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Conditional conservatism and disaggregated bad news indicators in accrual models

Dmitri Byzalov[1] · **Sudipta Basu**[1]

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Abstract Conditional conservatism is an integral but often unmodeled part of the normal accrual process. The standard economic determinants of accruals contain information about unrealized losses. We argue that accountants recognize these unrealized losses as disaggregated write-downs for small asset pools. Modeling disaggregated impairments yields new economic insights about accruals and improved accrual models. We predict that accrual conservatism manifests as a sum of asymmetries for a vector of news indicators, rather than as an asymmetry for a scalar aggregate news proxy. We argue that more detailed segment-level and quarterly indicators have an incremental effect on annual firm-level accruals. We also predict a dynamic effect of successive loss indicators because accountants look for consistent patterns in these variables. Empirical results for U.S. firms support our predictions. The asymmetries in accruals are consistent with conservatism in validation tests. We also document improved statistical power and type I error in earnings management tests.

Keywords Asset impairment · Timely loss recognition · Lower of cost or market rule · Abnormal accruals · Materiality

JEL Classification C5 · D8 · M41

✉ Dmitri Byzalov
dbyzalov@temple.edu

Sudipta Basu
Sudipta.Basu@temple.edu

[1] Fox School of Business, Temple University, Philadelphia, PA, USA

1 Introduction

Research on abnormal accruals requires a good understanding of the normal accrual process (e.g., Dechow et al. 1995). We argue that this normal process should incorporate conditional conservatism—more timely recognition of bad news than good news (Basu 1997). We examine how accrual conservatism arises from asset impairment tests and predict that these impairments are triggered by a vector of loss indicators that is mismeasured by aggregated scalar proxies for bad news. Using the Allen et al. (2013) model of working capital accruals as a benchmark, we find large asymmetric effects of individual bad news indicators, consistent with conservatism at a low aggregation level. Our analysis offers new insights about accruals and improved benchmark models for earnings management tests.

Using stock return as an aggregate proxy for news, Basu (1997) shows that net income and accruals incorporate bad news more quickly than good news and infers conditional conservatism. Numerous studies verify this asymmetric effect and show that it varies in agreement with conservatism theory (e.g., Ball et al. 2000; Watts 2003b; Ball et al. 2013; Collins et al. 2014a).

Unlike conservatism research, the accruals literature typically uses a linear specification with multiple economic determinants of accruals, such as sales growth and gross property, plant, and equipment in the Jones (1991) model and multi-period cash flows in the Dechow and Dichev (2002) model. Bushman et al. (2011b) and Allen et al. (2013) combine and refine these standard models, using changes in sales and total employees as measures of firm growth and past, current, and future cash flows as proxies for the matching role of working capital accruals.

These economic variables likely contain information about unrealized losses. For example, negative cash flow can indicate a rise in uncollectible accounts or a decline in selling prices (Ball and Shivakumar 2005, 2006). A sales decrease likely predicts lower demand for the inventory on hand. Layoffs likely reflect managers' expectation of an enduring demand decrease. These unfavorable indicators can trigger asset write-downs (i.e., negative accruals). In contrast, favorable indicators rarely lead to asset write-ups under U.S. GAAP.

We build our predictions from the micro-foundations of conservatism—asset impairment tests. Different asset classes, such as inventory and receivables, are tested for impairment separately, and accountants can divide each asset class into smaller pools (e.g., they can test total inventory as a single pool or test distinct inventory items in separate pools). The composition of these pools affects impairment amounts (e.g., Kieso et al. 2013, p. 477). Suppose that a firm has an unrealized loss of \$10 on asset X and an unrealized gain of \$10 on asset Y. If these assets are combined into a single pool, then the impairment is zero based on total value change for the pool ($\Delta X + \Delta Y = -\$10 + \$10 = \$0$). If the assets are tested separately, then the impairment is \$10 based on their individual value changes ($\Delta X = -\$10$, which triggers a write-down, and $\Delta Y = \$10$, which does not lead to a write-up). Thus the firm can conceal the unrealized loss on asset X by pooling it with the unrealized gain on asset Y or the firm can disclose this loss by using disaggregated asset pools.

Disaggregated losses convey useful information. For example, when a firm has large unrealized losses on inventory of an unsuccessful product, the firm's future performance can be improved by eliminating, redesigning, or repositioning this product. This information is likely viewed as material by stakeholders (Statement of Financial Accounting Concepts 2, FASB 1980). Therefore impairment tests are likely conducted separately for small pools of assets (e.g., narrow inventory categories such as subcompact economy cars, mid-size economy cars, or mid-size luxury cars) to identify disaggregated losses. The write-down determinants likely differ across these pools. Therefore we predict that working capital accruals exhibit asymmetries for a vector of bad news indicators because each indicator triggers impairment for some of the pools.

Second, we argue that segment and quarterly indicators influence total write-downs. Even when firm sales are increasing, a segment with declining sales likely has impaired assets. Even when annual sales increase, a fourth quarter sales decrease can indicate impairment of assets at fiscal year-end. Therefore, conditional on the asymmetric effects of annual firm-level indicators, these more detailed indicators will have an asymmetric effect on annual firm-level accruals.

Third, we argue that, because repeated cash losses are unlikely to be caused by normal variation in working capital (Dechow 1994; Ball and Shivakumar 2006), they signal permanent impairment. Therefore asymmetric timeliness is likely greater for successive cash losses.

We use U.S. Compustat/CRSP data from 1962–2007. The results support our predictions and are robust. Vuong (1989) tests show that conservatism in firm-year data should be modeled using asymmetries for individual news indicators rather than a single asymmetry for a summary measure of news (that aggregates the same underlying indicators).[1] These asymmetries are consistent with conservatism in additional tests, and they improve statistical power (by up to 15 %) and type I error (by a factor of 10 in some cases) in earnings management tests.

Our main contribution is to develop new insights about accruals. Conservatism pervades accounting practice (e.g., Sterling 1967; Basu 2009) and standards (e.g., Lawrence et al. 2013), such as Accounting Standards Codification (ASC) topics 310 and 330 for receivables and inventory, respectively (FASB 2016c, d).[2] Although asymmetric loss recognition via accruals is widely documented (e.g., Basu 1997; Ball and Shivakumar 2005, 2006; Hsu et al. 2011, 2012), these insights have not yet influenced the standard accrual models. With few exceptions, this research does not

[1] Ball and Shivakumar (2006) argue that multiple indicators can play a role in conservatism because they help mitigate measurement error in the bookable component of firm value. This measurement-error argument suggests that accountants estimate the total bookable value change using all available indicators and recognize impairment when this estimate as a whole indicates bad news (i.e., there is a single asymmetry for this summary measure).

[2] The pre-codification accounting rules for inventory and receivables were based on Accounting Research Bulletins (ARB) 29 and 30 (CAP 1947a, b), respectively, and later incorporated into ARB 43 (CAP 1953). All of the main provisions of this earlier guidance, such as the lower-of-cost-or-market rule for inventory (Statement 6 in ARB 29) and the parallel rule for receivables (Statement 9 in ARB 30), were retained in ASC 310 and 330. We cite only the ASCs to avoid duplication. Basu (1995, 2009) reports that accounting was conservative in the early 1400s, long before prevailing best practices were codified in mandatory standards.

examine the role of detailed accounting data. Furthermore, while prior research often assumes that accrual asymmetry reflects conservatism, we test it against alternative explanations, such as curtailment (Lawrence et al. 2016) and cost stickiness (Banker et al. 2016b).

We develop the hypotheses in Sect. 2, describe the data and the estimation models in Sect. 3, present the empirical results in Sect. 4, and conclude in Sect. 5.

2 Hypotheses development

Prior research has identified two primary drivers of working capital accruals. First, many accruals relate to firm growth (e.g., Jones 1991; Dechow et al. 1998). For example, to support higher sales, a firm will likely increase its inventory and accounts receivable. Second, accruals play a matching role by aligning related cash inflows and outflows in the same period (e.g., Dechow 1994; Dechow and Dichev 2002). For example, if a customer pays for merchandise later than usual, this will manifest as a temporary decrease in cash flow and a temporary increase in accounts receivable, both of which will reverse when the payment is received. Bushman et al. (2011b) and Allen et al. (2013) integrate the growth component, as in the Jones (1991) model, and the matching component, as in the Dechow and Dichev (2002) model, and show that the combined model yields new insights.[3] They model the growth component as a linear function of percentage changes in sales and number of employees and model the matching component as a linear combination of lagged, current, and future cash flows (Dechow and Dichev 2002). We use the Allen et al. (2013) model as the benchmark model for our analysis.

While accrual models are typically linear, conservatism research identifies an important asymmetry in both earnings and accruals. Conditional conservatism is interpreted as the higher verification threshold to recognize good news as gains than to recognize bad news as losses (Basu 1997; Watts 2003a). Basu shows that conservatism implies asymmetric timeliness of earnings and accruals with respect to good versus bad news. Using stock return as a summary measure of news about future cash flows, he finds that net income and accruals respond more to negative returns (bad news) than to positive returns (good news), consistent with his predictions. Ball and Shivakumar (2005) introduce cash flow as a conservatism indicator for private firms that lack stock prices. Ball and Shivakumar (2006) document asymmetric timeliness for both stock return and cash flow in multi-indicator accrual models, which increase explanatory power over linear models.[4]

[3] McNichols (2002) combined the Jones (1991) and Dechow and Dichev (2002) models and found that both models have incremental explanatory power. Allen et al. (2013) argue that the combined model is preferable conceptually because it captures two distinct economic roles of accruals.

[4] Lu et al. (2011), Call et al. (2014), He (2015), and others use Ball and Shivakumar's model in robustness checks but primarily use symmetric accrual models. Dechow and Ge (2006) show that the role of accruals differs in growing and declining firms, with much greater use of conservative accounting rules for the latter, and examine the implications for earnings persistence. Hsu et al. (2011, 2012) and Collins et al. (2014a) argue that asymmetric timeliness models in conservatism research should be estimated using operating accruals rather than earnings but do not examine implications for accruals research.

Conservatism research shows that asymmetric timeliness is pervasive (see reviews by Watts 2003b; Mora and Walker 2015; Ruch and Taylor 2015) and that it varies predictably with various drivers of conservatism (Watts 2003a), such as litigation exposure (Basu 1997; Holthausen and Watts 2001; Qiang 2007; Chung and Wynn 2008), country and industry characteristics (Pope and Walker 1999; Ball et al. 2000, 2008; Dhaliwal et al. 2014), corporate governance (Garcia Lara et al. 2009), managerial stock ownership (LaFond and Roychowdhury 2008), debt contracting (Zhang 2008; Wittenberg-Moerman 2008; Nikolaev 2010; Jayaraman and Shivakumar 2013), and information asymmetry (LaFond and Watts 2008).

For consistency with Allen et al. (2013), we focus on working capital accruals, but the predictions generalize to broader accrual measures.[5] Conditional conservatism can have an asymmetric effect on many working capital accounts. For example, bad news about the value of inventory on hand is likely to trigger an inventory write-down, i.e., a negative accrual that reflects these expected future losses per the lower-of-cost-or-market rule (ASC 330-10-35-1).[6] Similarly, unrealized losses on receivables are likely to be recognized early (ASC 310-10-35-41). In contrast, unrealized gains on inventory and receivables cannot be recognized early as an asset write-up (ASC 310-10-35-41 and ASC 330-10-35-16, respectively).[7] Therefore working capital accruals incorporate bad news more quickly and fully than good news, resulting in an asymmetric relation between accruals and various indicators of future gains and losses.

Decreases in sales and total employees can signal unrealized losses. Because sales changes are persistent (Fairfield et al. 2009), a current sales decrease predicts further deterioration in demand. Future selling prices for inventory on hand will likely be lower than originally expected, which can lead to an inventory write-down.[8] Receivables are appraised "in the light of the current economic

Footnote 4 continued
Banker et al. (2015, 2016b) report that sales change has an asymmetric effect on operating accruals. We discuss other potential sources of accrual asymmetry in Sect. 4.1.

5 Banker et al. (2016a) argue that asset impairment is based on predicted cash flow during the asset's expected life. Because net income incorporates impairments of current assets, long-lived tangible assets, and infinite-lived goodwill, they predict that conservatism incorporates multiple indicators that best match the different expected lives of these asset classes. Whereas they focus on time horizon differences across assets, we show that multiple indicators are informative even for current assets, all of which have a comparable expected life of less than 1 year.

6 The "market" in this rule is determined by current replacement cost and net realizable value (i.e., estimated sales value net of the cost of completion and disposal). If the net realizable value is below the replacement cost, then the market is based on this lower amount (ASC 330-10-35-4). However, if the replacement cost is lower than the net realizable value less the normal profit margin, then the market is based on the latter (ASC 330-10-35-5). Therefore inventory write-downs primarily reflect decreases in the net realizable value relative to the replacement cost, which are usually caused by selling price decreases.

7 The allowance for doubtful accounts reflects expected future write-offs of receivables and can be adjusted both upward and downward (ASC 310-10-35-37). When a particular receivable is deemed uncollectible, it is written off and deducted from the allowance; if the receivable is subsequently recovered, this good news is recognized only when the cash has been received (ASC 310-10-35-41).

8 Companies often cite sales decreases as the reason for inventory write-downs. For example, in 2001 Cisco Systems Inc. had an inventory write-down of $2.25 billion due to "a sudden and significant decrease in demand" (source: https://www.sec.gov/Archives/edgar/data/858877/000109581101505065/

environment" (ASC 310-10-35-10), which includes expected demand trends. Therefore a sales decrease can also signal impairment of receivables. Pessimistic managers are more willing to lay off workers (e.g., Banker et al. 2014). Therefore a reduction in the number of employees signals additional bad news, which can trigger further write-downs.

Lagged, current, and future cash flows likely influence impairments. For example, negative current period cash flow can indicate that the proportion of uncollectible receivables is higher than expected or that the selling prices are lower than expected, which can cause impairments of receivables and inventory, respectively (Ball and Shivakumar 2005, 2006).

How accountants combine these indicators depends on the composition of asset pools in impairment tests. For example, suppose that a firm has two assets X and Y with current book values of \$100 each. The fair value estimates for these assets are $\$x$ and $\$y$, respectively, which we assume are observable for simplicity. If the assets are tested for impairment as a single pool, then the fair value of the pool *as a whole* ($\$x + \$y$) is compared to its book value (\$200). When $\$x + \$y < \$200$, the pool is written down to its fair value $\$x + \$y$. The resulting asset write-down (coded as a negative number) is $min\{0, \$x + \$y - \$200\}$, i.e., an asymmetric function of the linear combination $\$x + \$y$. In contrast, if the assets are tested as two separate pools, then the fair value of each asset ($\$x$ or $\$y$) is compared to its book value (\$100). When $\$x < \$100$, asset X is written down to $\$x$ (regardless of $\$y$), and when $\$y < \$100$, Y is written down to $\$y$. The total firm-level write-down is $min\{0, \$x - \$100\} + min\{0, \$y - \$100\}$, i.e., the sum of asymmetric functions of the individual indicators $\$x$ and $\$y$. Thus, depending on the composition of asset pools, conservatism in firm-level data can manifest either as an asymmetry for a scalar summary measure ($\$x + \$y$) or as a sum of asymmetries for the components of the vector ($\$x, \$y$).

These scenarios have different implications for the firm's stakeholders. Suppose that the fair values of assets X and Y are \$90 and \$110, respectively, i.e., the firm has an unrealized loss of \$10 on X and an unrealized gain of \$10 on Y. If X and Y are combined into a single pool, the total write-down is \$0 [= $min\{0, \$90 + \$110 - \$200\}$] because the loss on X is offset by the gain on Y. Thus managers can conceal bad news through aggregation of loss and gain assets (Basu 2005).[9] In contrast, if X and Y are separate pools, then the total write-down is \$10 [= $min\{0, \$90 - \$100\} + min\{0, \$110 - \$100\}$], i.e., bad news about asset X is revealed quickly. The write-down reduces reported earnings by \$10, which can decrease managers' performance-based compensation and trigger accounting-based

Footnote 8 continued
0001095811-01-505065.txt). In 2012, Research in Motion Ltd. recorded an inventory write-down of \$485 million, citing "lower than anticipated demand" for its Blackberry Playbook tablet (source: https://www.sec.gov/Archives/edgar/data/1070235/000119312513132586/0001193125-13-132586.txt).

[9] Basu (2005) points out that aggregation adds friction to impairments because it reduces the probability and size of write-downs for economically impaired assets, giving rise to the "uncertain impairment trigger" of Beaver and Ryan (2005). Contrarily, a firm can credibly commit to greater conservatism by choosing disaggregated inventory pools, because the pool definitions must be applied consistently from year to year (ASC 330-10-35-10).

debt covenants. Notably, this disaggregated scenario gives managers an incentive to quickly terminate, restructure, or adapt unprofitable projects (Burgstahler and Dichev 1997), improving the firm's economic performance.

We argue that impairment tests are conducted for multiple asset pools and that the fair value determinants (i.e., write-down triggers) differ across these pools. First, asset classes such as inventory and receivables are tested for impairment separately (ASC topics 330 and 310, respectively). The fair value of receivables reflects the last stage of the operating cycle, i.e., conversion of sales into future cash. The fair value of inventory reflects an earlier stage, i.e., conversion of inventory into future sales, and is likely based on different indicators. For example, because firms commit labor resources in advance to produce goods, change in the number of employees is a forward-looking indicator of managers' future sales plans. Therefore it likely has a stronger association with the fair value of inventory on hand (which is the source of future sales) than with the fair value of receivables (which is expected cash from past sales). Because inventory is converted into cash with a longer lag than receivables, additional forward-looking indicators may also have a greater impact. Thus the relevant indicators for inventory and receivables likely differ and cannot be combined into a summary news measure that would accurately capture value changes for both asset classes.

Second, each asset class comprises asset subsets with distinct fair value determinants. For example, consider a firm that sells economy cars to low-income customers and luxury cars to high-income customers. The fair value of inventory is based on the expected selling prices. The prices likely vary with the demand shocks for each customer type and competition in each product category. These price determinants likely differ between economy and luxury cars. For example, income shocks likely have a greater impact on purchases for low-income customers, and price competition is likely more intense in the economy category. The fair value of receivables from sale of these cars reflects expected collections from low-income and high-income customers, respectively, which likely have different determinants (e.g., Bhat et al. 2014). The fair value determinants could also vary with the product's expected life. For example, a short-term demand decrease likely has a much greater impact on prices of perishable inventory, which must be sold quickly, than on prices of long-lived inventory, which can be sold after the demand recovers. After controlling for short-term demand indicators, a long-term demand decrease likely has a much smaller effect on perishable inventory than on long-lived inventory because perishable inventory on hand will be sold or discarded quickly.

Disaggregated impairments for these dissimilar items can convey important information to stakeholders. For example, if a firm reports impairment for an unsuccessful product, then this suggests that future profitability can be improved by eliminating, refining or repositioning the product. In contrast, if a firm conceals the impairment through aggregation with successful products, then it communicates mediocre profitability for the pool without a clear path to improvement. Therefore, if accountants aim to report informative impairments, they will form separate pools for distinct subsets of inventory. Similarly, they will likely form distinct pools of receivables based on economic factors such as customer types or time outstanding (e.g., ASC 310-10-50-7A).

Although accountants exercise limited discretion in forming pools within each asset class, they are unlikely to try to cover up disaggregated losses by pooling economically dissimilar assets. Statement of Financial Accounting Concepts 2 (FASB 1980) explains that even small items can be material "if they arise in abnormal circumstances" (paragraph 123). Economic impairment constitutes "abnormal circumstances" and is likely to be interpreted as material information that must be disclosed. Staff Accounting Bulletin (SAB) 99 of the Securities and Exchange Commission (SEC 1999) clarifies that an economic fact is material if it significantly alters the total mix of available information that affects various stakeholders. For example, even when an unrealized loss on a particular subset of inventory is offset by unrealized gains for other inventory items, this loss can be material because its disclosure (1) conveys essential information to investors about unsuccessful economic activities of the firm, (2) reduces reported earnings, (3) can reduce managers' performance compensation (e.g., Potepa 2014) or the market value of their equity holdings, and (4) can trigger debt covenants and other contractual restrictions that are based on reported earnings.[10] Therefore accountants likely recognize unrealized losses at a low aggregation level, treating asset subsets with distinct fair value determinants as separate pools.

In annual firm-level data for accruals, this disaggregated process is best modeled as a sum of asymmetric effects of individual explanatory variables, rather than an asymmetric effect of a single summary measure (that aggregates these variables in a way that best fits the data). The firm-level explanatory variables are likely associated with the detailed internal indicators used by accountants (e.g., firm-level sales growth reflects the total of product-level sales changes). For some of the disaggregated asset pools, the fair value will relate most closely to sales growth (e.g., perishable inventory and short-term receivables, which are most affected by trends in the immediate future). Write-downs for these pools will be an asymmetric function of firm-level sales growth (as an empirical proxy for detailed internal sales growth indicators). For some of the other pools, employee growth will be more relevant (e.g., long-lived inventory that is sensitive to indicators of sustained demand decreases such as layoffs). The associated write-downs will be an asymmetric function of employee growth.

Ball and Shivakumar (2005, 2006) predict and find that current period cash flow has an asymmetric effect on accruals. We extend their analysis to future and lagged cash flows. Future cash flow is an ex post proxy for forward-looking information that managers have in the current period (Dechow and Dichev 2002). When future cash flow is negative (as observed ex post by a researcher), this suggests that the forward-looking information in the current period is likely unfavorable, which can trigger write-downs for some of the pools. Conservatism for expected future cash flow also leads to an asymmetry of the opposite sign in deferred recognition of

[10] SAB 99 (SEC 1999) states that even a small misstatement is likely material if it masks a trend in earnings, changes a loss into a profit, increases managers' compensation, or affects a firm's compliance with contractual requirements. The U.S. Auditing Standards Board (ASB) provides similar examples of qualitative criteria for materiality in AU-C 450 paragraph A23 (AICPA 2015). Eilifsen and Messier (2015) survey eight large U.S. audit firms and find that all of them use these qualitative criteria (in addition to quantitative criteria for materiality).

lagged cash flow, because lagged cash losses were likely recognized previously.[11] The firm-level accrual includes total write-downs for all pools, i.e., the sum of all of these asymmetric effects.

H1 Conservatism for firm-level accruals is better approximated by a sum of asymmetric effects of individual news indicators than by an asymmetric effect of an aggregate summary measure of news that combines all of these indicators.

H2a Accruals exhibit asymmetric timeliness with respect to concurrent sales growth and growth in the number of employees.

H2b Accruals exhibit asymmetric timeliness with respect to future cash flow and an asymmetry in the opposite direction with respect to lagged cash flow.

While accrual models typically use annual firm-level indicators, they can be enriched with more detailed indicators. To maintain focus, we only decompose variables from our main model in ways that are relevant to impairment practice. First, in multi-segment firms, most asset impairment tests are conducted within individual segments. Even when aggregate firm sales are increasing, segments with decreasing sales will likely have asset write-downs, whereas segments with increasing sales are unlikely to have asset write-ups.[12] Therefore, conditional on firm-level information, segment-level sales changes will have an asymmetric effect on firm-level accruals.

H3 After controlling for the asymmetric effects of the firm-level news indicators, firm-level accruals exhibit asymmetric timeliness with respect to segment-level sales growth.

Assets are tested for impairment at the date of the financial statements (e.g., ASC 330-10-35-2 and ASC 310-10-35-8 for inventory and receivables, respectively). If sales increase for the full year but deteriorate in the fourth quarter, signaling a decrease in future revenue from the available inventory at fiscal year-end, the firm will likely write down inventory. Sales changes for earlier fiscal quarters are less likely to have an asymmetric effect on annual accruals. First, many unrealized gains and losses from the interim quarters are fully realized by the fiscal year end;

[11] Pope and Walker (1999), Giner and Rees (2001), and Ryan and Zarowin (2003) examine an asymmetric effect of lagged stock returns on current period earnings in a multi-period extension of the Basu (1997) model. Unlike lagged cash flow in our model, lagged stock return is a forward-looking indicator with a long horizon. Therefore the predicted asymmetry in these papers has an ambiguous sign (Beaver and Ryan 2005) because it reflects not only deferrals but also early recognition of unrealized future losses that are embedded in lagged stock return.

[12] Impairment tests are conducted for multiple asset pools within each segment and likely use more detailed information than is available in segment-level disclosures. We do not decompose our indicators beyond individual segments because the required data is not publicly available. We use segment-level data only for sales because segment data for cash flow and number of employees is unavailable for most firms. Although firms have some discretion in how to define operating segments, they can aggregate these segments only if they have similar economic characteristics and are similar in all of the following areas: nature of products or services, nature of production processes, type of customers, distribution method, and regulatory environment (ASC 280-10-50-11, FASB 2016b; previously codified in SFAS 131, FASB 1997). Therefore firms are unlikely to aggregate dissimilar operations.

therefore they are recognized symmetrically in accruals. Second, each interim period is primarily viewed as an integral part of the fiscal year (ASC 270-10-45-1, FASB 2016a; previously mandated in APB Opinion 28, APB 1973), and interim financial statements need not be audited before issuance (ASC 270-10-S99-1). Firms allocate many annual estimates to interim quarters and typically adjust for estimation errors at the fiscal year-end (Rangan and Sloan 1998). Because auditors tend to prefer more conservatism than managers, and auditor adjustments typically flow through fourth quarter earnings, conservatism increases in the fourth quarter (Elliott and Hanna 1996; Basu et al. 2002). Therefore sales change in the fourth quarter (but not necessarily in other quarters) will have an incremental asymmetric effect on annual accruals.[13]

H4 After controlling for the asymmetric effects of annual firm-level variables, annual accruals exhibit asymmetric timeliness with respect to sales growth in the fourth quarter.

Temporary fluctuations in cash flow subsequently reverse (e.g., Dechow 1994; Ball and Shivakumar 2006). For example, if a firm had unusually large sales at the end of year $t-1$ and paid the supplier at the beginning of year t, then its cash flow is higher than usual in year $t-1$ and lower than usual in year t. Thus, if cash flow is negative in the current period but positive in adjacent periods, then this likely reflects normal variation in the timing of cash flows rather than an economic loss. This is unlikely to be sufficient evidence for a write-down (ASC 310-10-35-4 and 330-10-35-4). However, if cash flow is negative 2 years in a row (i.e., there is no reversal or the loss is persistent), then it provides stronger evidence of permanent impairment. Therefore we predict that asymmetric timeliness for cash flow in year t is greater when it is accompanied by a negative cash flow in year $t+1$, which indicates that accountants do not expect a reversal in year $t+1$ based on their forward-looking information.[14] Similarly, gain recognition for a positive cash flow in year t is likely to be weaker when it is followed by a negative cash flow in year $t+1$.

H5a Gain recognition for current period cash flow is smaller when future cash flow is negative.

H5b Asymmetric loss recognition for current period cash flow is greater when future cash flow is negative.

[13] Quarterly data include cash flow. However, cash flow fluctuates predictably due to seasonal factors (e.g., Frankel et al. 2016). Furthermore, a temporary seasonal decrease in the market price does not require an inventory write-down (ASC 330-10-55-2). Therefore negative cash flow for a quarter is not a reliable impairment indicator.

[14] Prior multi-indicator accrual models assume independent additive impacts of each indicator. In contrast, we predict that the total impact of two successive negative cash flows is greater than the sum of their individual impacts. The parallel predictions for successive cash losses in years t–1 and t are ambiguous. Because these losses likely triggered some write-downs in year t–1, write-downs in year t might be smaller. However, because these successive losses indicate more persistent bad news in year t, write-downs in year t might be bigger.

Although Hypotheses 1–5 arise from some major provisions of U.S. GAAP, they require more than just formal compliance with the accounting standards. Lawrence et al. (2013) distinguish between nondiscretionary conservatism, which arises from unbiased application of U.S. GAAP, and voluntary conservatism, which reflects accountants' discretion in implementing the accounting guidance. For example, while firms must follow the lower-of-cost-or-market rule, they have leeway in the implementation details. If their objective is to report accurate estimates, then they will form disaggregated asset pools for distinct inventory items (Hypothesis 1), use all relevant predictors (Hypotheses 2–4), and examine cash flows for multiple periods (Hypothesis 5). However, they can also disregard much of this information without violating the standards.[15] Similarly, the guidance for receivables allows for substantial discretion (ASC 310-10-35-4). Thus our predictions hinge on accountants' trying to faithfully represent the economic drivers of impairment rather than just the formal structure of accounting standards.

3 Data and empirical models

3.1 Sample selection and descriptive statistics

We use annual Compustat/CRSP data from 1962 to 2007. We end the sample in 2007 to exclude the financial crisis, which triggered massive write-downs for many firms, but the results are robust to extending the sample to 2014. Following Allen et al. (2013), we exclude financial firms (SIC codes 6000–6999) and restrict the sample to domestic firms (Compustat items POPSRC = D and FIC = USA) traded on a major U.S. exchange (CRSP exchange codes 1–3).

All variables used in the paper are defined in Table 1. We use Allen et al.'s definitions of accruals and cash flows, which they measure using the balance sheet approach. Working capital accruals are defined as the change in noncash current assets less the change in current operating liabilities (Compustat items ΔACT $-$ ΔCHE $-$ [ΔLCT $-$ ΔDLC $-$ ΔTXP]). Cash flows are computed as operating income (Compustat item OIBDP) less accruals, using an income measure that incorporates working capital accruals and excludes special items, depreciation, extraordinary items and discontinued operations.[16] Accruals and cash flows are scaled by average total assets (Compustat item AT).

[15] For example, accountants could mechanically focus on current cash flow. When cash flow is positive (and other indicators are negative), they could argue that the evidence does not "indicate clearly that a loss has been sustained," which is the verification threshold for impairment in ASC 330-10-35-4. When cash flow is negative, they could interpret this as sufficient evidence of impairment. This would manifest as an asymmetric effect of concurrent cash flow, consistent with Ball and Shivakumar (2005, 2006), but would not reproduce our Hypotheses 1–5.

[16] Allen et al. (2013) use the balance sheet method because it provides a comprehensive measure of working capital accruals that are classified as arising from operating activities (such as purchasing inventory from a supplier) and investing activities (such as obtaining inventory in an acquisition). Dechow (1994) explains that, while net cash flow is measured objectively, operating cash flow includes an accrual adjustment for investing and financing activities that involves accounting judgment. For example, accountants can choose whether to classify receivables as short-term or long-term and whether

We discard firm-year observations with changes in fiscal year-end, missing or invalid data for the main regression variables, and two-digit SIC codes with insufficient data for industry-specific estimation.[17] Following Allen et al., we winsorize scaled accruals and cash flows at ± 1 (the results are robust to winsorizing at the 1 and 99 percentile levels). All other variables are winsorized at the bottom and top 1 %. The final sample comprises 109,735 observations for 10,962 firms.

The univariate descriptive statistics are presented in Panel A of Table 2. On average, working capital accrual (*ACC*) equals 1.7 % of total assets, and the median is 1.1 %. Average (median) annual sales growth (*SGR*) is 15.6 % (9.9 %). Sales decreases ($DS = 1$) are 25.2 % of the sample. Average (median) growth rate for total employees (*EGR*) is 7.4 % (2.6 %). Decreases in total employees ($DE = 1$) account for 36.7 % of the sample. On average, cash flow (*CF*) equals 9.6 % of total assets, and the median is 11.8 %. 16.8 % of observations have negative cash flow ($DC = 1$).

Panel B of Table 2 presents the correlation matrix. Working capital accrual is positively associated with changes in both sales and total employees (cor(ACC, SGR) = 0.280 and cor(ACC, EGR) = 0.291, respectively), indicating that many accruals relate to firm growth (Jones 1991). Working capital accrual is negatively correlated with concurrent cash flow (cor(ACC, CF_t) = −0.323) and is positively correlated with lagged and future cash flow (cor(ACC, CF_{t-1}) = 0.100 and cor(ACC, CF_{t+1}) = 0.110, respectively), consistent with the matching role of accruals (Dechow 1994; Dechow and Dichev 2002). The correlations between each of the growth variables and each of the matching variables are all less than 0.1, which suggests that these two groups of variables capture different economic factors.

In Panel C of Table 2, we test for asymmetric association of accruals with each of the independent variables. We partition the sample based on the sign of the respective variable and compute its correlation with accruals within each subsample. Accrual is more correlated with decreases in sales and employees than with increases in these variables (cor(ACC, SGR) = 0.217 for negative *SGR* versus 0.188 for positive *SGR*, and cor(ACC, EGR) = 0.232 versus 0.201, respectively;

Footnote 16 continued
to expense or capitalize certain items (Dechow et al. 2008). These choices affect reported operating cash flow and earnings. Basu (1997) examines conservatism in both operating and investing accruals (reported as the difference between XE, CFO, and CFOI in his Table 2) because the categorization of cash flows as "investing" or "operating" might be influenced by conservatism-related accounting judgments (see also Hsu et al. 2012). For consistency with our accrual definition, our empirical cash-flow measure incorporates short-term investment activities associated with current assets but excludes longer-term activities such as investment in new property, plant, and equipment. Operating cash flows and accruals can also be computed using data from the statement of cash flows. However, this method does not capture working capital accruals classified as arising from investing activities, and the required data is available only beginning in 1987. Our results are robust to both methods.

[17] Following Allen et al. (2013), we estimate the models at the two-digit SIC level and then aggregate the industry-specific estimates using the Fama and MacBeth (1973) approach. Allen et al. discard industries that have fewer than 30 firm-year observations; we also require at least five bad news observations (i.e., $DS = 1$, $DE = 1$, or $DC = 1$) per industry to reduce the noise in asymmetric timeliness estimates. The results are robust to alternative screening criteria and continue to hold when we use pooled estimation with two-way clustering by firm and year.

Table 1 Variable definitions

ACC	= working capital accrual, computed using the balance sheet approach as the change in noncash current assets (Compustat items ACT − CHE) less the change in current operating liabilities (LCT − DLC − TXP) and scaled by average total assets (AT)
SGR	= sales growth, computed as percentage change in sales (Compustat item SALE) from year $t-1$ to year t
EGR	= growth in total employees, computed as percentage change in the number of employees (Compustat item EMP) from year $t-1$ to year t
CF	= cash flow, computed using the balance sheet approach as operating income before depreciation (Compustat item OIBDP) less accruals and scaled by average total assets (AT)
Bad news indicators	
DS	= a dummy variable that equals 1 if *SGR* is negative and zero otherwise
DE	= a dummy variable that equals 1 if *EGR* is negative and zero otherwise
DC	= a dummy variable that equals 1 if *CF* is negative and zero otherwise
Variables used in additional analyses	
$segSGR^{-}$	= sum of segment-level sales changes (Compustat item *SALE* from segment data) for all segments of a firm that have decreasing sales in year *t*, scaled by lagged firm-level sales
segDS	= a dummy variable that equals 1 if $segSGR^{-}$ is negative and zero otherwise
IS	= a dummy variable for firm-level sales increases, defined as 1 − *DS*
*SGR*4	= fourth-quarter sales growth, computed as percentage change in quarterly sales (Compustat item SALEQ) from year $t-1$ to year t
*DS*4	= a dummy variable that equals 1 if *SGR*4 is negative and zero otherwise
ΔAR	= change in accounts receivable (Compustat item RECT), scaled by average total assets
ΔINV	= change in inventory (Compustat item INVT), scaled by average total assets
WD	= long-lived asset write-down (Compustat item WDP), scaled by average total assets
GW	= goodwill impairment (Compustat item GDWLIP), scaled by average total assets
ROA	= return on assets, computed as earnings before extraordinary items and discontinued operations (Compustat item IB) and scaled by average total assets
adj. ROA	= adjusted ROA, which is based on earnings net of working capital accruals, and is computed as *ROA* – *ACC*

both differences are significant). These results are consistent with conservatism for the growth variables (Hypothesis 2a). For both concurrent and future cash flow, we find a significantly higher correlation of accrual with cash losses than with cash profits, consistent with asymmetric recognition of contemporaneous and future cash losses (Ball and Shivakumar 2005 and Hypothesis 2b, respectively). As expected, the correlation pattern for lagged cash flow is reversed (i.e., accrual is more correlated with cash profits than with cash losses), indicating less deferred recognition of past cash losses relative to past cash profits (Hypothesis 2b).

Table 2 Descriptive statistics

Panel A: Univariate statistics

	Mean	SD	Q1	Median	Q3
ACC	0.017	0.099	−0.020	0.011	0.054
SGR	0.156	0.369	−0.001	0.099	0.224
EGR	0.074	0.282	−0.046	0.026	0.134
CF_{t-1}	0.094	0.180	0.043	0.118	0.185
CF_t	0.096	0.175	0.045	0.118	0.184
CF_{t+1}	0.096	0.175	0.046	0.118	0.184
Bad news indicators					
DS	0.252	0.434	0.000	0.000	1.000
DE	0.367	0.482	0.000	0.000	1.000
DC_{t-1}	0.173	0.378	0.000	0.000	0.000
DC_t	0.168	0.374	0.000	0.000	0.000
DC_{t+1}	0.165	0.372	0.000	0.000	0.000

Panel B: Correlation matrix

	ACC	*SGR*	*EGR*	CF_{t-1}	CF_t	CF_{t+1}
ACC		0.280	0.291	0.100	−0.323	0.110
SGR	0.358		0.498	−0.206	−0.113	−0.062
EGR	0.324	0.552		*0.000*	−0.065	−0.016
CF_{t-1}	0.106	−0.027	0.089		0.654	0.591
CF_t	−0.343	0.049	0.006	0.547		0.647
CF_{t+1}	0.078	0.098	0.045	0.487	0.543	

Panel C: Pearson correlation of accruals with each of the growth and cash flow variables, after partitioning the sample based on the sign of that variable

	Cor(*ACC*, *X*)		*T*-statistic for the difference[a]
	$X > 0$	$X < 0$	
$X = SGR$	0.188	0.217	2.68***
$X = EGR$	0.201	0.232	3.07***
$X = CF_{t-1}$	0.100	0.032	−6.15***
$X = CF_t$	−0.360	−0.031	22.22***
$X = CF_{t+1}$	0.055	0.119	5.85***

[a]Pearson correlation between *ACC* and *X* is equal to the slope coefficient in a regression of *ACC*/*SD*(*ACC*) on *X*/*SD*(*X*), where *SD*(*ACC*) and *SD*(*X*) refer to the standard deviations within the relevant subsample (e.g., Stock and Watson 2007, p. 144). We jointly estimate the correlation coefficients in both subsamples using a pooled regression with interactions (i.e., the intercept and *X*/*SD*(*X*) are interacted with dummy variables identifying each subsample) and then use a standard regression *t* test with clustering by firm to compare the two correlation coefficients. *** indicates significance at the 1 % level in a two-tailed test

The table presents summary statistics for a sample of 109,735 firm-year observations from 1962 to 2007. The mean, standard deviation, median, and first (Q1) and third (Q3) quartiles are reported in Panel A. Pearson (Spearman) correlations are reported above (below) the diagonal in Panel B. All correlations in Panel B except the one highlighted in italics are statistically significant at the 5 % level in a two-tailed test. Panel C presents the Pearson correlations of accruals with $X = SGR$, EGR, CF_{t-1}, CF_t, and CF_{t+1} after partitioning the sample based on the sign of X. The variables are defined in Table 1

3.2 Empirical models

Allen et al. (2013) and Bushman et al. (2011b) use the following model for scaled accruals:

$$ACC_t = \alpha_0 + \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1} + \varepsilon_t, \qquad (1)$$

where SGR_t is percentage change in sales; EGR_t is percentage change in total employees; and $CF_{t-1} \ldots CF_{t+1}$ are lagged, current, and future cash flows, respectively, scaled by average total assets for the corresponding year. The firm index is omitted for brevity. Because working capital accruals exclude depreciation, Allen et al. (2013) and Bushman et al. (2011b) do not control for gross property, plant and equipment, as in the Jones (1991) model. We expect a negative coefficient on CF_t and positive coefficients on CF_{t-1} and CF_{t+1} due to the matching role of accruals (Dechow 1994; Dechow and Dichev 2002) and positive coefficients on the growth variables *SGR* and *EGR*.

We examine two asymmetric models for firm-year variables. First, we build on the measurement error argument of Ball and Shivakumar (2006) and Roychowdhury and Watts (2007), in which accountants infer the total bookable value change from multiple noisy indicators and then use this total value change to assess impairment. This argument is best modeled as asymmetric loss recognition with respect to a summary measure of news:

$$\begin{aligned} ACC_t &= \alpha_0 + \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1} \\ &\quad + \beta_1 DX_t + \beta_2 DX_t \times X_t + \eta_t \\ X_t &= \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1}, \end{aligned} \qquad (2)$$

where DX_t is a dummy variable that equals 1 if the linear combination of indicators X_t is negative and zero otherwise. $DX_t = 1$ indicates that this linear combination *as a whole* conveys bad news. We estimate this model using nonlinear least squares.[18] Conditional conservatism implies that the coefficient on $DX \times X$ is positive, i.e., the linear combination X_t (our empirical summary measure of news) has a greater impact on accruals when it indicates bad news.

In our main asymmetric specification, we model conservatism for firm-level accruals as a sum of asymmetric effects of the individual indicators:

[18] Standard data-reduction methods such as principal-components analysis seek to find a summary measure that best captures variation in the *independent* variables (but does not necessarily describe the dependent variable well). In contrast, we find a summary measure that best fits the dependent variable (i.e., accruals), enabling tests against alternative models. We set the bad-news cutoff to zero for consistency with the standard bad-news definitions of Basu (1997) and Ball and Shivakumar (2005, 2006). Because both X_t and DX_t are functions of the parameters $\alpha_1 \ldots \alpha_5$, we substitute these functions into the first line of Eq. (2) and estimate the resulting nonlinear model for each industry using Stata command *nl*. We then combine these industry-specific estimates using the Fama and MacBeth (1973) approach.

$$\begin{aligned} ACC_t = {} & \alpha_0 + \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1} \\ & + \beta_1 DS_t + \beta_2 DS_t \times SGR_t + \beta_3 DE_t + \beta_4 DE_t \times EGR_t \\ & + \beta_5 DC_{t-1} + \beta_6 DC_{t-1} \times CF_{t-1} + \beta_7 DC_t + \beta_8 DC_t \times CF_t + \beta_9 DC_{t+1} \\ & + \beta_{10} DC_{t+1} \times CF_{t+1} + \omega_t, \end{aligned} \tag{3}$$

where DS_t, DE_t, and DC_{t-1} … DC_{t+1} are dummy variables for bad news, which equal 1 if SGR_t, EGR_t, and CF_{t-1} … CF_{t+1}, respectively, are negative and zero otherwise. This model extends Ball and Shivakumar's (2006) multi-indicator accrual models by incorporating asymmetries for all of the included indicators, which is a key implication of our disaggregated-impairment theory.

Hypothesis 1 predicts that model (3) better fits the data than the aggregate model (2) because it captures asymmetries at a low aggregation level. Hypothesis 2a predicts that the coefficients on $DS \times SGR$ and $DE \times EGR$ are positive, i.e., accruals are more sensitive to decreases than to increases in sales and employees, reflecting asymmetric loss recognition for the growth variables. The coefficient on $DC_t \times CF_t$ is expected to be positive (Ball and Shivakumar 2005), representing conservatism with respect to concurrent cash flow. Hypothesis 2b implies that the coefficient on $DC_{t-1} \times CF_{t-1}$ is negative and the coefficient on $DC_{t+1} \times CF_{t+1}$ is positive, i.e., accruals exhibit lower deferred recognition and higher early recognition of cash losses relative to cash profits.

To test Hypothesis 3, we add a measure of segment-level sales decreases

$$segSGR_t^- \equiv \sum\nolimits_s \Delta segSALES_{s,t}^- \Big/ SALES_{t-1}, \tag{4}$$

where $\sum_s \Delta segSALES_{s,t}^-$ is the sum of sales changes for all segments s that have decreasing sales in year t, and $SALES_{t-1}$ is lagged firm-level sales.[19] If all segments have sales decreases, then $segSGR_t^-$ equals the firm-level SGR_t. However, if some segments have a sales increase, then $segSGR_t^-$ adds information. We estimate the following model for multi-segment firms:

$$\begin{aligned} ACC_t = {} & \alpha_0 + \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1} \\ & + \beta_1 DS_t + \beta_2 DS_t \times SGR_t + \beta_3 DE_t + \beta_4 DE_t \times EGR_t \\ & + \beta_5 DC_{t-1} + \beta_6 DC_{t-1} \times CF_{t-1} + \beta_7 DC_t + \beta_8 DC_t \times CF_t + \beta_9 DC_{t+1} \\ & + \beta_{10} DC_{t+1} \times CF_{t+1} + \delta_1 segDS_t + \delta_2 segDS_t \times segSGR_t^- + \mu_t, \end{aligned} \tag{5}$$

where $segDS_t$ is a dummy variable equal to 1 if any of the firm's segments has a sales decrease in year t and zero otherwise, and the remaining variables were

[19] Segment-level accrual is a piecewise-linear function of segment-level sales change. Firm-level accrual is the sum of these asymmetries. This sum can be rewritten as the main effect of the sum of segment-level sales changes (i.e., firm-level *SGR*) plus an incremental effect of the sum of segment-level decreases (i.e, $segSGR^-$). Following Berger and Hann (2007), we use data for business and operating segments (Compustat segment types BUSSEG and OPSEG, respectively), restrict the sample to multi-segment firms, and discard firm-year observations if the sum of segment-level sales deviates by more than 5 % from the firm-level sales. Business segment data under SFAS No. 14 (FASB 1976) begins in 1976, and more detailed operating segment data under SFAS No. 131 (FASB 1997) begins in 1998.

defined previously. Hypothesis 3 predicts that the coefficient on $segDS \times segSGR$ is positive, i.e., even after incorporating the asymmetric effects of all firm-level variables from model (3), including sales growth SGR_t, segment-level sales decrease plays an incremental role in asymmetric loss recognition.

To test Hypothesis 4, we include fourth-quarter sales growth in the model for annual accruals, adapting the approach of Stubben (2010):

$$\begin{aligned} ACC_t = {} & \alpha_0 + \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1} \\ & + \beta_1 DS_t + \beta_2 DS_t \times SGR_t + \beta_3 DE_t + \beta_4 DE_t \times EGR_t \\ & + \beta_5 DC_{t-1} + \beta_6 DC_{t-1} \times CF_{t-1} + \beta_7 DC_t + \beta_8 DC_t \times CF_t + \beta_9 DC_{t+1} \\ & + \beta_{10} DC_{t+1} \times CF_{t+1} + \delta_1 DS4_t + \delta_2 SGR4_t + \delta_3 DS4_t \times SGR4_t + v_t, \end{aligned} \tag{6}$$

where $SGR4_t$ is percentage change in sales in the fourth quarter of year t, computed relative to the same quarter of year $t-1$ to remove seasonality; $DS4_t$ is a dummy variable equal to 1 if $SGR4_t$ is negative and zero otherwise; and the remaining variables are defined previously and refer to annual data. We omit interim fiscal quarters for brevity but include them in robustness checks. Hypothesis 4 implies that the coefficient on $DS4 \times SGR4$ is positive, i.e., annual accruals exhibit an incremental asymmetry with respect to fourth quarter sales growth.

We examine the effect of successive cash losses (Hypothesis 5) using the following model:

$$\begin{aligned} ACC_t = {} & \alpha_0 + \alpha_1 SGR_t + \alpha_2 EGR_t + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1} \\ & + \beta_1 DS_t + \beta_2 DS_t \times SGR_t + \beta_3 DE_t + \beta_4 DE_t \times EGR_t \\ & + \beta_5 DC_{t-1} + \beta_6 DC_{t-1} \times CF_{t-1} + \beta_7 DC_t + \beta_8 DC_t \times CF_t + \beta_9 DC_{t+1} \\ & + \beta_{10} DC_{t+1} \times CF_{t+1} + \delta_1 DC_{t-1} \times DC_t + \delta_2 DC_t \times DC_{t+1} + DC_t \\ & \times (\delta_3 CF_{t-1} + \delta_4 DC_{t-1} \times CF_{t-1}) + DC_{t-1} \times (\delta_5 CF_t + \delta_6 DC_t \times CF_t) \\ & + DC_{t+1} \times (\delta_7 CF_t + \delta_8 DC_t \times CF_t) + DC_t \times (\delta_9 CF_{t+1} + \delta_{10} DC_{t+1} \\ & \times CF_{t+1}) + \varsigma_t, \end{aligned} \tag{7}$$

where all variables are as defined earlier. Hypothesis 5a predicts that the interaction coefficient on $DC_{t+1} \times CF_t$ is negative, i.e., gain recognition for current period cash flow (the full coefficient on CF_t) is smaller when future cash flow is expected to be negative ($DC_{t+1} = 1$). Hypothesis 5b implies that the interaction coefficient on $DC_{t+1} \times DC_t \times CF_t$ is positive, i.e., asymmetric loss recognition for current cash flow (the full coefficient on $DC_t \times CF_t$) is greater when the current period cash loss is not expected to reverse ($DC_{t+1} = 1$). For completeness, we also control for the parallel interactions of current period cash losses ($DC_t = 1$) with lagged and future cash flows.

Table 3 Estimates of the Allen et al. (2013) model and asymmetric models for annual firm-level working capital accruals

		Allen et al. model (1)	Ball and Shivakumar model	Aggregate asymmetric model (2)	Main asymmetric model (3)
Intercept		0.007***	0.016***	0.017***	0.035***
		(3.61)	(9.62)	(40.92)	(13.46)
SGR	+	0.082***	0.084***	0.074***	0.054***
		(9.65)	(9.63)	(10.47)	(8.28)
EGR	+	0.038***	0.036***	0.033***	0.015***
		(8.05)	(8.13)	(8.51)	(4.87)
CF_{t-1}	+	0.256***	0.251***	0.202***	0.274***
		(40.45)	(43.84)	(26.58)	(62.63)
CF_t	−	−0.496***	−0.555***	−0.413***	−0.559***
		(−38.08)	(−50.55)	(−26.33)	(−73.02)
CF_{t+1}	+	0.211***	0.205***	0.165***	0.181***
		(38.50)	(37.41)	(21.87)	(32.78)
Aggregate bad news dummy *DX* that is based on $X \equiv \alpha_1 SGR + \alpha_2 EGR + \alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1}$					
DX				0.000	
				(0.19)	
$\boldsymbol{DX \times X}$	+			**0.526*** **	
				(7.51)	
Bad news dummies *DS*, *DE*, $DC_{t-1} \ldots DC_{t+1}$ that are based on individual annual firm-level indicators					
DS					−0.022***
					(−10.69)
$\boldsymbol{DS \times SGR}$	+				**0.095*** **
					(9.96)
DE					−0.010***
					(−8.53)
$\boldsymbol{DE \times EGR}$	+				**0.038*** **
					(4.79)
DC_{t-1}					−0.001
					(−0.78)
$\boldsymbol{DC_{t-1} \times CF_{t-1}}$	−				**−0.085*** **
					(−7.70)
DC_t			0.002		0.009***
			(1.60)		(6.96)
$\boldsymbol{DC_t \times CF_t}$	+		**0.140*** **		**0.127*** **
			(8.21)		**(6.88)**
DC_{t+1}					0.006***
					(4.11)
$\boldsymbol{DC_{t+1} \times CF_{t+1}}$	+				**0.054*** **
					(4.60)

Table 3 continued

	Allen et al. model (1)	Ball and Shivakumar model	Aggregate asymmetric model (2)	Main asymmetric model (3)
adj. R^2 (%)	52.8	53.8	54.0	57.4
Incremental adj. R^2 of asymmetry in:				
Growth component				3.0
Matching component				1.5
Vuong *Z*-statistic in a test of the model in each column against:				
Ball and Shivakumar	−11.40***		1.78*	30.02***
Model (2)	−11.77***	−1.78*		24.52***
Model (3)	−30.26***	−30.02***	−24.52***	

The table presents Fama–MacBeth estimates, which are based on industry-by-industry estimation at the two-digit SIC level. Model (2) is estimated using nonlinear least squares (NLS) in the inner loop of Fama–MacBeth estimation; all other models use ordinary least squares (OLS). The sample comprises 109,735 firm-year observations from 1962 to 2007. The numbers in parentheses are the Fama–MacBeth *t*-statistics. *, **, and *** indicate significance at 10, 5, and 1 % levels, respectively, in two-tailed tests. A positive (negative) Vuong *Z*-statistic indicates that the model in the column performs better (worse) than the benchmark model in the respective row. The variables are defined in Table 1

4 Empirical results

The estimates of models (1)–(3) are presented in Table 3. Consistent with Allen et al. (2013) and Bushman et al. (2011b), working capital accruals in the symmetric Allen et al. model (1) incorporate both a significant growth component (i.e., positive coefficients on *SGR* and *EGR*) and a significant matching component (a negative coefficient on CF_t and positive coefficients on CF_{t-1} and CF_{t+1}).

Asymmetric models have incremental explanatory power. First, we add an asymmetry for concurrent cash flow ($DC_t \times CF_t$ in the second column), following Ball and Shivakumar (2006). The adjusted R^2 increases by 1.0 percentage points (=53.8 − 52.8). We then replace it with an aggregate news measure $X \equiv \alpha_1 SGR + \alpha_2 EGR + \alpha_3 CF_{t\text{-}1} + \alpha_4 CF_t + \alpha_5 CF_{t+1}$, which combines all five indicators with weights α_i that best fit the dependent variable in model (2). This change increases the adjusted R^2 by 0.2 percentage points (=54.0 – 53.8), which is statistically significant (Vuong $Z = 1.78$). Thus aggregation of multiple indicators results in a slightly more informative measure of bad news than current period cash loss alone.

Our main model (3) incorporates asymmetric effects of individual bad news indicators ($DS \times SGR$, $DE \times EGR$, $DC_{t-1} \times CF_{t-1}$, $DC_t \times CF_t$, and $DC_{t+1} \times CF_{t+1}$). Consistent with Hypothesis 1, this decomposition of conservatism into multiple asymmetries improves explanatory power considerably relative to model (2). The incremental adjusted R^2 is 3.4 percentage points (=57.4 − 54.0), significant at the 1 % level (Vuong $Z = 24.52$).[20] Model (3) also significantly outperforms the Ball

[20] In untabulated tests, our main model (3) also significantly outperforms an extended aggregate model that uses separate linear combinations of indicators to capture good and bad news, and another model that uses $\alpha_1 SGR + \alpha_2 EGR$ and $\alpha_3 CF_{t-1} + \alpha_4 CF_t + \alpha_5 CF_{t+1}$ as partly aggregated news proxies.

and Shivakumar model (the incremental adjusted R^2 is 3.6 percentage points, Vuong $Z = 30.02$). Thus the accrual process for firm-level data is best approximated by asymmetric effects of the individual explanatory variables in model (3) due to the disaggregated nature of asset impairment tests. To examine whether these asymmetries reflect disaggregation across or within asset classes, we estimate our models for changes in inventory and receivables. As expected, we find significant differences between the estimates for inventory and receivables ($F = 113.84$ and 154.80 in models (2) and (3), respectively; untabulated). For both variables, model (3) significantly outperforms model (2) (Vuong Z = 16.66 and 16.83, respectively; untabulated). This suggests that the asset pools in impairment tests are disaggregated not only across asset classes but also within each asset class.

As expected (Hypothesis 2a), the coefficients on $DS \times SGR$ and $DE \times EGR$ in model (3) are positive and significant, indicating that accruals are more sensitive to decreases in sales and total employees than to increases. The slope coefficient on sales change SGR is 0.054 for sales increases versus 0.149 (=0.054 + 0.095) for sales decreases, i.e., the sensitivity to bad news is 176 % larger (=[0.149/0.054] − 1). The coefficient on change in total employees EGR is 0.015 for increases versus 0.053 (=0.015 + 0.038) for decreases, a difference of 253 % (=[0.053/0.015] − 1). These results are consistent with conservatism for the growth variables. Furthermore, these variables primarily capture decline accruals, such as write-downs of inventory or receivables, rather than growth accruals related to firm expansion.

The coefficient on $DC_t \times CF_t$ indicates conservatism for concurrent cash flow (Ball and Shivakumar 2005). As predicted (Hypothesis 2b), the coefficient on $DC_{t+1} \times CF_{t+1}$ is positive and significant, indicating quicker recognition of expected future cash losses, while the coefficient on $DC_{t-1} \times CF_{t-1}$ is negative and significant, indicating smaller deferrals of past cash losses. Current period accrual incorporates 23.5 % (=0.181 + 0.054) of next period's cash losses versus just 18.1 % of next period's cash profits, i.e., early recognition is 30 % (=[23.5/18.1] − 1) greater for losses. It incorporates 27.4 % of lagged cash profits versus 18.9 % (=0.274 − 0.085) of lagged cash losses, i.e., deferred recognition is 45 % (=[27.4/18.9] − 1) greater for profits.

The relative asymmetry in the growth component (176–253 % for SGR and EGR) is much larger than that in the matching component (less than 50 % for CF_{t-1}, CF_t, and CF_{t+1}). The growth component asymmetries also have greater explanatory power than the matching component asymmetries. The incremental adjusted R^2s are 3.0 and 1.5 percentage points, respectively. These results suggest that asymmetric timeliness primarily flows through accruals related to firm growth and decline, a new effect that we predict in Hypothesis 2a, rather than through the matching component, which was the focus of prior asymmetric accrual models.

In Table 4, we examine the effect of segment information in model (5), after controlling for the asymmetric effects of all firm-level variables from our main model (3). The incremental adjusted R^2 of segment sales data is 0.4 percentage points (=64.0 − 63.6). Consistent with Hypothesis 3, we find a significant positive coefficient on $segDS \times segSGR^-$, which indicates asymmetric timeliness with respect to segment-level sales decreases. The size of this effect (0.069) is

Table 4 Effect of segment-level sales decreases on annual firm-level working capital accruals

		Allen et al. model (1)	Main asymmetric model (3)	Asymmetric model with segment sales data (5)	Extended model with interactions of firm and segment data
Intercept		0.008***	0.029***	0.032***	0.032***
		(3.57)	(11.07)	(11.09)	(10.83)
SGR		0.101***	0.071***	0.068***	0.068***
		(11.77)	(10.26)	(10.28)	(10.36)
EGR		0.020***	0.002	0.003	0.003
		(5.12)	(0.81)	(1.19)	(1.17)
CF_{t-1}		0.262***	0.267***	0.269***	0.270***
		(32.60)	(40.38)	(41.05)	(41.08)
CF_t		−0.527***	−0.562***	−0.566***	−0.566***
		(−44.81)	(−68.01)	(−68.38)	(−68.41)
CF_{t+1}		0.194***	0.181***	0.179***	0.179***
		(29.01)	(26.26)	(25.17)	(24.85)
DS			−0.012***	−0.009***	−0.009***
			(−8.07)	(−6.52)	(−2.59)
$DS \times SGR$			0.103***	0.071***	0.078***
			(9.40)	(6.06)	(6.36)
DE			−0.009***	−0.008***	−0.008***
			(−9.03)	(−8.89)	(−8.85)
$DE \times EGR$			0.035***	0.037***	0.037***
			(4.20)	(4.47)	(4.52)
DC_{t-1}			−0.002	−0.001	−0.001
			(−0.63)	(−0.37)	(−0.21)
$DC_{t-1} \times CF_{t-1}$			−0.046	−0.051*	−0.047
			(−1.54)	(−1.67)	(−1.53)
DC_t			0.005**	0.005**	0.005**
			(2.08)	(2.17)	(2.01)
$DC_t \times CF_t$			0.078**	0.076**	0.071*
			(2.10)	(2.03)	(1.86)
DC_{t+1}			0.006***	0.007***	0.007***
			(3.35)	(3.73)	(3.84)
$DC_{t+1} \times CF_{t+1}$			0.006	0.009	0.012
			(0.31)	(0.40)	(0.56)
Effect of segment-level sales decreases					
segDS				−0.004***	
				(−5.73)	
$\boldsymbol{segDS \times segSGR^-}$	+			**0.069*** **	
				(6.76)	
Effect of segment-level sales decreases during firm-level sales decreases (*DS*)					
$DS \times segDS$					−0.004
					(−1.42)
$\boldsymbol{DS \times segDS \times segSGR^-}$	+				**0.058*** **
					(3.76)

Table 4 continued

		Allen et al. model (1)	Main asymmetric model (3)	Asymmetric model with segment sales data (5)	Extended model with interactions of firm and segment data
Effect of segment-level sales decreases during firm-level sales increases ($IS \equiv 1 - DS$)					
$IS \times segDS$					−0.004***
					(−4.43)
$\boldsymbol{IS \times segDS \times segSGR^{-}}$	+				**0.089*** **
					(4.86)
adj. R^2 (%)		59.2	63.6	64.0	64.1

The table presents Fama–MacBeth estimates, which are based on industry-by-industry estimation at the two-digit SIC level. The sample comprises 30,149 firm-year observations from 1976 to 2007 for multi-segment firms with valid segment sales data. The numbers in parentheses are the Fama–MacBeth *t*-statistics. *, **, and *** indicate significance at 10, 5, and 1 % levels, respectively, in two-tailed tests. The variables are defined in Table 1

comparable to that for annual sales (0.071 for $DS \times SGR$ in the same model), i.e., the segment data plays an economically significant asymmetric role in firm-level accruals. In the last column, we interact the segment variables *segDS* and $segDS \times segSGR^{-}$ with dummies for firm-level sales decreases and increases (*DS* and *IS*, respectively). The asymmetry for segment sales is smaller during firm-level sales decreases ($DS \times segDS \times segSGR^{-}$) than during firm-level sales increases ($IS \times segDS \times segSGR^{-}$), but both are significant. Thus, even when firm sales are decreasing, segment sales decreases add information (e.g., a large negative $segSGR^{-}$ can signal very poor performance for some of the segments). When firm sales are increasing, segment decreases are even more useful because they convey material contrarian information.

Table 5 presents the effect of fourth-quarter sales change *SGR*4 in model (6), after controlling for the piecewise-linear effects of all annual variables from our main model. Consistent with Hypothesis 4, we find a significant asymmetry for the quarterly sales change ($DS4 \times SGR4$). The incremental adjusted R^2 of this variable is 0.4 percentage points (=57.6 − 57.2). The results are robust to controlling for sales changes in the interim quarters (untabulated). In the last column, we estimate the effect of *SGR*4 separately for annual sales decreases and increases (*DS* and *IS*, respectively). The asymmetry for *SGR*4 is smaller during annual sales decreases ($DS \times DS4 \times SGR4$) than during annual sales increases ($IS \times DS4 \times SGR4$), but both are positive and significant. Thus, even when a fourth quarter sales decrease is a part of an annual decrease, it is incrementally informative (e.g., a rapid demand decrease in the fourth quarter can signal large unrealized losses at fiscal year-end). It has an even greater impact when it provides a contrarian indicator of a more recent demand decrease, which is not visible in annual data.

In Table 6, we examine the effect of successive cash losses in model (7). The adjusted R^2 improves by 1.6 percentage points (=59.0 – 57.4), relative to our main model (3). Consistent with Hypothesis 5a, the interaction coefficient on $DC_{t+1} \times CF_t$ is negative and significant, i.e., gain recognition for current period cash flow (CF_t) is

Table 5 Effect of fourth-quarter sales change on annual firm-level working capital accruals

		Allen et al. model (1)	Main asymmetric model (3)	Asymmetric model with fourth-quarter sales data (6)	Extended model with interactions of annual and quarterly data
Intercept		0.005***	0.032***	0.034***	0.034***
		(2.91)	(13.36)	(13.73)	(13.87)
SGR		0.092***	0.064***	0.069***	0.069***
		(10.33)	(9.02)	(9.09)	(9.39)
EGR		0.034***	0.013***	0.015***	0.015***
		(8.03)	(4.36)	(4.88)	(5.01)
CF_{t-1}		0.254***	0.271***	0.270***	0.270***
		(36.05)	(53.90)	(51.48)	(51.67)
CF_t		−0.495***	−0.561***	−0.562***	−0.562***
		(−40.03)	(−75.66)	(−76.04)	(−76.42)
CF_{t+1}		0.206***	0.183***	0.184***	0.183***
		(45.31)	(30.94)	(31.43)	(31.23)
DS			−0.018***	−0.015***	−0.019***
			(−10.67)	(−10.62)	(−9.68)
$DS \times SGR$			0.092***	0.065***	0.070***
			(10.44)	(9.14)	(8.91)
DE			−0.009***	−0.009***	−0.008***
			(−8.02)	(−7.86)	(−7.92)
$DE \times EGR$			0.046***	0.036***	0.036***
			(5.95)	(4.91)	(4.86)
DC_{t-1}			−0.001	−0.001	−0.001
			(−0.64)	(−0.49)	(−0.42)
$DC_{t-1} \times CF_{t-1}$			−0.079***	−0.080***	−0.081***
			(−6.23)	(−6.32)	(−6.39)
DC_t			0.010***	0.010***	0.010***
			(7.17)	(7.42)	(7.55)
$DC_t \times CF_t$			0.153***	0.152***	0.153***
			(9.57)	(9.25)	(9.30)
DC_{t+1}			0.005***	0.006***	0.006***
			(3.10)	(3.60)	(3.65)
$DC_{t+1} \times CF_{t+1}$			0.043***	0.038***	0.039***
			(3.67)	(3.39)	(3.42)
Effect of fourth-quarter sales change					
*DS*4				−0.006***	
				(−5.01)	
*SGR*4				−0.009***	
				(−5.08)	
***DS*4×*SGR*4**	**+**			**0.046*** **	
				(8.29)	

Table 5 continued

		Allen et al. model (1)	Main asymmetric model (3)	Asymmetric model with fourth-quarter sales data (6)	Extended model with interactions of annual and quarterly data
Effect of fourth-quarter sales change during annual sales decreases (*DS*)					
$DS\times DS4$					0.000
					(0.22)
$DS\times SGR4$					−0.007
					(−1.36)
$\boldsymbol{DS\times DS4\times SGR4}$	**+**				**0.044*****
					(4.69)
Effect of fourth-quarter sales change during annual sales increases ($IS \equiv 1 - DS$)					
$IS\times DS4$					−0.008***
					(−6.41)
$IS\times SGR4$					−0.011***
					(−6.03)
$\boldsymbol{IS\times DS4\times SGR4}$	**+**				**0.056*****
					(6.47)
adj. R^2 (%)		52.9	57.2	57.6	57.7

The table presents Fama–MacBeth estimates, which are based on industry-by-industry estimation at the two-digit SIC level. The sample comprises 98,349 firm-year observations from 1962 to 2007. (The sample size is reduced due to missing quarterly data.) The numbers in parentheses are the Fama–MacBeth *t*-statistics. *, **, and *** indicate significance at 10, 5, and 1 % levels, respectively, in two-tailed tests. The variables are defined in Table 1

smaller when future cash flow is negative ($DC_{t+1} = 1$). When both CF_{t-1} and CF_{t+1} are positive, asymmetric timeliness for current period cash flow (the coefficient on $DC_t \times CF_t$) is −0.085, which indicates that a one-time cash loss in period t does not trigger conservatism. Consistent with Hypothesis 5b, the interaction coefficient on $DC_{t+1}\times DC_t\times CF_t$ is positive and significant, i.e., asymmetric timeliness for cash flow in period t ($DC_t\times CF_t$) is greater when a firm has a cash loss in period $t + 1$ ($DC_{t+1} = 1$). The asymmetric timeliness for CF_t increases to 0.115 (=−0.085 + 0.200, $t = 2.38$), which is consistent with conservatism. These results suggest that accountants distinguish between negative timing shocks, which reverse quickly, and adverse economic shocks, which cause persistent cash losses. In other words, they respond to consistent economic patterns rather than viewing each indicator in isolation.

The results in Tables 3, 4, 5 and 6 are robust to alternative definitions of cash flows and accruals, including measures derived from the SFAS 95 (FASB 1987) statement of cash flows, following Collins and Hribar (2002); measures that combine SFAS 95 data with earlier data from the funds flow statement, following Xie (2001); and broader accrual measures based on net income. The estimates are robust to controlling for market-to-book quintiles as a proxy for expected long-term growth (Collins et al. 2014b), realized changes in sales and employees in year $t + 1$ as a short-term expected growth proxy, asset market-to-book ratio above one as a

Table 6 Dynamic effects of successive cash losses on annual firm-level working capital accruals

		Main asymmetric model (3)		Asymmetric model with dynamic effects (7)	
		Coefficient	*T*-statistic	Coefficient	*T*-statistic
Intercept		0.035***	13.46	0.032***	13.25
SGR		0.054***	8.28	0.053***	8.10
EGR		0.015***	4.87	0.013***	4.64
CF_{t-1}		0.274***	62.63	0.268***	48.52
CF_t		−0.559***	−73.02	−0.532***	−63.10
CF_{t+1}		0.181***	32.78	0.178***	43.64
DS		−0.022***	−10.69	−0.021***	−10.58
$DS \times SGR$		0.095***	9.96	0.096***	10.56
DE		−0.010***	−8.53	−0.010***	8.55
$DE \times EGR$		0.038***	4.79	0.040***	4.95
DC_{t-1}		−0.001	−0.78	0.007**	2.18
$DC_{t-1} \times CF_{t-1}$		−0.085***	−7.70	−0.107***	−6.03
DC_t		0.009***	6.96	0.008***	3.05
$DC_t \times CF_t$		0.127***	6.88	−0.085***	−3.10
DC_{t+1}		0.006***	4.11	0.017***	7.66
$DC_{t+1} \times CF_{t+1}$		0.054***	4.60	0.022	0.89
$DC_{t-1} \times DC_t$				−0.005	−1.08
$DC_t \times DC_{t+1}$				−0.012***	−2.73
Effect of a current cash loss DC_t on the recognition of CF_{t-1}					
$DC_t \times CF_{t-1}$				−0.031***	−2.58
$DC_t \times DC_{t-1} \times CF_{t-1}$				0.030	1.02
Effect of a lagged cash loss DC_{t-1} on the recognition of CF_t					
$DC_{t-1} \times CF_t$				−0.071***	−3.12
$DC_{t-1} \times DC_t \times CF_t$				0.220***	6.19
Effect of a future cash loss DC_{t+1} on the recognition of CF_t					
$\boldsymbol{DC_{t+1} \times CF_t}$	**–**			**−0.089*** **	**−4.66**
$\boldsymbol{DC_{t+1} \times DC_t \times CF_t}$	**+**			**0.200*** **	**4.96**
Effect of a current cash loss DC_t on the recognition of CF_{t+1}					
$DC_t \times CF_{t+1}$				−0.026*	−1.74
$DC_t \times DC_{t+1} \times CF_{t+1}$				0.025	0.62
adj. R^2		57.4		59.0	
The full coefficient on $DC_t \times CF_t$ during successive cash losses in periods:					
t–1 and t				0.135***	3.05
t and t + 1	**+**			**0.115** **	**2.38**

The table presents Fama–MacBeth estimates, which are based on industry-by-industry estimation at the two-digit SIC level. The sample comprises 109,735 firm-year observations from 1962 to 2007. *, **, and *** indicate significance at 10, 5, and 1 % levels, respectively, in two-tailed tests. The variables are defined in Table 1 control for nondiscretionary conservatism (Lawrence et al. 2013), and fiscal-year stock return as a standard news indicator (Basu 1997; Ball and Shivakumar 2006). The results hold when we discard mergers (using Compustat footnote codes) and divestitures (using discontinued operations in excess of $10,000 as a proxy), where both criteria follow Collins and Hribar (2002).[21] The results also hold when we screen for mergers using the SDC data. The asymmetries in accruals increase significantly with the length of the operating cycle (Dechow 1994), consistent with the forward-looking nature of conservatism. We also examine alternative bad news thresholds (Basu 2005) for the growth and cash flow variables. We set the bad news indicators *DS*, *DE*, and *DC* to 1 if the corresponding continuous variable (*SGR*, *EGR*, and *CF*, respectively) is either below average or is in the bottom 20, 30, 40 or 50 % of its distribution, where the average and the percentiles are computed either for the pooled sample or separately for each two-digit industry. In all cases, the results continue to hold and are significant statistically and economically.

4.1 Tests of alternative explanations for accrual asymmetry

While accrual asymmetry is often interpreted as conditional conservatism (e.g., Basu 1997; Ball and Shivakumar 2006; Collins et al. 2014a), it could reflect asymmetric operational effects, such as cost stickiness (Banker et al. 2016b) or curtailment (Lawrence et al. 2016). In Table 7, we examine some of these alternative explanations.

Conservatism flows primarily through assets (Ijiri and Nakano 1989). We estimate model (3) for the main asset-related working capital accruals, i.e., changes in accounts receivable and inventory. We find significant asymmetries for both of these variables, consistent with conservatism (columns 1 and 2 in Panel A of Table 7).[22] Asset write-downs directly capture conservatism and are not confounded by other potential asymmetries in accruals (e.g., Lawrence et al. 2013). Compustat does not separately report current asset write-downs, which flow through working capital accruals, but has data on write-downs of long-lived tangible assets and goodwill, which flow through broader operating accruals. For both of these write-down categories, we find significant asymmetric effects of the growth variables and future cash flow (columns 3 and 4 in Panel A of Table 7), which indicates that these variables trigger conservatism.

[21] Collins and Kim (2014) find that mergers and acquisitions significantly distort annual growth rates because the business entity is not comparable across periods. Divestitures likely have a similar effect. Collins and Hribar (2002) find that both acquisitions and dispositions have a large impact on balance sheet accrual measures. Therefore the association between the growth variables and accruals in our full sample could partly reflect correlated measurement error due to mergers and divestitures. For example, if a firm acquires (divests) a segment equivalent to 10 % of its operations, then its sales, employees, and working-capital accounts will all increase (decrease) by 10 %. However, this mechanical association cannot explain the incremental *asymmetric* effects that we focus on. Furthermore, because mergers and divestitures add noise to our classification of good and bad news for the growth variables, they likely weaken our ability to detect conservatism, working against our findings.

[22] The asymmetry for the longer-term indicators (employee growth and realized future cash flow) is significant for inventory but not for receivables, consistent with our argument that inventory reflects an earlier stage of the operating cycle than receivables.

Banker et al. (2016b) show that the piecewise-linear effect of sales changes on operating accruals is partly attributable to sticky costs. Cost stickiness arises from asymmetric adjustment of physical resources such as employees and equipment (e.g., Anderson et al. 2003). It manifests as an asymmetry in operating costs, earnings, and major operating accrual components such as depreciation (Banker

Table 7 Validation tests for accrual asymmetry

Panel A: Estimates of model (3) for individual line items

		ΔAccounts Receivable	ΔInventory	Long-lived asset write-down	Goodwill impairment
Intercept		0.021***	0.023***	−0.002***	−0.003***
		(9.92)	(9.38)	(−13.05)	(−24.05)
SGR		0.043***	0.032***	0.000	0.001
		(12.36)	(6.95)	(1.18)	(1.34)
EGR		0.036***	0.033***	0.000	−0.001
		(13.79)	(8.61)	(0.97)	(−1.49)
CF_{t-1}		0.086***	0.093***	0.004***	0.008***
		(25.41)	(11.38)	(20.63)	(6.71)
CF_t		−0.166***	−0.154***	0.002***	0.006***
		(−32.16)	(−10.81)	(2.72)	(3.91)
CF_{t+1}		0.064***	0.015***	−0.003**	0.001
		(16.88)	(4.33)	(−2.31)	(0.80)
DS		−0.017***	−0.013***	−0.001***	−0.001***
		(−7.28)	(−8.57)	(−7.24)	(−3.36)
$\boldsymbol{DS \times SGR}$	+	**0.068*** **	**0.045*** **	**0.005*** **	**0.003*** **
		(11.03)	**(8.73)**	**(6.41)**	**(2.99)**
DE		−0.008***	−0.008***	−0.000**	−0.001***
		(−9.48)	(−7.70)	(−2.43)	(−3.20)
$\boldsymbol{DE \times EGR}$	+	**0.004**	**0.027*** **	**0.018*** **	**0.024*** **
		(1.34)	**(6.80)**	**(19.54)**	**(14.29)**
DC_{t-1}		−0.004***	−0.004***	−0.002***	−0.002
		(−4.50)	(−4.12)	(−3.61)	(−0.91)
$\boldsymbol{DC_{t-1} \times CF_{t-1}}$	−	**−0.037*** **	**−0.055*** **	**−0.016*** **	**−0.033**
		(−5.48)	**(−7.54)**	**(−5.26)**	**(−1.56)**
DC_t		0.011***	0.012***	−0.000	−0.003
		(8.68)	(9.21)	(−1.57)	(−1.47)
$\boldsymbol{DC_t \times CF_t}$	+	**0.085*** **	**0.103*** **	**0.003**	**0.001**
		(9.56)	**(8.74)**	**(1.10)**	**(0.28)**
DC_{t+1}		0.000	0.002*	−0.000***	−0.001*
		(0.32)	(1.67)	(−2.71)	(−1.87)
$\boldsymbol{DC_{t+1} \times CF_{t+1}}$	+	**−0.011**	**0.025*** **	**0.015*** **	**0.018*** **
		(−1.42)	**(3.92)**	**(3.47)**	**(4.23)**
adj. R^2 (%)		38.9	33.1	7.7	5.1

Table 7 continued

Panel B: Estimates of the interaction effect of the curtailment proxy on the asymmetry for SGR and EGR for working capital accruals

	Pred. sign under curtailment	Coefficient	T-statistic
Intercept		0.035***	13.35
SGR		0.056***	8.15
EGR		0.015***	4.49
CF_{t-1}		0.274***	62.70
CF_t		−0.559***	−72.97
CF_{t+1}		0.181***	32.87
DS		−0.024***	−8.95
$DS \times SGR$		0.095***	7.81
DE		−0.010***	−8.50
$DE \times EGR$		0.048***	4.46
DC_{t-1}		−0.001	−0.78
$DC_{t-1} \times CF_{t-1}$		−0.086***	−7.94
DC_t		0.009***	7.00
$DC_t \times CF_t$		0.128***	6.83
DC_{t+1}		0.006***	4.08
$DC_{t+1} \times CF_{t+1}$		0.050***	4.22
$DE \times DS$		0.005***	2.69
$DE \times SGR$		−0.009**	−2.37
$DS \times EGR$		−0.016**	−1.97
The interaction effect of the curtailment proxy ($DS = DE = 1$) on the asymmetry for *SGR* and *EGR*			
$\boldsymbol{DE \times DS \times SGR}$	**+**	**0.011**	**0.92**
$\boldsymbol{DS \times DE \times EGR}$	**+**	**0.006**	**0.48**
adj. R^2 (%)		57.6	

The table presents Fama–MacBeth estimates, which are based on industry-by-industry estimation at the two-digit SIC level. The main sample comprises 109,735 firm-year observations from 1962 to 2007. The write-downs sample in columns 3 and 4 of Panel A comprises 17,852 firm-year observations from 2001 to 2007 because the write-downs data in Compustat is unavailable before 2001. *, **, and *** indicate significance at 10, 5, and 1 % levels, respectively, in two-tailed tests. Write-downs of long-lived tangible assets and goodwill in Panel A enter the model with a negative sign for consistency with their impact on operating accruals. The variables are defined in Table 1

et al. 2016b). However, because cost stickiness affects costs rather than revenue, it cannot explain the asymmetric effect of sales changes ($DS \times SGR$) on receivables in Panel A of Table 7. For inventory, cost stickiness predicts an asymmetry of the opposite sign from conservatism. When production costs are sticky, they fall less for sales decreases than they rise for sales increases (Anderson et al. 2003). Because the carrying value of inventory embeds these costs, it will be less sensitive to sales decreases than to sales increases (i.e., the coefficient on $DS \times SGR$ will be negative). This is contrary to our estimates for inventory (column 2 in Panel A of Table 7).

Thus, while cost stickiness affects operating accruals as shown by Banker et al. (2016b), it does not explain our results for *working capital* accruals.

Lawrence et al. (2016) argue that the asymmetries in accruals are partly due to curtailment of underperforming operations. For example, if a firm discontinued an unsuccessful product line during the fiscal year, it likely liquidated the associated inventory and receivables. This could explain the asymmetries for the growth variables. Lawrence et al. (2016) argue that a sales decrease or an employee decrease by itself does not indicate curtailment and use simultaneous decreases in sales and employees as a proxy for curtailment. Thus, if the asymmetric effects of the growth variables on accruals primarily reflect curtailment (using Lawrence et al.'s proxy), then these asymmetries should be larger when both sales and employees are decreasing.

To test this prediction, we add higher-order interaction effects of simultaneous decreases in sales and employees ($DE \times DS \times SGR$ and $DS \times DE \times EGR$) in our main model (3). The estimates are presented in Panel B of Table 7. The coefficients on both $DE \times DS \times SGR$ and $DS \times DE \times EGR$ are insignificant, i.e., the asymmetric effects of sales and employees ($DS \times SGR$ and $DE \times EGR$, respectively) are not significantly associated with the curtailment proxy ($DS = DE = 1$).

While the results are consistent with conservatism, they do not rule out asymmetry in operations. For example, nonlinear changes in credit policy during demand decreases could generate an asymmetric effect of the growth variables on receivables even if conservatism does not play a major role. Physical inventory levels might be adjusted nonlinearly to smooth production or avoid capacity constraints. These operational decisions likely respond to forward-looking information that is also relevant for asset impairment. Furthermore, stakeholders demand conservatism *because* it gives managers an incentive to quickly adapt or terminate underperforming operations (e.g., Watts 2003a). Therefore conservatism could be a fundamental cause of many operational asymmetries. For example, if managers aggressively cut inventory and limit credit sales during demand decreases to avoid the risk of future write-downs, this incentive effect of conservatism can cause an asymmetry in inventory and receivables.[23] Managers might also incur additional costs to quickly adapt unprofitable projects (e.g., Collins et al. 2014a; Schrand 2014), causing further asymmetries. Thus conservatism and operational asymmetries likely co-exist and are intertwined both conceptually and empirically.

4.2 Implications for earnings management tests

Following prior studies (Dechow et al. 1995, 2012; Kothari et al. 2005; Collins et al. 2014b), we simulate earnings management tests for different accrual models. For brevity, we focus on four models: the Allen et al. model (1), the Ball and

[23] Bushman et al. (2011a) predict and find that conservatism leads to an asymmetry in firms' capital expenditures because it gives managers an incentive to quickly cut capital expenditures when investment opportunities decrease but does not have a comparable incentive effect when investment opportunities increase. Srivastava et al. (2015) show that greater conservatism is associated with quicker termination of unprofitable projects.

Shivakumar model, our main asymmetric model (3), and the extended asymmetric model (7) with dynamic effects of successive cash losses.[24]

First, we examine these models' power to detect earnings management. We randomly select 100 earnings management observations and add a discretionary accrual equal to 1 or 2 % of total assets following Dechow et al. (2012). We estimate each model and test whether the abnormal accrual (i.e., regression residual) in the earnings management years differs from zero.[25] We repeat all simulations 1000 times. Our asymmetric models incorporate more parameters than the Allen et al. and Ball and Shivakumar models, which could reduce test power (despite the increase in adjusted R^2) due to estimation noise. Thus, if test power improves, this would suggest that the added asymmetries in our models are sufficiently informative to outweigh this noise.

The results are presented in Panel A of Table 8. We use a significance level of 5 % in a one-tailed test. When accruals are managed upwards by 1 % of total assets for 100 firm-years, earnings management is detected in 43.9 % of simulations for the Allen et al. model and 47.1 % of simulations for the Ball and Shivakumar model. Test power improves to 48.0 % in our main asymmetric model (3) and 50.5 % in the extended asymmetric model with dynamic effects. Thus our extended model enhances the researcher's ability to detect moderate earnings management by 15 % (=[50.5/43.9] − 1), relative to the Allen et al. model, and by 7 % (=[50.5/47.1] − 1), relative to the Ball and Shivakumar model. When accruals are manipulated by 2 % of total assets, the rejection rate is 88.0 % in the Allen et al. model, 89.8 % in the Ball and Shivakumar model, 90.4 % in our main asymmetric model, and 91.5 % in our extended asymmetric model. In other words, the proportion of false inferences (nonrejection of a false null hypothesis) is reduced by almost one-third, from 12.0 % (=100 − 88) in the Allen et al. model to just 8.5 % (=100 − 91.5) in our extended asymmetric model. We find a comparable improvement in test power when we simulate a discretionary accrual of 0.25 or 0.5 % of total assets for 2000 observations (Collins et al. 2014b).

We next examine type I error. We randomly select "suspected earnings management" observations from either the full sample or subsamples with extreme economic performance. We estimate the models using the original accruals data for the full sample and test for earnings management in the suspect firm-years. By construction, the earnings management dummy has no causal effect on accruals, i.e., the null hypothesis of no earnings management is true. Therefore findings of a significant abnormal accrual constitute type I error or rejection of a true null hypothesis. When the suspect firm-years are drawn from a particular subsample,

[24] The simulation results for models (5) and (6) are not comparable because these models have additional data requirements that reduce sample size. We find a qualitatively similar improvement in test performance for models (5) and (6) relative to model (1), using a consistent sample to estimate both benchmarks (untabulated).

[25] For consistency with our main results in Tables 3–6, we estimate each model industry by industry at the two-digit SIC level. We then conduct a t test on regression residuals for the earnings management observations. Following Dechow et al. (2012), we also estimate pooled regressions with a dummy variable for earnings management years as an additional regressor and use two-way clustering by firm and year to assess the statistical significance of this dummy. Untabulated results in this robustness check resemble those in Table 8.

Table 8 Simulation results for earnings management tests

Panel A: Test power in samples with artificial earnings management

Extent of earnings management	Allen et al. model (1)	Ball and Shivakumar model	Main asymmetric model (3)	Asymmetric model with dynamic effects (7)
100 earnings management observations following Dechow et al. (2012)				
1 % of assets	43.9	47.1	48.0	50.5
2 % of assets	88.0	89.8	90.4	91.5
2000 earnings management observations following Collins et al. (2014b)				
0.25 % of assets	46.7	47.9	50.2	51.7
0.5 % of assets	94.8	94.8	96.0	96.2

Panel B: Type I error for the simulation protocol from Dechow et al. (2012)

Earnings management subsample	Allen et al. model (1)	Ball and Shivakumar model	Main asymmetric model (3)	Asymmetric model with dynamic effects (7)
Full sample	11.4	11.3	10.7	9.9
ROA				
Low	99.9	99.8	99.8	99.3
High	100.0	100.0	100.0	100.0
adj. ROA				
Low	14.4	12.7	10.5	8.3
High	97.5	64.6	50.2	58.1
SGR				
Low	94.5	93.1	10.1	10.2
High	14.7	13.9	14.5	17.2
EGR				
Low	74.8	75.1	10.0	9.9
High	23.5	24.9	10.0	10.2
CF_{t-1}				
Low	12.2	9.8	11.4	12.4
High	15.3	14.4	10.0	10.9
CF_t				
Low	11.8	10.6	11.0	8.8
High	49.1	10.1	12.1	11.7
CF_{t+1}				
Low	9.7	9.4	11.1	12.0
High	24.5	10.6	11.7	12.3

Panel C: Type I error for the simulation protocol from Collins et al. (2014b)

Earnings management subsample	Allen et al. model (1)	Ball and Shivakumar model	Main asymmetric model (3)	Asymmetric model with dynamic effects (7)
Full sample	10.0	9.2	9.2	9.7
ROA				

Table 8 continued

Panel C: Type I error for the simulation protocol from Collins et al. (2014b)

Earnings management subsample	Allen et al. model (1)	Ball and Shivakumar model	Main asymmetric model (3)	Asymmetric model with dynamic effects (7)
Low	100.0	100.0	100.0	100.0
High	100.0	100.0	100.0	100.0
adj. ROA				
Low	18.3	10.2	16.2	13.1
High	100.0	100.0	99.7	99.8
SGR				
Low	100.0	100.0	9.8	10.0
High	77.6	76.3	15.4	13.2
EGR				
Low	99.6	99.5	9.0	9.2
High	83.6	80.9	9.3	9.2
CF_{t-1}				
Low	11.0	9.0	9.8	9.6
High	16.6	14.2	11.3	10.3
CF_t				
Low	16.1	11.2	14.0	11.7
High	66.1	9.0	10.2	9.1
CF_{t+1}				
Low	13.2	9.0	9.5	10.2
High	9.7	18.3	17.8	15.7

The table presents simulation results for earnings management tests. The variables are defined in Table 1

Panel A presents the rejection rates for a false null hypothesis of no earnings management. We randomly select 100 (2000) earnings management observations from the full sample and seed them with upward earnings management equal to 1 or 2 % (0.25 or 0.5 %) of total assets. We then estimate each model industry by industry for all observations in the full sample and test whether the average abnormal accrual for the earnings management observations is significantly positive, using a one-tailed *t* test with a significance level of 5 %. The simulations are repeated 1000 times

Panel B (C) presents the rejection rates for a true null hypothesis of no earnings management for 100 (2000) suspected earnings management observations. In the performance subsamples in Panel B, the suspect observations are randomly selected from the top or bottom decile of the relevant performance variable, following the simulation protocol from Dechow et al. (2012). In the performance subsamples in Panel C, half of the 2000 suspect observations are randomly selected from the top or bottom decile of the relevant performance variable, and the other half are randomly selected from the remainder of the sample following Collins et al. (2014b). We estimate each model industry by industry for all observations in the full sample, using the original data for accruals, and test whether the average abnormal accrual for the suspect observations is significantly different from zero at the 10 % significance level in a two-tailed *t*-test. The number of rejections is equal to the total number of significantly positive and significantly negative estimates in one-tailed tests with a significance level of 5 %. The simulations are repeated 1000 times

they might be correlated with omitted determinants of accruals, which can result in mis-specified tests.

First, following Dechow et al. (1995, 2012), we draw 100 suspected earnings management observations from extreme performance deciles. Dechow et al. (1995)

report that all of their accrual models over-reject the null hypothesis of no earnings management for firm-years in the extreme deciles of earnings. Notably, because earnings incorporates concurrent accruals, the expected abnormal accrual in extreme earnings deciles *almost surely* differs from zero even without any earnings management.[26] In other words, even if a model correctly captures all the determinants of normal accruals, it will have excessive rejection rates for firms with extreme earnings performance due to selection on the dependent variable. To assess this selection problem, we use two earnings metrics: ROA (Compustat item IB, scaled by average total assets) as in prior studies, and adjusted ROA, which is based on earnings net of working capital accruals. We also examine the rejection rates for extreme deciles of our main news indicators to determine whether our models adequately control for these observable determinants of accruals.

The type I errors are presented in Panel B of Table 8. We combine significant positive and significant negative test results because both constitute false rejection of the null hypothesis and use a two-tailed test with a 10 % significance level. When the earnings management years are selected from the full sample, the rejection rates in all models are 9.9–11.4 %, consistent with the nominal significance level. All models have rejection rates above 99 % in extreme ROA deciles, consistent with our selection bias argument. As expected, the rejection rates improve when we form the performance deciles based on adjusted ROA. The rejection rates in the bottom decile decrease to 14.4 % for the Allen et al. model, 12.7 % for the Ball and Shivakumar model, 10.5 % for the main asymmetric model, and 8.3 % for the extended asymmetric model. In the top decile of adjusted ROA, all models over-reject the null hypothesis, indicating a confounding effect of correlated omitted variables. However, our asymmetric models partly mitigate the over-rejection, yielding type I error of 50.2–58.1 %, versus 97.5 % for the Allen et al. model and 64.6 % for the Ball and Shivakumar model.

Our piecewise-linear models are likely better specified in extreme deciles of the growth and cash flow variables than the linear Allen et al. model and the partly linear Ball and Shivakumar model. As expected, the rejection rates for our asymmetric models (3) and (7) are generally consistent with the nominal significance level, and even the largest rejection rate is just 17.2 %. In contrast, the symmetric model has a rejection rate of 94.5 % in the bottom sales growth decile, 74.8 % in the bottom employee growth decile, and 49.1 % in the top cash flow decile. The Ball and Shivakumar model incorporates asymmetry only for cash flow. As expected, it has valid rejection rates for the cash flow deciles but over-

[26] Consider a simple model in which earnings $X = CF + A + \varepsilon$, where CF is cash flow, A is normal accrual, and ε is abnormal accrual. Suppose that CF, A, and ε are drawn from independent normal distributions with mean zero and unit variance, and ε is independent of any potential driver of earnings management. The top decile of earnings corresponds to $X > 2.219$. Using standard formulas for multivariate normal distribution (e.g., Maddala 1983, p. 367), the expected abnormal accrual in the top earnings decile is $\mathrm{E}\{\ \varepsilon \mid X > 2.219\ \} = \mathrm{E}\{\ \varepsilon \mid CF + A + \varepsilon > 2.219\ \} = 1.013$, which is more than one standard deviation above the unconditional mean $\mathrm{E}\{\ \varepsilon\ \} = 0$. To determine the false rejection rate, we simulate CF, A, and ε for a sample of 100,000 firms, randomly select 100 firms from the top earnings decile, and test whether the average ε for these 100 observations is significantly different from zero. In all 1000 simulations, the average ε for these observations is positive and significant, indicating a false rejection rate of 100 %.

rejects considerably in the extreme growth deciles (e.g., the rejection rate is 93.1 % in the bottom sales growth decile and 75.1 % in the bottom employee growth decile). Thus a researcher should incorporate asymmetries for all indicators to avoid type I error due to mis-specified linear functional form.[27]

We next examine type I errors in the simulation protocol suggested by Collins et al. (2014b), who argue that the treatment sample should be larger and more heterogeneous. They simulate a suspect subsample of 2000 observations, half of which are selected from a given extreme performance partition and the other half from the remainder of the sample. The results are presented in Panel C of Table 8. Consistent with our selection bias argument, all models have a rejection rate of 100 % for the extreme ROA partitions. For partitions based on the growth variables, the rejection rates in our asymmetric models are 9.2–15.4 %. In contrast, the parallel rejection rates in both the Allen et al. model and the Ball and Shivakumar model are 76.3–100 %, indicating over-rejection due to functional form mis-specification.

5 Conclusion

We examine in depth the implications of conditional conservatism for accrual research. Study of abnormal accruals requires an accurate benchmark model of the normal accrual process (Ball 2013), which should incorporate the main features of accounting practice. Conservatism has been described as "the most ancient and probably the most pervasive principle" in accounting practice (Sterling 1967, p. 110). We examine the accounting guidance for working capital accounts (ASC topics 310 and 330 for receivables and inventory, respectively; previously based on ARB 29, 30, and 43) and show that these standards incorporate asymmetric treatment of unrealized losses versus unrealized gains for small asset pools. Many unrealized losses are recognized early as asset write-downs (i.e., negative accruals), whereas unrealized gains are not recognized as asset write-ups. We argue that the standard explanatory variables in accrual models signal future gains and losses for disaggregated asset pools and predict that conservatism in firm-year data is best approximated by a sum of asymmetric effects of individual news indicators (rather than an asymmetry for an aggregate news measure). We argue that segment-level and quarterly indicators have incremental explanatory power for annual firm-level accruals. Because accountants distinguish temporary and permanent cash losses, we predict a dynamic effect of successive negative cash flows.

Estimates for U.S. Compustat/CRSP data are consistent with our predictions. While Ball and Shivakumar (2006) document asymmetric timeliness of accruals with respect to concurrent cash flow (and additional indicators in some of the tests), we focus on how different firm-level and disaggregated indicators should be

[27] We also conduct the tests for performance-matched accruals following Kothari et al. (2005). Similar to Dechow et al. (2012), we find that performance matching on ROA is effective in extreme ROA deciles, yielding type I errors of 10.2–12.8 %, but is often unstable in other earnings management partitions. For example, performance-matched tests have a type I error of 63.0–95.4 % in extreme cash flow deciles and 73.2–99.7 % in extreme adjusted-ROA deciles. Banker et al. (2015) recommend matching on sales growth instead of ROA.

incorporated in accrual models. The results support our disaggregated-information argument for both firm-level indicators and more detailed segment-level and quarterly indicators. Our improved accrual models also have greater statistical power and lower type I error in earnings management tests.

Recent advances in empirical accrual research, such as Allen et al. (2013) and Bushman et al. (2011b), examine economic drivers of accruals. In contrast, we focus on disaggregated asymmetries in accruals to develop new insights and improved empirical tests for a variety of research settings. While we attribute the results to conservatism (and rule out some alternative explanations in validation tests), they could partly reflect asymmetries in firms' operations. Further, conservatism can cause operational asymmetries by giving managers an incentive to quickly adapt or terminate unsuccessful projects, while operational decisions can affect future cash flows that are relevant for conservatism. Thus it is conceptually difficult to fully disentangle conservatism from operational effects. While accrual asymmetry can have alternative interpretations, we show that the default linear specification of accrual models is unjustified both theoretically and empirically.

Because our asymmetric models have more parameters that the standard accrual models, researchers should exercise judgment to avoid unfocused variable proliferation (Roychowdhury and Martin 2013). For example, if a researcher seeks to identify new determinants of normal accruals, then a more parsimonious linear model might be preferred for expositional convenience (if the results are robust). If a researcher aims to provide credible evidence of earnings management (or its absence), then high statistical power and low type I error likely matter more than model parsimony. The evidence in Sect. 4.2 suggests that our asymmetric models perform better than the standard models in earnings management tests, but a researcher could (and probably should) conduct simulations for the specific empirical context to identify the most appropriate model. Similarly, if different metrics such as absolute versus signed discretionary accruals produce conflicting results (e.g., Hribar and Nichols 2007), a researcher could examine whether a more extensive asymmetric model resolves the conflict.[28] Future research should consider the asymmetric nature of accruals.

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[28] For example, unmodeled normal write-downs in standard models reduce signed discretionary accruals (which suggests higher earnings quality) but increase absolute discretionary accruals (which suggests lower earnings quality), leading to conflicting results. Incorporating conservatism in the model could resolve this conflict.

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