models and operating activities (e.g., Dechow et al. 1998; Barth et al. 2001). For example, the adjusted R^2 from estimating predictive ability equation (5) ranges from 21.4% for the textile & printing industry to 54.3% for the pharmaceuticals industry. These differences, together with the differences in bad news timeliness across industries, illustrate the importance of partitioning the sample into industries in our research design. It is important to note that in Table 4 we use only bad news observations (i.e., observations with negative abnormal returns) to estimate the predictive ability of accruals because we are interested in how variation in timely loss recognition, which is manifested in bad news periods, affects the ability of accruals generated in those bad news periods to predict future cash flows.

We next consider the relation between bad news timeliness and the incremental predictive ability of the accrual component relative to the cash flow component of earnings with respect to one-period ahead future cash flows (CF_{t+1}). Column (1) of Table 5 presents the results from

[29] We use the median leverage in each industry because our main analyses rely on within-industry variation in leverage.

estimating equation (6). Consistent with our hypothesis, we observe a positive and significant coefficient estimate for BT_k (coef = 0.249; t-statistic = 3.11), suggesting that more timely recognition of economic losses improves the predictive ability of accruals with respect to future cash flows. The coefficients on most of the control variables have the expected sign but are not statistically significant. The lack of significance could be because the control variables are calculated as the average of firm-year observations in each industry-leverage group and there are only 92 observations (i.e., industry-leverage groups) in the sample, which limits the power of testing for the significance of these regression coefficients.

Column (2) of Table 5 presents the results from estimating equation (6) where the dependent variable is the incremental predictive ability of accruals with respect to one-year-ahead earnings. Consistent with the results in column (1), the coefficient estimate for BT_k is positive and significant (coef = 0.266; t-statistic = 2.42). Overall, Table 5 shows that more timely recognition of economic losses improves the ability of accruals to predict both future cash flows and future earnings.[30] These results are consistent with the notion that accruals not only improve contracting efficiency through increased timely loss recognition, but also enhance the valuation role of earnings by improving the predictive ability of accruals with respect to future cash flows and future earnings in bad news periods.

We also examine the association between *asymmetric* timeliness and the predictive ability of accruals with respect to future cash flows and earnings. Here, we focus on the *asymmetric* predictive ability of accruals in bad news versus good news periods because differences in

[30] We also examine the association between bad news timeliness and the predictive ability of accruals with respect to two-year-ahead and three-year ahead cash flows and earnings. We observe positive but insignificant coefficients on *BT* in all regressions. A potential reason that we do not find significant results is that our test power is reduced due to fewer industry-leverage groups. We obtain 81 (64) industry-leverage groups when the cash flows prediction window is two (three) years ahead, compared with 92 industry-leverage groups when the prediction window is one-year ahead (see section 4.1 for our sample selection procedure).

asymmetric timeliness (across industry-leverage groups) could be due to differences in bad news timeliness or differences in good news timeliness (or both). Given the results in Table 5, we expect a greater difference in the predictive ability of accruals in bad news versus good news periods when asymmetric timeliness is greater. Asymmetric timeliness is estimated as β_3 from equation (3), and the asymmetric predictive ability of accruals is calculated as the predictive ability of accruals in bad news periods minus the predictive ability of accruals in good news periods, where the predictive ability of accruals is estimated from equations (4) and (5). Table 6 reports a positive and significant association between asymmetric timeliness (*AT*) and asymmetric predictive ability of accruals (*Asym_PA_ACC*) with respect to future cash flows (coef = 0.579; t-stat = 4.22) and future earnings (coef = 0.29; t-stat = 1.66) in column (1) and (2) respectively. The results in Table 6 suggest that the greater the asymmetric timeliness, the greater the difference in the predictive ability of accruals in bad news versus good news periods.

5. Additional Analyses

5.1 Asset-based accrual bad news timeliness and predictive ability

We conduct several additional analyses to address the possibility that the results presented in Table 5 are driven by factors other than timely loss recognition. Ijiri and Nakano (1989) and Hsu et al. (2012) argue that conditional conservatism is more likely to manifest in asset-related accruals (e.g., loan loss provisions, LCM rule for inventories, asset impairments, goodwill write-offs, and restructuring charges) than in liability accruals.[31] Therefore, we rerun our estimates of timely loss recognition and the predictive ability of accruals after excluding from accruals the changes in accounts payable. If the increased predictive ability of accruals with respect to future

[31] We continue to include depreciation and amortization expenses (DPC) in our measure of asset-based accruals because these expenses are subject to timely loss recognition. Managers can recognize economic losses more timely by reducing the estimated useful lives of long-term assets thereby increasing the depreciation expense estimates (e.g., Basu 1997; Hsu et al. 2012; Collins et al. 2014).

cash flows is attributable to increases in timely loss recognition that occur through asset-based accruals, we should find the positive relation for accruals consisting of ΔAR, ΔINV, DPC, $OTHER$, and SI, but not for ΔAP. We use the following equation to estimate the bad news timeliness associated with accruals excluding changes in accounts payable ($ACCxAP$):

$$ACCxAP^{*}_{itk} = \beta_{0k} + \beta_{1k}D_{itk} + \beta_{2k}AbRet_{itk} + \beta_{3k}AbRet_{itk} * D_{itk} + \epsilon_{itk} \quad (7)$$

where $ACCxAP^{*}_{itk}$ indicates the unexpected component of accruals excluding changes in accounts payable and is calculated as $ACCxAP_{itk} - ACCxAP_{i,t-1,k}$. The other variables are as previously defined. $\beta_{2k} + \beta_{3k}$ captures the bad news timeliness associated with $ACCxAP_{itk}$.

We examine the predictive ability of $ACCxAP$ with respect to future cash flows by calculating the incremental R-squared of equation (9) over equation (8).

$$\bar{R}^2_{3k}: \quad CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AP_{itk} + \mu_{itk} \quad (8)$$

$$\bar{R}^2_{4k}: \quad CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AR_{itk} + \beta_{5k}\Delta INV_{itk}$$
$$+\beta_{6k}\Delta AP_{itk} + \beta_{7k}DPC_{itk} + \beta_{8k}OTHER_{itk} + \beta_{9k}SI_{itk} + \mu_{itk} \quad (9)$$

where $\bar{R}^2_{4k} - \bar{R}^2_{3k}$ reflects the incremental predictive ability of $ACCxAP$. We then estimate equation (6) to examine whether timely recognition of economic losses improves the predictive ability of $ACCxAP$ with respect to future cash flows. Additionally, we replace the dependent variables in equations (8) and (9) with future earnings ($E_{i,t+1,k}$) and use equation (6) to examine whether timely loss recognition enhances the predictive ability of $ACCxAP$ for future earnings.

Table 7 reports the results of this analysis. The coefficient on BT_k in column (1) for predicting future cash flows with asset-based accruals is positive and significant (coef = 0.139; t-statistic = 1.97), indicating that increases in the timely loss recognition associated with $ACCxAP$ are positively related to increases in the ability of $ACCxAP$ to predict future cash flows. We also find the coefficient on BT_k in column (2) for predicting future earnings with asset-based accruals is positive and significant (coef = 0.200; t-statistic = 2.09). Columns (3) and (4) report results for the association between timely loss recognition associated with ΔAP and the predictive ability of ΔAP accruals with respect to future cash flows and future earnings respectively. Neither of the coefficients on BT_k is significant when using these liability-based accruals. Thus, the results in Table 7 indicate that the association between timely loss recognition and predictive ability is concentrated in asset-related accruals. These results provide additional support for our main hypothesis by demonstrating that the asset-based accrual components that contribute to the increase in timely loss recognition are the same accruals that exhibit a greater ability to predict future cash flows and future earnings.

5.2 Partitioning variables in addition to leverage

We conduct our primary analyses using industry-leverage groups. One potential issue with forming groups based on leverage, however, is that in addition to the positive relation between timely loss recognition and leverage, firms with more predictable future cash flows likely have greater access to external credit and could therefore have higher leverage. Although we address this concern in our main analysis by including leverage as a control variable in equation (6), we also conduct our analyses using (i) groups formed by industry and information asymmetry and (ii) groups formed by industry and investment cycle length. More specifically, we follow the same procedure as outlined in section 3 (results reported in Table 5), except instead of using industry-leverage groups we use industry-information asymmetry groups and industry-investment cycle groups. The advantage of partitioning on information asymmetry and investment cycle is that prior literature suggests that both variables are positively related to timely loss recognition (e.g., LaFond and Watts 2008; Khan and Watts 2009) but are likely to be *negatively* related to the predictability of future cash flows (e.g., Dechow et al. 1998; Healy and Palepu 2001; Nallareddy et al. 2020).

Consistent with the results in Table 5, the results of these additional tests reported in Table 8 indicate a positive relation between timely loss recognition and the ability of accruals to predict future cash flows. Using information asymmetry as the partitioning variable the coefficient (t-statistic) on *BT* is 0.213 (1.95) and using investment cycle the coefficient (t-statistic) is 0.296 (2.25). Although the coefficient estimates for *BT* are positive when the dependent variable is the incremental predictive ability of accruals with respect to future earnings, they are not significant at conventional levels. Overall, these results provide additional evidence that timely loss recognition improves predictive ability of accruals with respect to future cash flows.

5.3 Out-of-sample analysis of predictive ability

We conduct an out-of-sample analysis to mitigate the concern that our findings are driven by the look-ahead bias inherent in within-sample testing. Consistent with prior literature (e.g., Clark and West 2007; Rouxelin et al. 2018), we use root mean squared errors (RMSE) to evaluate the out-of-sample forecasting performance of accruals with respect to future cash flows. If timely loss recognition improves the ability of accruals to predict future cash flows, the accruals of firms exhibiting more time loss recognition should produce better out-of-sample predictions of future cash flows evidenced by lower RMSE.

The out-of-sample analysis is built on the research design outlined in section 3. Specifically, we partition the sample by industry because the ability of accruals to predict future cash flows varies by industry. We further partition the observations in each industry into two groups according to leverage. Partitioning observations into two, rather than ten, leverage groups allow us to have enough observations in each industry-leverage-year to calculate a meaningful RMSE. Our holdout period is from 2001 to 2016. Consistent with our in-sample analysis, we assess the improvement in out-of-sample forecasting performance with respect to future cash flows when accrual components are included as additional predictor variables. The results (untabulated) show that the accruals in firms with higher leverage (i.e., firms exhibiting more timely loss recognition) reduce the RMSE of predicted future cash flows to a larger extent. The finding is consistent with our hypothesis that timely loss recognition improves the ability of accruals to predict future cash flows. We also conduct an out-of-sample analysis on predicting future earnings and find that accruals of firms with higher leverage play a larger role in reducing the RMSE of predicted future earnings, though the effect is not significant at conventional levels. We provide the additional details of this analysis in appendix B.

5.4 Generated regressor

The variable of interest (*BT*) in equation (6) is the set of bad news timeliness coefficients generated from industry-leverage group regressions of equation (3), i.e., this variable (*BT*) is a generated regressor. Although the OLS estimators of the coefficients for generated regressors are consistent, the OLS estimators of the standard errors are inconsistent and often understated (e.g., Pagan 1984; Murphy and Topel 1985). To address this issue, we follow prior literature (e.g., Ashraf and Galor 2013; Faulkender, Flannery, Hankins, and Smith 2012; Chen, Melessa, and Hribar 2023) and employ a bootstrap algorithm to compute consistent standard errors. Specifically, for each industry-leverage group, we randomly draw (with replacement) the same number of observations as the number of observations in our sample used in section 3. We then use the drawn sample to obtain a coefficient estimate on *BT* by following steps 2-4. We repeat the above procedure 200 times and use the standard deviation of the estimated coefficients on *BT* as the bootstrapped standard error (see Efron and Tibshirani 1993). The results show that the coefficient estimates on *BT* in equation (6) are statistically significant when the dependent variable is the ability to predict future cash flows (t-stat = 2.14) and when the dependent variable is the ability to predict future earnings (t-stat = 2.05). Thus, although the bootstrapped standard errors are larger than the OLS standard errors, our main results remain statistically significant. Overall, these results are consistent with our hypothesis that timely loss recognition enhances the ability of accruals to predict future cash flows and future earnings.

5.5 Potential confounds to measuring timely loss recognition

Banker et al. (2016) document that cost stickiness is a confounding factor in the Basu (1997) measure of asymmetric timeliness. Additionally, Lawrence et al. (2017) find that business curtailments are a significant factor contributing to the Basu (1997) measure. Thus, we evaluate whether cost stickiness and business curtailments affect the results in Table 5. To control for cost stickiness, we estimate the bad news timeliness of accruals following the approach in Banker et al. (2016) and to control for curtailments we follow the approach in Lawrence et al. (2017). Next, we use the same approach as specified in equations (4) and (5) to calculate the incremental predictive ability of accruals with respect to future cash flows. We then use equation (6) to examine the relation between bad news timeliness and the predictive ability of accruals. The results of our analyses (untabulated) indicate that the positive relation between timely loss recognition and the predictive ability of accruals with respect to future cash flows documented in Table 5 is not driven by cost stickiness or curtailments.

To further alleviate concerns about potential bias in the measure of timely loss recognition, we conduct placebo tests similar to those in Patatoukas and Thomas (2011), which use lagged unexpected accruals to measure bad news timeliness. Specifically, we substitute lagged unexpected accruals as the dependent variable in equation (3), and then follow the same procedure as specified in equations (4)-(6). Our main results in Table 5 indicate a positive relation between bad news timeliness and the predictive ability of accruals with respect to future cash flows and future earnings. However, the results of the placebo tests (untabulated) show that timely loss recognition as measured using lagged accruals is negatively associated with the ability of accruals to predict future cash flows (coef = -0.170, t-stat = -2.07) and future earnings (coef = -0.181, t-stat = -1.60).[32] These results provide additional evidence that our main findings are not driven by biases in the measure of bad news timeliness we employ.

6. Conclusion and implications

In this study we consider whether timely loss recognition detracts from or enhances the valuation role of accruals as reflected in the predictive ability of accruals with respect to future cash flows. Prior research (e.g., Gjesdal 1981; Holthausen and Watts 2001; Heflin et al. 2015) argues that increases in the contracting usefulness of accounting numbers (increased timeliness of loss recognition) result in a decrease in the value relevance of those numbers. In contrast to the claim made in these studies, our study shows that increased timely loss recognition enhances rather than diminishes the valuation role of earnings by improving the predictive ability of accruals with respect to future cash flows and future earnings in bad news periods.

We argue that if timely loss recognition improves contracting efficiency by providing early warnings of declines in future cash flows from assets in place, then *accruals* should provide better predictions of the future cash flows that are used in valuation. To test this hypothesis, we partition our sample into industry-leverage groups with varying timely loss recognition and predictive ability of accruals with respect to future cash flows. Across industry-leverage groups we find a positive association between timely loss recognition and the predictive ability of accruals with respect to future cash flows and future earnings. We also conduct several additional analyses to strengthen the validity of our results. Collectively, our results are consistent with timely loss

[32] In addition, we find only 3 of 92 bad news timeliness coefficients are statistically positive when estimating equation (3) using lagged unexpected accruals as the dependent variable.

recognition not only facilitating the contracting role of earnings, but also assisting investors in firm valuation by improving forecasts of future cash flows and earnings.

Our findings have important implications for regulators. The FASB in SFAC No. 8 (2010) removed conservatism as an important qualitative characteristic of accounting. The IASB, however, includes in its Conceptual Framework the idea of "prudence" in conditions of uncertainty as a desirable qualitative characteristic of accounting. One of the primary objectives of financial reporting is to provide information helpful to market participants in assessing the amount and timing of future cash flows. The findings in this study provide evidence on the valuation benefits of conservative reporting (timely loss recognition).

Appendix A: Definition of Variables

Variables	Definition (Compustat data items in parentheses)
E	Income before extraordinary items and discontinued operations from the statement of cash flows (IBC), scaled by lagged market value of equity.
CF	Net cash flow from operating activities (OANCF) less the accrual portion of extraordinary items and discontinued operations reported on the statement of cash flows (XIDOC), scaled by lagged market value of equity.
ACC	Total operating accruals, calculated as $E - CF$.
ACC^*	Unexpected accruals calculated as total operating accruals minus lagged operating accruals ($ACC - LagACC$).
SI	After-tax special items (SPI*(1-35%)), scaled by lagged market value of equity. We apply a tax rate of 35% to all firm-years.
$AbRet$	Size and book-to-market adjusted abnormal return, calculated by using 5×5 size and book-to-market portfolio returns as the proxy for expected returns. These reference portfolios are constructed annually, and the portfolio returns are obtained from Ken French's data library. The average return for each portfolio is used as a measure of expected return for the portfolio firms.
ΔAR	Change in accounts receivable from the statement of cash flows (RECCH), scaled by lagged market value of equity. If RECCH is missing, then ΔAR is calculated as the change in accounts receivable (RECT) from the balance sheet, scaled by lagged market value of equity.
ΔINV	Change in inventory from the statement of cash flows (INVCH), scaled by lagged market value of equity. If INVCH is missing, then ΔINV is calculated as the change in inventory (INVT) from the balance sheet, scaled by lagged market value of equity.
ΔAP	Change in accounts payable and accrued liabilities from the statement of cash flows (APALCH), scaled by lagged market value of equity. If APALCH is missing, then ΔAP is calculated as the change in accounts payable (AP) plus accrued expenses (XACC) from the balance sheet, scaled by lagged market value of equity.
DPC	Depreciation and amortization expense (DPC), scaled by lagged market value of equity.

$OTHER$	Net amount of all other accruals calculated as $ACC - (SI + \Delta AR + \Delta INV - \Delta AP - DPC)$.
PA_ACC	Predictive ability of accruals with respect to future cash flows or future earnings.
Asym_PA_ACC	Asymmetric predictive ability of accruals with respect to future cash flows or future earnings.
BT	Bad news timeliness, calculated as $\beta_{2k} + \beta_{3k}$ from estimating equation (3).
AT	Asymmetric timeliness, i.e., the difference between bad news timeliness and good news timeliness, calculated as β_{3k} from estimating equation (3).
ACCxAP	Total operating accruals excluding changes in accounts payable ($ACC - \Delta AP$).
$ACCxAP^*$	Unexpected *ACCxAP* calculated as *ACCxAP* minus lagged *ACCxAP*.
FirmAge	The average firm age of all firm-year observations within an industry-leverage group, where the age of a firm in a given year is measured as the length (in number of years) of the firm's return history in CRSP.
InvCycle	The average investment cycle of all firm-year observations within an industry-leverage group, where the investment cycle of a firm in a given year is measured as the depreciation expense of the firm deflated by lagged total assets.
Volatility	The average volatility of all firm-year observations within an industry-leverage group, where the volatility of a firm in a given year is measured as the standard deviation of the daily stock returns in the year.
InfoAsym	The average information asymmetry of all firm-year observations within an industry-leverage group, where the information asymmetry of a firm in a given year is measured as the average daily bid-ask spreads scaled by the midpoint of the spread in the year.
Size	The average size of all firm-year observations within an industry-leverage group, where the size of a firm in a given year is measured as the log of the market value of equity.
MTB	The average MTB of all firm-year observations within an industry-leverage group, where the MTB of a firm in a given year is measured as the market value of equity divided by the book value of equity.

Lev	The average leverage of all firm-year observations within an industry-leverage group. The leverage of a firm in a given year is calculated as (DLTT+DLC)/(PRCC*CSHO), where DLTT is the amount of long-term debt (maturities exceeding one year), DLC is debt in current liabilities, including the portion of long-term debt due within one year, PRCC is the year-end common share price, and CSHO is the year-end number of common shares outstanding.

Appendix B: Out-of-Sample Test

We first partition the sample by industry because the ability of accruals to predict future cash flows varies by industry. We further partition the observations in each industry into two groups according to leverage. We perform the out-of-sample analysis in each industry-leverage group. Our holdout period is from 2001 to 2016. In order to predict cash flows in year t+1, we first use observations from 1988 to year t, where t+1 indicates a year in the holdout period, to estimate coefficients of the following two regressions.

$$CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \mu_{itk}$$

$$CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AR_{itk} + \beta_{5k}\Delta INV_{itk} + \beta_{6k}\Delta AP_{itk} + \beta_{7k}DPC_{itk} + \beta_{8k}OTHER_{itk} + \beta_{4k}SI_{itk} + \mu_{itk}$$

where i, t, and k indicate firm, year, and industry-leverage group respectively. We then use accounting variables in year t and the estimated coefficients from the above regressions to calculate predicted cash flows in t+1, $\widehat{CF}_{b1,i,t+1,k}$ and $\widehat{CF}_{b2,i,t+1,k}$ respectively.

The root mean squared errors (RMSE) of the predicted future cash flows are calculated as follows:

$$RMSE_{b1,t+1,k} = \sqrt{\frac{\sum_{i=1}^{N}(CF_{i,t+1,k} - \widehat{CF}_{b1,i,t+1,k})^2}{N}}\ ; \qquad RMSE_{b2,t+1,k} = \sqrt{\frac{\sum_{i=1}^{N}(CF_{i,t+1,k} - \widehat{CF}_{b2,i,t+1,k})^2}{N}}$$

where *N* indicates the number of observations in an industry-leverage-year group. $RMSE_{b2,t+1,k}$ is expected to be smaller than $RMSE_{b1,t+1,k}$, because accrual components are included in predicting $\widehat{CF}_{b2,i,t+1,k}$. The difference between $RMSE_{b1,t+1,k}$ and $RMSE_{b2,t+1,k}$ ($\Delta RMSE_{t+1,k} = RMSE_{b1,t+1,k} - RMSE_{b2,t+1,k}$) captures the incremental ability of accruals to predict future cash flows. We require at least 30 observations in each industry-leverage-year to calculate RMSE, and this requirement results in a sample that comprises five industries, which account for 80% of the entire sample. As the holdout period is from 2001 to 2016 and there are five industries, we obtain 80 (16*5) $\Delta RMSE$s for firms with higher leverage (firms exhibiting more timely loss recognition) and the same number of $\Delta RMSE$s for firms with lower leverage. We test whether the mean of $\Delta RMSE$ is larger for firms exhibiting more timely loss recognition.

REFERENCES

Abarbanell, J. S., and B. J. Bushee. 1997. Fundamental Analysis, Future Earnings, and Stock Prices. *Journal of Accounting Research* 35 (1):1-24.

Ahmed, A. S., B. K. Billings, R. M. Morton, and M. Stanford-Harris. 2002. The Role of Accounting Conservatism in Mitigating Bondholder-Shareholder Conflicts over Dividend Policy and in Reducing Debt Costs. *Accounting Review* 77 (4):867-890.

Armstrong, C. S., W. R. Guay, and J. P. Weber. 2010. The role of information and financial reporting in corporate governance and debt contracting. *Journal of Accounting and Economics* 50 (2–3):179-234.

Ashraf, Q., and O. Galor. 2013. The "Out of Africa" Hypothesis, Human Genetic Diversity, and Comparative Economic Development. *American Economic Review* 103 (1): 1–46.

Ball, R., 2001. Infrastructure requirements for an economically efficient system of public financial reporting and disclosure. Brookings-Wharton Papers on Financial Services. Brookings Institution Press, Washington, DC, pp.127–169.

Ball, R., S. P. Kothari, and V. V. Nikolaev. 2013. On Estimating Conditional Conservatism. *Accounting Review* 88 (3):755-787.

Ball, R., S. P. Kothari, and A. Robin. 2000. The effect of international institutional factors on properties of accounting earnings. *Journal of Accounting and Economics* 29 (1):1-51.

Ball, R., A. Robin, and G. Sadka. 2008. Is financial reporting shaped by equity markets or by debt markets? An international study of timeliness and conservatism. *Review of Accounting Studies* 13 (2/3):168-205.

Ball, R., and L. Shivakumar. 2005. Earnings quality in UK private firms: comparative loss recognition timeliness. Journal of Accounting and Economics 39: 83–128

Ball, R., and L. Shivakumar. 2006. The Role of Accruals in Asymmetrically Timely Gain and Loss Recognition. *Journal of Accounting Research* 44 (2):207-242.

Bandyopadhyay, S. P., C. Chen, A. G. Huang, and R. Jha. 2010. Accounting Conservatism and the Temporal Trends in Current Earnings' Ability to Predict Future Cash Flows versus Future Earnings: Evidence on the Trade-off between Relevance and Reliability. *Contemporary Accounting Research* 27 (2):413-460.

Banker, R. D., S. Basu, D. Byzalov, and J. Y. S. Chen. 2016. The confounding effect of cost stickiness on conservatism estimates. *Journal of Accounting and Economics* 61 (1):203-220.

Banker, R., S. Basu, and D. Byzalov. 2017. Implications of Impairment Decisions and Assets' Cash-Flow Horizons for Conservatism Research. *Accounting Review* 92 (2): 41-67.

Banker, R. D., R. Huang, and R. Natarajan. 2009. Incentive Contracting and Value Relevance of Earnings and Cash Flows. *Journal of Accounting Research* 47 (3):647-678.

Barth, M. E., D. P. Cram, and K. K. Nelson. 2001. Accruals and the Prediction of Future Cash Flows. *The Accounting Review* 76 (1):27-58.

Barth, M. E., W. R. Landsman, V. Raval, and S. Wang. 2020. Asymmetric Timeliness and the Resolution of Investor Disagreement and Uncertainty at Earnings Announcements. *The Accounting Review* 95 (4):23-50.

Basu, S. 1997. The conservatism principle and the asymmetric timeliness of earnings1. *Journal of Accounting and Economics* 24 (1):3-37.

Brown, L. D., and M. L. Caylor. 2005. A Temporal Analysis of Quarterly Earnings Thresholds: Propensities and Valuation Consequences. *The Accounting Review* 80 (2):423-440.

Burgstahler, D., J. Jiambalvo, and T. Shevlin. 2002. Do Stock Prices Fully Reflect the Implications of Special Items for Future Earnings? *Journal of Accounting Research* 40 (3):585-612.

Bushman, R., E. Engel, and A. Smith. 2006. An Analysis of the Relation between the Stewardship and Valuation Roles of Earnings. *Journal of Accounting Research* 44 (1):53-83.

Clark, T. E., and K. D. West. 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138: 291–311.

Chen, C.-W., S. Melessa, R. Mergenthaler, and H. Ohn. 2018. Surrogate Measures of Cash Flows: Problems and Solutions. *working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3075461*.

Chen, W, D. Collins, P. Hribar, and D. Volant. 2022. Negatively Correlated Measurement Error in Independent Regressors: Implications for Empirical Research. Working paper, University of Iowa.

Chen, W., S. Melessa, P. Hribar. 2023. Incorrect Inferences When Using Generated Regressors in Accounting Research. *Journal of Accounting Research*.

Chung, H. H., and J. P. Wynn. 2008. Managerial legal liability coverage and earnings conservatism. *Journal of Accounting and Economics* 46 (1):135-153.

Collins, D. W., and S. P. Kothari. 1989. An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. Journal of Accounting and Economics 11(23): 143–181.

Collins, D., and J. Kim. 2019. The persistence and pricing of asset growth: The role of M&A activity," Working paper. Tippie College of Business, University of Iowa. *working paper, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2172843*.

Collins, D. W., P. Hribar, and X. Tian. 2014. Cash flow asymmetry: Causes and implications for conditional conservatism research. *Journal of Accounting and Economics* 58 (2–3):173-200.

Collins, D. W., E. L. Maydew, and I. S. Weiss. 1997. Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics* 24 (1):39-67.

Cready, W., T. J. Lopez, and C. A. Sisneros. 2010. The Persistence and Market Valuation of Recurring Nonrecurring Items. *The Accounting Review* 85 (5):1577-1615.

Cready, W. M., T. J. Lopez, and C. A. Sisneros. 2012. Negative Special Items and Future Earnings: Expense Transfer or Real Improvements? *Accounting Review* 87 (4):1165-1195.

DeAngelo, H., L. DeAngelo, and D. Skinner. 1994. Accounting choice in troubled companies. Journal of Accounting and Economics 17: 113–143.

Dechow, P., and W. Ge. 2006. The persistence of earnings and cash flows and the role of special items: Implications for the accrual anomaly. *Review of Accounting Studies* 11 (2/3):253-296.

Dechow, P. M. 1994. Accounting earnings and cash flows as measures of firm performance JO - Journal of Accounting and Economics. 18 (1):3-42.

Dechow, P. M., S. P. Kothari, and R. L. Watts. 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics* 25 (2):133-168.

Degeorge, F., J. Patel, and R. Zeckhauser. 1999. Earnings Management to Exceed Thresholds. *Journal of Business* 72 (1):1-33.

Dichev, I. D., and V. W. Tang. 2009. Earnings volatility and earnings predictability. *Journal of Accounting and Economics* 47 (1):160-181.

Dietrich, J. R., K. Muller, and E. Riedl. 2007. Asymmetric timeliness tests of accounting conservatism. *Review of Accounting Studies* 12 (1):95-124.
Faulkender, M., and M. J. Flannery, K. W. Hankins, and J. M. Smith. 2012. Cash flows and leverage adjustments. *Journal of Financial Economics* 103: 632–646.
Finger, C. A. 1994. The Ability of Earnings to Predict Future Earnings and Cash Flow. *Journal of Accounting Research* 32 (2):210-223.
Francis, J., D. Hanna, and L. Vincent. 1996. Causes and effects of discretionary asset write-offs. Journal of Accounting Research 34: 117–134.
Francis, J., and K. Schipper. 1999. Have Financial Statements Lost Their Relevance? *Journal of Accounting Research* 37 (2):319-352.
García Lara, J. M., B. García Osma, and F. Penalva. 2016. Accounting conservatism and firm investment efficiency. *Journal of Accounting and Economics* 61 (1):221-238.
Givoly, D., C. K. Hayn, and A. Natarajan. 2007. Measuring Reporting Conservatism. *The Accounting Review* 82 (1):65-106.
Gjesdal, F. 1981. Accounting for Stewardship. *Journal of Accounting Research* 19 (1):208-231.
Graham, J. R., C. R. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics* 40 (1):3-73.
Guay, W., and R. Verrecchia. 2006. Discussion of an economic framework for conservative accounting and Bushman and Piotroski (2006). Journal of Accounting and Economics 42: 149–165
Healy, P., and K. G. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics 31: 405–440
Heflin, F., C. Hsu, and Q. Jin. 2015. Accounting conservatism and Street earnings. *Review of Accounting Studies* 20 (2):674-709.
Holthausen, R. W., and R. L. Watts. 2001. The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics* 31 (1–3):3-75.
Hribar, P., and D. W. Collins. 2002. Errors in Estimating Accruals: Implications for Empirical Research. *Journal of Accounting Research* 40 (1):105-134.
Hsu, A., J. O'Hanlon, and K. Peasnell. 2012. The Basu Measure as an Indicator of Conditional Conservatism: Evidence from UK Earnings Components. *European Accounting Review* 21 (1):87-113.
Hsu, A. W.-H., J. O'Hanlon, and K. E. N. Peasnell. 2011. Financial Distress and the Earnings-Sensitivity-Difference Measure of Conservatism. *Abacus* 47 (3):284-314.
Ijiri, Y., and I. Nakano. 1989. Generalizations of Cost-or-Market Valuation. *Accounting Horizons* 3 (3):1-11.
Khan, M., and R. L. Watts. 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics* 48 (2–3):132-150.
Kim, M., and W. Kross. 2005. The Ability of Earnings to Predict Future Operating Cash Flows Has Been Increasing-Not Decreasing. *Journal of Accounting Research* 43 (5):753-780.
Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31 (1–3):105-231.
Kothari, S. P., K. Ramanna, and D. J. Skinner. 2010. Implications for GAAP from ananalysis of positive research in accounting. Journal of Accounting and Economics 50: 246–286

Lawrence, A., R. Sloan, and E. Sun. 2017. Why Are Losses Less Persistent Than Profits? Curtailments vs. Conservatism. *Management Science* 64 (2):673-694.

Murphy, K. M., and R. Topel. 1984. Estimation and Inference in Two-Step Econometric Models. *Journal of Business and Economic Statistics*: 370–379.

Myers, J., L. Myers, and D. Skinner. 2007. Earnings momentum and earnings management. Journal of Accounting, Auditing and Finance 22: 249–284.

Nallareddy, S., M. Sethuraman, and M. Venkatachalam. 2020. Changes in accrual properties and operating environment: Implications for cash flow predictability. *Journal of Accounting and Economics* 69: 1-23.

Nikolaev, V. V. 2010. Debt Covenants and Accounting Conservatism. *Journal of Accounting Research* 48 (1):51-89.

Nissim, D., and S. H. Penman. 2001. Ratio Analysis and Equity Valuation: From Research to Practice. *Review of Accounting Studies* 6 (1):109-154.

Ohlson, J. A. 1995. Earnings, Book Values, and Dividends in Equity Valuation. *Contemporary Accounting Research* 11 (2):661-687.

Pagan, A., 1984. Econometric issues in the analysis of regressions with generated regressors. *International Economic Review* 25: 154–193.

Patatoukas, P. N., and J. K. Thomas. 2011. More Evidence of Bias in the Differential Timeliness Measure of Conditional Conservatism. *Accounting Review* 86 (5):1765-1793.

———. 2016. Placebo Tests of Conditional Conservatism. *Accounting Review* 91 (2):625-648.

Richardson, S., İ. Tuna, and P. Wysocki. 2010. Accounting anomalies and fundamental analysis: A review of recent research advances. *Journal of Accounting and Economics* 50 (2–3):410-454.

Rouxelin, F., W. Wongsunwai, and N. Yehuda. 2018. Aggregate Cost Stickiness in GAAP Financial Statements and Future Unemployment Rate. *Accounting Review* 93 (3):299–325.

Ryan, S. 2006. Identifying Conditional Conservatism. *European Accounting Review* 15 (4): 511-525

Theil, H. 1971. Principles of Econometrics, John Wiley & Sons, Inc. New York, NY.

Tucker, J. W., and P. A. Zarowin. 2006. Does income smoothing improve earnings informativeness? Accounting Review 81(1): 251–270.

Watts, R. L. 2003a. Conservatism in Accounting Part I: Explanations and Implications. *Accounting Horizons* 17 (3):207-221.

———. 2003b. Conservatism in Accounting Part II: Evidence and Research Opportunities. *Accounting Horizons* 17 (4):287-301.

Wittenberg-Moerman, R. 2008. The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market. *Journal of Accounting and Economics* 46 (2):240-260.

Zhang, J. 2008. The contracting benefits of accounting conservatism to lenders and borrowers. *Journal of Accounting and Economics* 45 (1):27-54.

Table 1: Derivation of the Sample

Compustat firm-years with non-negative total assets and book value.	170,457
Firm-years excluding financial firms, regulated firms, holding firms, ADRs, and limited partnerships, firm-years with stock price less than $1.	109,841
Firm-years with non-missing annual returns.	84,105
Firm-years without M&A and divestiture transactions in year *t* and year *t+1*.	39,504
Firm-years with available earnings, cash flows, and accrual components, and one-year-ahead cash flows (earnings). All continuous variables are truncated at the top and bottom 2%, and a minimum of 40 bad news observations (negative abnormal returns) is required in each industry-leverage group.	28,113

Table 2: Summary Statistics of Variables

Panel A: Distributional Statistics

Variables	N	Mean	Median	Std Dev	Q1	Q3
E	28113	0.014	0.040	0.104	-0.022	0.073
CF	28113	0.070	0.068	0.124	0.003	0.131
ACC	28113	-0.056	-0.035	0.097	-0.092	-0.004
SI	28113	-0.006	0.000	0.019	-0.003	0.000
ΔAR	28113	0.013	0.005	0.049	-0.003	0.025
ΔInv	28113	0.010	0.001	0.044	-0.001	0.018
ΔAP	28113	0.010	0.005	0.042	-0.006	0.022
DPC	28113	0.056	0.036	0.059	0.016	0.073
Other	28113	-0.008	-0.005	0.044	-0.022	0.008

Panel B: Pearson (Spearman) Correlations Above (Below) the Diagonal

Variables	E	CF	ACC	SI	ΔAR	ΔInv	ΔAP	DPC	Other
E		0.65	0.24	0.35	0.20	0.18	0.10	0.06	0.16
CF	0.64		-0.58	0.03	-0.08	-0.17	0.16	0.56	-0.15
ACC	0.12	-0.58		0.34	0.32	0.40	-0.09	-0.65	0.36
SI	0.25	0.04	0.21		0.08	0.09	0.02	-0.14	-0.03
ΔAR	0.23	-0.05	0.30	0.09		0.16	0.41	0.07	-0.12
ΔInv	0.20	-0.13	0.37	0.08	0.18		0.31	0.00	-0.04
ΔAP	0.14	0.13	-0.07	0.03	0.37	0.26		0.08	0.08
DPC	0.22	0.57	-0.56	-0.07	0.07	-0.01	0.07		-0.04
Other	0.05	-0.15	0.32	-0.06	-0.09	-0.01	0.05	-0.02	

Table 2 shows summary statistics of the variables. The samples are Compustat firm-years from 1988 to 2017. Panel A illustrates the distributional statistics, and Panel B demonstrates the Pearson (Spearman) correlations among variables. E is income before extraordinary items and discontinued operations from the statement of cash flows (IBC). CF is net cash flow from operating activities (OANCF) less the accrual portion of extraordinary items and discontinued operations reported on the statement of cash flows (XIDOC). ACC is total operating accruals, calculated as $(E - CF)$. SI is after-tax special items (SPI*(1-35%)). ΔAR is change in accounts receivable from the statement of cash flows (RECCH). ΔINV is change in inventory from the statement of cash flows (INVCH). ΔAP is change in accounts payable and accrued liabilities from the statement of cash flows (APALCH). If RECCH, INVCH, or APALCH is missing, then ΔAR, ΔINV, and ΔAP are calculated as the change in accounts receivable (RECT), inventory (INVT), and accounts payable (AP) plus accrued expenses (XACC), respectively. DPC is depreciation and amortization expense (DPC). $Other$ is the net of all other accruals, calculated as $(ACC - (SI + \Delta AR + \Delta INV - \Delta AP - DPC)$. All variables are scaled by lagged market value of equity. See appendix A for variable definitions. All correlations are significant at the 0.01 level except for the Spearman correlation between Δ*INV* and *DPC* (insignificant), the Spearman correlation between Δ*INV* and *Other* (insignificant), and the Pearson correlation between Δ*INV* and *DPC* (insignificant).

Table 3: Analysis of Timely Loss Recognition

Panel A: Timely Loss Recognition by Industry

Industry	N	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{BT(\beta_2+\beta_3)}$
Food	939	-0.004	0.010	0.032	-0.000	0.032
		(-0.53)	(0.88)	(2.20)**	(-0.00)	(1.16)
Textiles &	1699	0.004	0.003	-0.014	0.053	0.039
Printing/Publishing		(0.65)	(0.28)	(-0.85)	(1.77)*	(2.41)
Chemicals	795	-0.002	0.015	0.031	0.052	0.084
		(-0.22)	(1.22)	(1.66)*	(1.45)	(7.55)***
Pharmaceuticals	2668	0.007	-0.002	-0.005	-0.002	-0.007
		(1.64)	(-0.28)	(-0.69)	(-0.16)	(0.28)
Extractive	1057	0.002	0.003	0.005	0.020	0.025
		(0.28)	(0.24)	(0.34)	(0.55)	(0.61)
Durable	8565	0.001	0.007	0.025	0.041	0.066
manufacturers		(0.35)	(1.40)	(4.21)***	(3.23)***	(35.68)***
Computers	4445	0.004	0.008	0.005	0.047	0.052
		(0.87)	(1.20)	(0.72)	(2.88)***	(13.16)***
Transportation	1375	0.003	-0.002	-0.004	0.010	0.006
		(0.41)	(-0.22)	(-0.26)	(0.36)	(0.06)
Retail	4046	0.006	0.001	0.011	0.049	0.060
		(1.40)	(0.20)	(1.09)	(2.63)***	(14.17)***
Services	2524	-0.001	0.005	-0.001	0.028	0.026
		(-0.08)	(0.58)	(-0.10)	(1.21)	(1.85)

Panel B: Comparison of Timely Loss Recognition for High vs. Low Leverage Groups

	Low Leverage	**High Leverage**	**Difference**
$BT(\beta_2+\beta_3)$	0.012	0.026	0.014
	(5.78)***	(8.09)***	(3.82)***

Panel A of Table 3 reports the results of estimating timely loss recognition by industry with the following equation:

$$ACC^*_{itk} = \beta_{0k} + \beta_{1k}D_{itk} + \beta_{2k}AbRet_{itk} + \beta_{3k}AbRet_{itk} * D_{itk} + \epsilon_{itk}$$

where i, t, and k indicate firm, year, and industry respectively. ACC^*_{itk} indicates unexpected accruals, calculated as total operating accruals minus lagged accruals ($ACC_{itk} - ACC_{i,t-1,k}$). $AbRet_{itk}$ is size and book-to-market adjusted abnormal return, and D_{itk} is a dummy variable equal to one if $AbRet_{itk} < 0$, and zero otherwise. N indicates the number of firm-year observations, and *BT* indicates the bad news timeliness ($\beta_2 + \beta_3$). The numbers in parentheses are t-statistics (f-statistics for the column $\beta_2 + \beta_3$). Panel B presents bad news timeliness for firm-year observations with high versus low leverage. The sample is partitioned into low-leverage group and high-leverage group according to the median leverage in each industry. The numbers in parentheses are t-statistics. Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively (two-tailed).

Table 4: Predictive Ability of Accruals with respect to Future Cash Flows by Industry

Industry	**N**	$\boldsymbol{R_1^2}$	$\boldsymbol{R_2^2}$	$\boldsymbol{PA\_ACC}$
Food	511	16.5%	28.3%	11.8%
Textiles & Printing/Publishing	1047	16.2%	21.4%	5.2%
Chemicals	498	22.8%	33.9%	11.1%
Pharmaceuticals	1605	51.1%	54.3%	3.3%
Extractive	621	38.2%	44.5%	6.3%
Durable manufacturers	5219	26.4%	34.8%	8.4%
Computers	2680	32.8%	38.0%	5.3%
Transportation	807	51.2%	53.5%	2.3%
Retail	2466	19.4%	27.2%	7.9%
Services	1656	38.8%	45.9%	7.1%

Table 4 reports the adjusted R^2 values from estimating the following equations for bad news observations (observations with negative abnormal returns) in each industry:

$$\bar{R}_{1k}^2: \quad CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \mu_{itk}$$

$$\bar{R}_{2k}^2: \quad CF_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AR_{itk} + \beta_{5k}\Delta INV_{itk} + \beta_{6k}\Delta AP_{itk} + \beta_{7k}DPC_{itk} + \beta_{8k}OTHER_{itk} + \beta_{9k}SI_{itk} + \mu_{itk}$$

where CF is net cash flow from operating activities (OANCF) less the accrual portion of extraordinary items and discontinued operations reported on the statement of cash flows (XIDOC). ACC is total operating accruals, calculated as $(E - CF)$. SI is after-tax special items (SPI*(1-35%)). ΔAR is change in accounts receivable from the statement of cash flows (RECCH). ΔINV is change in inventory from the statement of cash flows (INVCH). ΔAP is change in accounts payable and accrued liabilities from the statement of cash flows (APALCH). If RECCH, INVCH, or APALCH is missing, then ΔAR, ΔINV, and ΔAP are calculated as the change in accounts receivable (RECT), inventory (INVT), and accounts payable (AP) plus accrued expenses (XACC), respectively. DPC is depreciation and amortization expense (DPC). $OTHER$ is the net of all other accruals, calculated as $(ACC - (SI + \Delta AR + \Delta INV - \Delta AP - DPC)$. All variables are scaled by lagged market value of equity. N indicates the number of observations. $\bar{R}_{1k}^2$ and $\bar{R}_{2k}^2$ are the adjusted R^2 of the regressions above. PA_ACC captures the incremental explanatory power of $\bar{R}_{2k}^2$ over $\bar{R}_{1k}^2$ (i.e., $\bar{R}_{2k}^2 - \bar{R}_{1k}^2$). See appendix A for variable definitions.

Table 5: Timely Loss Recognition and Predictive Ability of Accruals for CF_{t+1} and E_{t+1}

	Dependent Variable: PA_ACC	
	CF_{t+1} (1)	E_{t+1} (2)
Constant	-0.067	-0.125
	(-0.31)	(-0.42)
BT	0.249***	0.266**
	(3.11)	(2.42)
FirmAge	0.000	-0.006
	(0.01)	(-1.36)
InvCycle	-0.940	-1.422
	(-0.99)	(-1.09)
Volatility	4.463	-0.163
	(1.21)	(-0.03)
InfoAsym	-1.706	2.341
	(-1.10)	(1.10)
Size	0.009	0.058*
	(0.36)	(1.67)
MTB	0.010	0.011
	(0.56)	(0.48)
Lev	0.001	-0.051*
	(0.06)	(-1.86)
Industry Fixed Effect	Yes	Yes
Observations	92	92
Adjusted R-squared	5.83%	22.87%

Table 5 examines the relation between bad news timeliness and the incremental predictive ability of accruals with respect to one-period ahead (t+1) cash flows and earnings with the following equation:

$$PA\_ACC_k = \beta_0 + \beta_1 BT_k + \beta_2 FirmAge_k + \beta_3 InvCycle_k + \beta_4 Volatility_k + \beta_5 InfoAsym_k + \beta_6 Size_k + \beta_7 MTB_k + \beta_8 Lev_k + Industry\ Fixed\ Effects + e$$

where k indicates industry-leverage group, PA_ACC indicates the incremental explanatory power of accruals with respect to one-period ahead cash flows (column 1) and earnings (column 2), and *BT* is bad news timeliness. *FirmAge* is measured for each firm-year observation as the length (in number of years) of the firm's return history in CRSP. *InvCycle* indicates investment cycle, calculated as the depreciation expense of the firm deflated by lagged total assets. *Volatility* is calculated for each firm-year observation as the standard deviation of the daily stock returns in the year. *InfoAsym* is calculated as the average daily bid-ask spreads scaled by the midpoint of the spread in the year. *Size* is calculated as the log of the market value of equity for the firm-year. *MTB* is calculated as the market value of equity divided by the book value of equity. *Lev* is calculated as $(DLTT + DLC)/(PRCC * CSHO)$. All control variables are calculated as the average value within each group. See appendix A for variable definitions. The presence of zero-leverage firms has led to the uneven distribution of groups. Some groups that include zero-leverage firms are disproportionately large, while others have fewer observations. This imbalance has resulted in a total of 92 industry-leverage groups instead of the anticipated 100. The numbers in parentheses are t-statistics. Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively (two-tailed).

Table 6: Asymmetric Timely Loss Recognition and Asymmetric Predictive Ability of Accruals for CF_{t+1} and E_{t+1}

	Dependent Variable: $Asym\_PA\_ACC$	
	CF_{t+1} (1)	E_{t+1} (2)
Constant	0.251	-0.430
	(0.45)	(-0.61)
AT	0.579***	0.29*
	(4.22)	(1.66)
FirmAge	-0.017	-0.003
	(-1.58)	(-0.20)
InvCycle	-0.002	-1.199
	(-0.00)	(-0.45)
Volatility	-11.849	-11.958
	(-1.12)	(-0.88)
InfoAsym	7.332	14.012**
	(1.46)	(2.18)
Size	0.075	0.088
	(1.28)	(1.18)
MTB	-0.050	0.035
	(-1.34)	(0.74)
Lev	-0.173**	-0.167*
	(-2.30)	(-1.74)
Industry Fixed Effect	Yes	Yes
Observations	71	71
Adjusted R-squared	23.80%	2.57%

Table 6 examines the relation between asymmetric timeliness and asymmetric predictive ability of accruals (the differential predictive ability of accruals between bad news observations and good news observations) with respect to one-period ahead (*t*+1) cash flows and earnings with the following equation:

$$Asym\_PA\_ACC_k = \beta_0 + \beta_1 AT_k + \beta_2 FirmAge_k + \beta_3 InvCycle_k + \beta_4 Volatility_k$$
$$+\beta_5 InfoAsym_k + \beta_6 Size_k + \beta_7 MTB_k + \beta_8 Lev_k + Industry\ Fixed\ Effects + e$$

where *k* indicates industry-leverage group, $Asym\_PA\_ACC$ indicates the asymmetric predictive ability of accruals with respect to one-period ahead cash flows (column 1) and earnings (column 2). $Asym\_PA\_ACC$ is calculated as PA_ACC of bad-news observations minus PA_ACC of good-news observations; PA_ACC is estimated with equations (4) and (5). AT is asymmetric timeliness, estimated as β_3 in equation (3). We first separate our sample into the 13 industries as defined in Barth et al. (2001), and then form deciles of firm-year observations within each industry. See appendix A for variable definitions. In addition to the requirements specified in table 5, we require a minimum of 40 good news observations (observations with positive abnormal returns) for each group, leading to 71 industry-leverage groups. The numbers in parentheses are t-statistics. Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively (two-tailed).

Table 7: Timely Loss Recognition and Predictive Ability of Asset-Based Accruals for CF_{t+1} and E_{t+1}

	Dependent Variable:			
	PA_ACCxAP		PA_AP	
	CF_{t+1} (1)	E_{t+1} (2)	CF_{t+1} (3)	E_{t+1} (4)
Constant	0.138	0.152	-0.452***	-0.265
	(0.69)	(0.55)	(-3.13)	(-1.64)
BT	0.139*	0.200**	0.101	0.089
	(1.97)	(2.09)	(0.99)	(0.78)
FirmAge	-0.002	-0.007*	0.005**	0.004
	(-0.78)	(-1.69)	(2.37)	(1.65)
InvCycle	-0.404	-1.342	-0.273	0.529
	(-0.45)	(-1.11)	(-0.42)	(0.74)
Volatility	0.817	-2.788	6.009**	4.778*
	(0.23)	(-0.59)	(2.40)	(1.71)
InfoAsym	-1.733	2.109	1.124	0.065
	(-1.17)	(1.05)	(1.05)	(0.05)
Size	-0.001	0.029	0.027	0.010
	(-0.05)	(0.90)	(1.60)	(0.51)
MTB	-0.001	0.001	0.012	-0.004
	(-0.08)	(0.05)	(1.09)	(-0.30)
Lev	-0.003	-0.052**	0.003	-0.021
	(-0.16)	(-2.01)	(0.20)	(-1.42)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Observations	92	92	92	92
Adjusted R-squared	-4.43%	20.20%	11.53%	3.70%

Table 7 examines the relation between bad news timeliness and predictive ability separately for asset-based accruals (accruals excluding ΔAP) and ΔAP with the following equation:

$$Y_k = \beta_0 + \beta_1 BT_k + \beta_2 FirmAge_k + \beta_3 InvCycle_k + \beta_4 Volatility_k + \beta_5 InfoAsym_k + \beta_6 Size_k + \beta_7 MTB_k + \beta_8 Lev_k + Industry\ Fixed\ Effects + e$$

where k indicates industry-leverage group. For asset-based accruals, Y is PA_ACCxAP, indicating the incremental explanatory power of asset-based accruals with respect to future cash flows (column 1) and future earnings (column 2). PA_ACCxAP is estimated as $\bar{R}^2_{4k} - \bar{R}^2_{3k}$ from the following equations:

$$\bar{R}^2_{3k}: \quad CF_{i,t+1,k}\ or\ E_{i,t+1,k} = \beta_{0k} + \beta_{1k} CF_{i,t-1,k} + \beta_{2k} ACC_{i,t-1,k} + \beta_{3k} CF_{itk} + \beta_{4k} \Delta AP_{itk} + \mu_{itk}$$

$$\bar{R}^2_{4k}: \quad CF_{i,t+1,k}\ or\ E_{i,t+1,k} = \beta_{0k} + \beta_{1k} CF_{i,t-1,k} + \beta_{2k} ACC_{i,t-1,k} + \beta_{3k} CF_{itk} + \beta_{4k} \Delta AR_{itk} + \beta_{5k} \Delta INV_{itk} + \beta_{6k} \Delta AP_{itk} + \beta_{7k} DPC_{itk} + \beta_{8k} OTHER_{itk} + \beta_{9k} SI_{itk} + \mu_{itk}$$

BT is bad news timeliness associated with asset-based accruals, estimated from equation (7). For ΔAP, Y is PA_AP, capturing the incremental explanatory power of changes in accounts payable with respect to future cash flows (column 3) and future earnings (column 4). PA_AP is calculated as $\bar{R}^2_{6k} - \bar{R}^2_{5k}$ from the following equations:

$$\bar{R}^2_{5k}: \quad CF_{i,t+1,k} \text{ or } E_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AR_{itk} + \beta_{5k}\Delta INV_{itk} + \beta_{6k}DPC_{itk} + \beta_{7k}OTHER_{itk} + \beta_{8k}SI_{itk} + \mu_{itk}$$

$$\bar{R}^2_{6k}: \quad CF_{i,t+1,k} \text{ or } E_{i,t+1,k} = \beta_{0k} + \beta_{1k}CF_{i,t-1,k} + \beta_{2k}ACC_{i,t-1,k} + \beta_{3k}CF_{itk} + \beta_{4k}\Delta AR_{itk} + \beta_{5k}\Delta INV_{itk} + \beta_{6k}\Delta AP_{itk} + \beta_{7k}DPC_{itk} + \beta_{8k}OTHER_{itk} + \beta_{9k}SI_{itk} + \mu_{itk}$$

BT is bad news timeliness associated with changes in accounts payable, estimated as $\beta_2 + \beta_3$ from the following equation:

$$-\Delta AP^*_{itk} = \beta_{0k} + \beta_{1k}D_{itk} + \beta_{2k}AbRet_{itk} + \beta_{3k}AbRet_{itk} * D_{itk} + \epsilon_{itk}$$

where ΔAP^*_{itk} is the unexpected component of ΔAP_{itk}, calculated as $\Delta AP_{itk} - \Delta AP_{i,t-1,k}$. *FirmAge* is measured for each firm-year observation as the length (in number of years) of the firm's return history in CRSP. *InvCycle* indicates investment cycle, calculated as the depreciation expense of the firm deflated by lagged total assets. *Volatility* is calculated for each firm-year observation as the standard deviation of the daily stock returns in the year. *InfoAsym* is calculated as the average daily bid-ask spreads scaled by the midpoint of the spread in the year. *Size* is calculated as the log of the market value of equity for the firm-year. *MTB* is calculated as the market value of equity divided by the book value of equity. *Lev* is calculated as $(DLTT + DLC)/(PRCC * CSHO)$. All control variables are calculated as the average value within each industry-leverage group. The numbers in parentheses are t-statistics. Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively (two-tailed).

Table 8: Partition Sample according to (i) Industry and Information Asymmetry and (ii) Industry and Investment Cycle

	Dependent Variable:			
	Information Asymmetry		Investment Cycle	
	CF_{t+1} (1)	E_{t+1} (2)	CF_{t+1} (3)	E_{t+1} (4)
Constant	0.138	0.220	0.009	0.555*
	(0.87)	(1.02)	(0.03)	(1.90)
BT	0.213*	0.113	0.296**	0.173
	(1.95)	(0.77)	(2.25)	(1.49)
FirmAge	0.007**	0.004	-0.004	0.001
	(2.04)	(0.87)	(-0.88)	(0.19)
InvCycle	0.946	-0.350	-0.132	0.645**
	(0.60)	(-0.16)	(-0.36)	(2.02)
Volatility	-2.023	-5.036*	-4.000	-1.787
	(-0.91)	(-1.67)	(-0.76)	(-0.39)
InfoAsym	0.244	0.789	2.001	-3.065
	(0.32)	(0.76)	(0.74)	(-1.29)
Size	-0.016	-0.026	0.061	-0.074*
	(-0.96)	(-1.17)	(1.34)	(-1.84)
MTB	-0.004	0.048	-0.025	-0.013
	(-0.14)	(1.41)	(-0.78)	(-0.47)
Lev	-0.069	0.106	-0.082	0.196**
	(-0.67)	(0.76)	(-0.74)	(2.01)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Observations	100	100	100	100
Adjusted R-squared	0.294	0.071	0.094	0.316

Table 8 examines whether timely loss recognition enhances the predictive ability of accruals when we partition sample according to (i) industry and information asymmetry; and (ii) industry and investment cycle. We use the same research design as outlined in section 3.

$$PA\_ACC_k = \beta_0 + \beta_1 BT_k + \beta_2 FirmAge_k + \beta_3 InvCycle_k + \beta_4 Volatility_k + \beta_5 InfoAsym_k + \beta_6 Size_k + \beta_7 MTB_k + \beta_8 Lev_k + Industry\ Fixed\ Effects + e$$

where k indicates partition group, PA_ACC indicates the incremental explanatory power of accruals with respect to one-period ahead cash flows and earnings, and BT is bad news timeliness. The information asymmetry of a firm-year is measured as the average daily bid-ask spreads scaled by the midpoint of the spread in the year. The investment cycle of a firm-year is measured as the depreciation expense of the firm deflated by lagged total assets. All regression variables are defined in appendix A. The numbers in parentheses are t-statistics. Asterisks *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively (two-tailed).