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Implications of Impairment Decisions and Assets' Cash-Flow Horizons for Conservatism Research

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ABSTRACT: Accountants examine multiple indicators when assessing whether individual assets are impaired. Different indicators predict cash flows over varying time horizons, and their importance varies with how far into the future individual assets are expected to generate cash flows. We predict that earnings exhibits asymmetric timeliness with respect to multiple indicators, including stock return, sales change, and operating cash flow change, which differentially explain write-downs of current assets, long-lived tangible assets, and indefinite-lived goodwill. We predict an interaction effect between indicators, such that the total impact of several consistent indicators is greater than the sum of their individual impacts. Empirical estimates for U.S. firms are consistent with our predictions and yield new insights about the effects of multiple indicators for both conservatism and impairment research. Our multi-indicator asymmetric models also change inferences about the relative explanatory power of economic factors versus reporting incentives in asset impairments.

Keywords: timely loss recognition; asset write-downs; bookable gains and losses.

JEL Classifications: G32; L25; M41; M42.

I. INTRODUCTION

We study how accountants use data about future cash flows in their impairment decisions. Prior research shows that bad news is recognized in earnings more quickly than good news, and infers the presence of conditional conservatism from this finding (Basu 1997; Watts 2003b). Appealing to market efficiency, this research typically uses stock return as a proxy for news about future cash flows, and interprets the piecewise-linear effect of stock return on earnings as a measure of more timely loss recognition by firms. We examine recent U.S. impairment accounting standards (Financial Accounting Standards Board [FASB] 1995, 2001a, 2001b, Statements of Financial Accounting Standards [SFAS] 121, 142, and 144, respectively) and develop new insights and expanded empirical models for both conservatism and impairment research.

Earnings likely responds asymmetrically to multiple indicators (e.g., Ball and Shivakumar 2006). Different asset classes, such as inventory and long-lived tangible assets, are tested for impairment separately. Therefore, accountants will use indicators that best predict future cash flows for these individual asset classes. For example, a sales decrease can signal a selling price decrease that reduces the expected short-term cash flow from inventory on hand, which can trigger an inventory write-down even if stock return is positive. A negative stock return reflects a decline in the present value of expected cash flows over a long time horizon, and likely has a greater impact on write-downs of long-lived assets. Thus, indicators relevant for any asset class will have an incremental asymmetric effect on earnings through write-downs.

We identify sales change as an important new indicator in conservatism research. Impairment tests for long-lived assets are based on operating cash flow forecasts. Sales is the fundamental driver of cash inflows and outflows (Dechow, Kothari, and

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Watts 1998). Therefore, the sales forecast is a major input in the operating cash flow forecast (e.g., Easton, McAnally, Sommers, and Zhang 2012, Chapter 11; Horngren, Datar, and Rajan 2014, Chapter 6). Because sales forecasts are typically formed by projecting recent sales trends (e.g., Chase 2013), current sales change is likely to be an important determinant of accountants' cash flow forecasts.

Ball and Shivakumar (2006) report that operating cash flow indicators have an asymmetric effect on earnings after controlling for the stock return asymmetry. Operating cash flow includes transitory noise due to normal variation in working capital (Dechow 1994; Ball and Shivakumar 2006), poor matching of uncapitalized expenditures such as research and development (R&D) and advertising (Dichev and Tang 2008), and gradual adjustment of resources in response to economic shocks (e.g., Horngren et al. 2014, Chapter 10). Because these factors do not distort sales, sales change likely adds information in impairment tests. Therefore, we predict that sales change has an asymmetric effect on earnings conditional on both stock return and cash flow change asymmetries.

Second, we predict that multiple indicators interact with each other. Prior studies combining several indicators (e.g., Giner and Rees 2001; Ball and Shivakumar 2006) assumed independent additive impacts of each indicator. However, discrepancies between indicators can signal measurement error, affecting accountants' assessment of the indicators' precision. When multiple indicators are consistent with one another, the measurement errors are likely small. Therefore, these indicators are more credible and are each likely to be recognized to a greater extent in earnings (i.e., their total effect is stronger than a sum of independent additive effects). In other words, indicator consistency likely affects not only the level of earnings (as in the prior multi-indicator models), but also the asymmetric sensitivity of earnings to each of the indicators.

We also predict that these multiple indicators have differential effects on write-downs of tangible assets and goodwill. Tangible assets have a finite expected useful life, whereas goodwill has an indefinite life. Because stock return reflects discounted cash flows over an infinite horizon, it will have a greater impact on goodwill impairment, whereas tangible asset write-downs will be influenced more by short-term indicators such as sales change or operating cash flow change.

We test these predictions using U.S. Compustat/CRSP data from 1987–2007. Empirical findings are consistent with all of our predictions and are robust. When we include stock return, operating cash flow change, and sales change concurrently, we observe significant asymmetric timeliness for all three indicators. As expected, sales decreases trigger substantial loss recognition. For example, earnings falls by 23.3 cents, on average, per dollar of a sales decrease (bad news), but rises by just 5.9 cents, on average, per dollar of a sales increase (good news).

As predicted, we find large interaction effects of multiple indicators. Gain recognition for positive stock return, operating cash flow change, and sales change is stronger when the other indicators are favorable. Asymmetric loss recognition for negative indicators is higher when the other indicators confirm the bad news. When sales change is unfavorable, asymmetric timeliness for stock return is increased by 83 percent. When the stock return is unfavorable, asymmetric timeliness for sales change and operating cash flow change is more than quadrupled. Thus, the full impact of consistent indicators on earnings is greater than the sum of their individual impacts.

The short-term indicators, sales change and operating cash flow change, have a greater impact on write-downs of (finite-lived) tangible assets, whereas stock return plays a greater role for (indefinite-lived) goodwill. This is consistent with our argument that the indicators in impairment tests are weighted based on the time horizon of expected cash flows from the asset.

Analysis of the impairment process suggests two refinements for asset impairment models (e.g., Riedl 2004). First, although these models seek to capture asymmetric loss recognition using censored regression (a piecewise-linear transformation of the explained variable), we argue that they should also incorporate piecewise-linear effects of individual indicators (explanatory variables). This modification changes inferences about the relative importance of economic versus reporting factors in the observed impairments. Second, we document that the impairment triggers for stock return and sales change are "loose" (i.e., they correspond to extreme bad news; Beaver and Ryan [2005]) and that they differ predictably between tangible assets and goodwill.

Our results suggest that the various cash flow indicators are weighted differently based on the consistency between the expected useful life of assets and these indicators' cash flow horizon, which reveals more refined contextual judgment than often assumed in academic research. We contribute a better understanding of "normal" accounting practice (Ball 2013), using accounting standards as a lagging indicator of best practices, and propose expanded empirical models.

We develop the hypotheses in Section II, describe the data and the estimation models in Section III, present the empirical results in Section IV, examine the implications of our findings for impairment research in Section V, and conclude in Section VI.

II. HYPOTHESIS DEVELOPMENT

Conditional conservatism is defined as the higher degree of verification used to recognize good news as gains than to recognize bad news as losses (Basu 1997; Watts 2003a).[1] Conditional conservatism implies asymmetric timeliness of earnings

[1] In contrast, unconditional conservatism represents news-independent understatement of net assets such as accelerated depreciation (Basu 1997, 2001, 2005; Ball and Shivakumar 2005; Beaver and Ryan 2005).

with respect to good versus bad news about future cash flows. Basu (1997) estimates asymmetric timeliness using a piecewise-linear regression of net income on stock return, where positive (negative) unexpected return is a proxy for good (bad) news. He finds that the slope coefficient and R^2 are higher for negative return than for positive return, i.e., net income reflects bad news more quickly than good news, as predicted. Basu's (1997) asymmetric timeliness coefficient has been widely used to measure conditional conservatism (for reviews, see Watts 2003b; Mora and Walker 2015; Ruch and Taylor 2015).[2] This measure varies predictably with the theoretical sources of demand for conservatism (Watts 2003a), such as country-specific factors (Pope and Walker 1999; Ball, Kothari, and Robin 2000), litigation exposure (Basu 1997; Holthausen and Watts 2001; Qiang 2007; Chung and Wynn 2008), and debt contracting (Zhang 2008; Wittenberg-Moerman 2008; Nikolaev 2010).[3]

Asset write-downs are the most fundamental manifestation of conservatism.[4] However, conservatism research primarily focuses on earnings (rather than impairments) because of its central contracting role (e.g., Schrand 2014) and because of the limited quality, availability, and scope of impairment data in Compustat (Johnson, Lopez, and Sanchez 2011; Roychowdhury and Martin 2013). Therefore, we use the asset impairment guidance as a theoretical foundation to develop insights into conservatism for earnings (e.g., Lawrence, Sloan, and Sun 2013).

Impairment tests are conducted for asset groups "at the lowest level for which identifiable cash flows are largely independent of the cash flows of other assets and liabilities" (SFAS 144, para. 10). Therefore, indicators that help predict future cash flows for individual asset classes will be relevant for impairment. In a semi-strong efficient market, these indicators are embedded in the stock price, which incorporates all public information about firm value (Fama 1970). Hence, researchers typically use stock return (rather than individual indicators) as the main proxy for unrealized gains and losses (e.g., Basu 1997; Ryan 2006; Ball et al. 2013a). However, stock return reflects the change in total discounted cash flows over an infinite horizon, whereas many impairment tests focus on asset cash flows over a much shorter horizon. These shorter-term cash flows are likely better predicted by short-term indicators than by stock return.

The relative weights on these individual indicators likely vary with the remaining useful life of the asset or asset group.[5] Consider a firm that has current assets, such as inventory, and long-term assets, such as retail space or production facilities. Current assets are expected to generate operating cash flows within a year. Therefore, write-downs of current assets will reflect factors that influence expected short-term cash flows, such as current demand trends, but not factors that influence long-term cash flows, such as technological developments. Thus, if the stock price declines because of reduced long-term investment opportunities, but the short-term demand prospects are still positive, then the firm will not write down inventory on hand because its value has not decreased. Conversely, if a firm has a positive stock return due to improved long-term investment opportunities, but demand for some existing products falls sufficiently to predict likely selling price declines, then the firm will likely write down its inventory. Long-term tangible assets and many intangibles have finite expected lives. Therefore, write-downs of these assets will combine short-term factors with some (but not all) of the long-term factors embedded in stock return. Thus, the relevant information for total write-downs is best captured by a vector of indicators that help predict future cash flows for different time horizons, rather than by a one-dimensional summary measure like stock return.[6]

SFAS 144 requires a two-step impairment test for long-lived assets.[7] This test can be triggered by indicators of potential impairment, including a significant adverse change in the business climate (for example, declining sales) or deterioration in

[2] A few papers use other proxies for conservatism, such as asymmetric persistence of losses (Basu 1997; Ball and Shivakumar 2005), skewness of earnings and operating accruals (Basu 1995; Peek, Cuijpers, and Buijink 2010), and asymmetric association of accruals with realized future operating cash flow (Ball and Shivakumar 2006; Srivastava and Tse 2010).

[3] Despite econometric critiques by Dietrich, Muller, and Riedl (2007), Givoly, Hayn, and Natarajan (2007), and Patatoukas and Thomas (2011), the asymmetric timeliness regression model is defended by Ryan (2006), Basu (2009), Ball, Kothari, and Nikolaev (2013a, 2013b), and Collins, Hribar, and Tian (2014). We analyze commonly used asymmetric timeliness regressions, and address potential biases in robustness checks.

[4] Most liabilities do not exhibit conservatism (Ijiri and Nakano 1989). A major exception is contingent liabilities, which incorporate loss contingencies quickly, while gain contingencies are recognized more slowly as contingent assets (FASB 1975, SFAS 5, paras. 8 and 17).

[5] Other accounting measurements also match indicators to the asset's expected life. For example, in computing the present value of an asset, accountants use the risk-free interest rate with the same maturity as the last cash flows (FASB 2006, SFAS 157, para. B2 [now FASB 2014c, ASC 820-10-55]), such as the T-Bill yield for current assets and long-term Treasury bond yields for long-lived assets. While the yield curve provides the denominator for present value, we focus on the best proxies for the *numerator,* i.e., expected cash flows during the remaining asset life.

[6] Ball and Shivakumar (2006), Roychowdhury and Watts (2007), and Beaver and Ryan (2009) point out that stock return measures total "bookable" gains and losses with error, because stock return includes changes in the market value of unbooked rents and of debt. These papers suggest that additional indicators can have an incremental effect because they mitigate this measurement error. In contrast, we argue that even when there is no measurement error (such as for an all-equity firm without unrecognized intangibles), additional indicators are incrementally informative because different asset classes with varying time horizons are tested for impairment separately.

[7] The two-step impairment procedure was introduced in SFAS 121, which preceded SFAS 144 for long-lived assets and SFAS 142 for goodwill. Other provisions of SFAS 142 and 144 arose in SFAS 121, including the grouping of assets at the lowest level with identifiable and largely independent cash flows (SFAS 121, para. 8), the use of multiple indicators (SFAS 121, paras. 5 and 7), and the use of all available evidence with weights "commensurate with the extent to which the evidence can be verified objectively" (SFAS 121, para. 9). These provisions also appear in FASB Accounting Standards Codifications (ASC) 350 and 360, which superseded SFAS 142 and 144 in 2009.

current or projected future cash flows (SFAS 144, para. 8).[8] The first step tests whether the book value of the asset (or asset group) is less than the sum of *undiscounted* future cash flows from the asset, where the cash flow estimates "shall consider all available evidence" (SFAS 144, para. 17). Because operating cash flow projections are normally based on sales forecasts less cost forecasts (e.g., Horngren et al. 2014, Chapter 6), the relevant evidence includes various predictors of future sales and costs.

If the asset is deemed to be impaired based on this comparison, then in the second step, the asset is written down to its fair value, estimated as the sum of *discounted* future cash flows (in the absence of quoted market prices) or based on market prices (for assets traded in active markets). Indicators of a reduction in expected future cash flows, such as a decrease in current sales or operating cash flow, increase both the *probability* (in step 1) and the *magnitude* (in step 2) of the asset impairment.[9] Therefore, conditional on stock return, which combines gains for some assets and losses for others, firms will recognize unrealized losses reflected in additional unfavorable indicators, but will not recognize unrealized gains reflected in additional favorable indicators.

Similarly, the FASB recommends using multiple indicators to assess whether goodwill is impaired. Even when the fair value of a reporting unit can be determined based on market prices of equity, SFAS 142, para. 23 cautions that market capitalization "may not be representative of the fair value" and, therefore, stock prices "need not be the sole measurement basis of the fair value of a reporting unit." Alternative measurement methods include present-value techniques using all available evidence (SFAS 142, para. 24) and valuation based on "multiples of earnings or revenue or a similar performance measure" (SFAS 142, para. 25). Therefore, goodwill impairment under SFAS 142 is likely influenced by indicators beyond stock return.[10]

In summary, the impairment standards for both long-lived assets (SFAS 144 [now FASB 2014b, ASC 360]) and goodwill (SFAS 142 [now FASB 2014a, ASC 350]) suggest that accountants will quickly recognize unrealized losses reflected in unfavorable short-term indicators such as decreasing sales or operating cash flow. Therefore, after controlling for stock return, earnings is likely to exhibit asymmetric loss recognition with respect to multiple additional indicators, including (but not limited to) sales change and operating cash flow change.

Ball and Shivakumar (2006) showed that operating cash flow change has an asymmetric effect on earnings incremental to that of stock return. We propose sales change as a major new indicator motivated by the standard cash flow forecasting procedures used by both internal and external analysts (e.g., Horngren et al. 2014, Chapter 6; Easton et al. 2012, Chapter 11, respectively). Because revenue is the primary driver of operating cash inflows and outflows (Dechow et al. 1998), future sales are predicted first. The sales projection in the standard time-series methods, such as exponential smoothing or autoregressive integrated moving average (ARIMA) modeling (e.g., Chase 2013), is a function of the most recent sales change (e.g., Steele and Trombley 2012). The sales projection is next used to forecast the income statement and balance sheet items, which, in turn, yield the cash flow forecast (Easton et al. 2012; Horngren et al. 2014). SFAS 144, para. 17 stipulates that the assumptions used in impairment tests should be consistent with internal budgets and projections. Therefore, accountants likely follow this standard forecasting approach in assessing asset impairment, and use current-period sales change as a major predictor of future cash flows.[11]

We predict that sales change has an asymmetric effect on earnings incremental to *both* stock return and operating cash flow change.[12] Operating cash flow incorporates noise due to variation in working capital during the normal course of

[8] Similarly, auditors must examine multiple indicators to evaluate whether the entity can continue as a going concern and if necessary evaluate the effect on financial statements of discontinued operations and asset impairment (American Institute of Certified Public Accountants [AICPA] 1989, Statement on Auditing Standards [SAS] 59, paras. 6, 10–11).

[9] Although bad news does not always trigger write-downs, it indicates an increased probability of a write-down, whereas the probability of a write-up is usually zero. Therefore, bad news will have an asymmetric effect on earnings, on average, even if the write-down probability is relatively low. Beaver and Ryan (2005) model and simulate the multi-period effects of probabilistic write-downs, while Basu (2005) develops the implications of probabilistic write-downs for modifying the contemporaneous Basu (1997) asymmetric timeliness regression.

[10] SFAS 142 for goodwill and SFAS 144 for tangible assets differ in a few details that do not change the predictions. For example, while goodwill must be tested annually (SFAS 142), both standards require testing for impairment when there are indicators of potential impairment (SFAS 144, para. 8 and SFAS 142, para. 26). Unfavorable indicators will reduce the estimates of undiscounted cash flows and fair value, increasing the probability and magnitude of impairment under both standards. Accounting Standards Updates (ASU) 2011-08 and 2012-02 (FASB 2011, 2012) later removed the annual testing requirement for goodwill.

[11] A recent survey by the Economist Intelligence Unit shows that 95 percent of companies integrate formal forecasts with their budgeting process. A majority of them use sophisticated forecasting tools such as Enterprise Resource Planning systems (used for forecasting by 40 percent of companies), off-the-shelf forecasting software (37 percent), custom-made forecasting and planning systems (23 percent), and specialist accounting software (17 percent). See: https://www.kpmg.com/dutchcaribbean/en/services/Advisory/Documents/forecasting-with-confidence.pdf

[12] Companies' impairment footnotes typically cite multiple triggers and often mention sales decreases. For example, General Motors Company stated in its 2012 10-K that it "performed below expectations relative to the key operating metrics of forecasted revenues, market share, and variable profit," resulting in impairment charges of $5.5 billion (see: http://www.sec.gov/Archives/edgar/data/1467858/000146785813000025/gm201210k.htm/, notes 11 and 13). In fiscal year 2012, Microsoft Corporation had a goodwill impairment charge of $6.2 billion, which was the result of its online services "experiencing slower than projected growth in search queries and search advertising revenue per query" (see: http://www.sec.gov/Archives/edgar/data/789019/000119312513310206/R18.htm). Chen, Ramnath, Rangan, and Rock (2011) report that inventory write-downs in the semiconductor industry are typically triggered when the available inventory is excessive relative to demand.

operations (Dechow 1994; Ball and Shivakumar 2006). Many expenditures are matched poorly with expected revenues (Dichev and Tang 2008). For example, because R&D and advertising expenditures are not capitalized as investments, they reduce current operating cash flow (but likely increase expected future cash flows). This mismatching adds more noise to operating cash flow. Because managers cannot adjust many resources on short notice (e.g., Horngren et al. 2014, Chapter 10), they adapt to economic shocks slowly. Thus, operating cash flow change reflects only partial resource adjustment in response to current shocks and is a noisy indicator of the impact of these shocks on future cash flows. Sales change is not affected by these sources of matching-related noise. Further, it likely captures the fundamental drivers of future cash flows, such as the overall performance of the firm's business model, providing significant incremental information for impairment tests:[13]

H1: After controlling for the asymmetric effects of both stock return and operating cash flow change, earnings exhibits asymmetric association with sales change.[14]

To obtain informed inferences from multiple indicators, accountants need to assess each indicator's precision using either statistical analysis or subjective judgment. Indicator consistency likely plays a key role in this assessment. Each indicator incorporates some information about future cash flows and some measurement error. When different indicators contradict one another, some of them are likely confounded by large measurement error, i.e., these indicators' precision (inverse of measurement error variance) is likely low. Conversely, when multiple indicators are consistent with each other, the measurement errors in all of them are likely small, and the indicators' precision is likely high. For subjective estimates, this statistical effect of indicator consistency could be reinforced by the representativeness heuristic (Tversky and Kahneman 1974), which implies that one's confidence in an indicator is greater when it is accompanied by additional similar indicators.

When a particular indicator is more precise, it likely has a greater weight in inferences. For example, in Bayesian inferences for a multivariate normal distribution, the optimal weight on each indicator is equal to the ratio of this indicator's precision to the total precision of all of the included information sources, including the prior distribution (e.g., Basilevsky 1994, 78). In agreement with this statistical result, paragraph 24 in SFAS 142 states that the weight given to a given piece of evidence "should be commensurate with the extent to which the evidence can be verified objectively" (as reflected in each indicator's statistical or perceived precision).

This inference process gives rise to interactions between multiple indicators. Because these indicators are likely more precise when they confirm, rather than contradict, one another, each of them receives a greater weight in inferences. This interaction affects the asymmetric sensitivity of earnings to each of the indicators, even after controlling for their asymmetric main effects. In particular, unrealized gains reflected in a given favorable indicator (such as positive stock return or increasing sales or operating cash flow) will be recognized to a greater extent when the other indicators are favorable, forming a consistent pattern of good news, than when the other indicators are unfavorable. Similarly, unrealized losses embedded in a given unfavorable indicator will be recognized more fully when this indicator is confirmed by other unfavorable evidence. In other words, accountants' response to a pattern of consistent indicators will be stronger than the sum of their typical responses to each of these individual indicators:[15]

H2a: After controlling for the asymmetric main effects of multiple indicators, gain recognition for a given favorable indicator (i.e., the slope coefficient for positive stock return, increasing sales, or increasing operating cash flow) is lower when the other indicators are unfavorable than when they are favorable.

H2b: After controlling for the asymmetric main effects of multiple indicators, asymmetric loss recognition for a given unfavorable indicator (i.e., the incremental slope coefficient for negative stock return, decreasing sales, or decreasing operating cash flow) is greater when the other indicators are unfavorable than when they are favorable.

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[13] Ertimur, Livnat, and Martikainen (2003) argue that sales is more homogeneous than costs and is more difficult to manipulate, which increases the informativeness of the sales indicator. Because operating cash flow is influenced by both sales and costs, it might help predict future costs. Stock return likely conveys incremental long-term information, which leads to the standard prediction of asymmetric timeliness for stock return.

[14] Because earnings = sales − costs, earnings is associated with sales change. However, this mechanical association is symmetric (e.g., Horngren et al. 2014, Chapter 3) and cannot explain the asymmetry that we predict in H1. Reported sales can be influenced by conservative revenue recognition, but because reported sales affects earnings dollar for dollar, such conservatism does not lead to a spurious asymmetry in the relation between sales and earnings. To validate the role of the sales indicator in conservatism, we directly examine the asymmetric effect of sales change on asset write-downs and also use cash sales instead of reported sales in robustness checks.

[15] Ghosh, Gu, and Jain (2005) document an interaction effect of sustained earnings growth and sales growth on earnings persistence, while Jegadeesh and Livnat (2006) find an interaction effect of earnings surprise and sales surprise on the market reactions to earnings surprises.

Compustat separates write-downs of goodwill (and other unamortized intangibles with indefinite future lives) from write-downs of tangible assets (and amortized intangibles with a definite future life). Because conservatism manifests most directly in asset write-downs, which are not confounded by other potential asymmetries in earnings, the write-down data let us verify that the asymmetric effect of a given indicator on earnings is attributable to conservatism.[16] These data also let us test our time-horizon argument for why accountants use different combinations of indicators for different asset classes. Future cash flows in impairment tests are estimated for the remaining useful life of the asset or asset group (e.g., SFAS 144, para. 18). Because tangible assets have a finite useful life, long-term data have limited relevance. Goodwill, by contrast, has an indefinite future life. Further, because the value of goodwill only incorporates cash flows that are not attributed to (finite-lived) assets in place, the long-term data are much more important. Therefore, short-term indicators, such as sales change or operating cash flow, will be relatively more relevant in assessing impairment of finite-lived tangible assets, whereas the long-term indicator, stock return, will be relatively more informative for goodwill impairment:[17]

H3a: The relative impact of short-term indicators, such as sales change or operating cash flow change, is greater for tangible asset write-downs than for goodwill impairments.

H3b: The relative impact of stock return is greater for goodwill impairments than for tangible asset write-downs.

Our hypotheses require more than just technical compliance with the impairment standards. First, although accountants are unlikely to violate generally accepted accounting principles (GAAP), they have substantial discretion in the implementation details. They can report impairments that faithfully represent the economic substance of events, choosing the most informative indicators for each asset class (as we assume in deriving H1–H3). However, they can also produce uninformative or misleading reports without violating the letter of the standards (e.g., Ball 2009). For example, suppose that firms manage earnings to avoid reporting losses and earnings decreases (Burgstahler and Dichev 1997). Both losses and earnings decreases are more likely when sales decrease. Therefore, firms might delay write-downs during sales decreases to manage earnings upward, contrary to H1. They might be even more likely to delay write-downs when multiple indicators are unfavorable, contrary to H2. Thus, our predictions might not hold if earnings management is prevalent.

Second, accountants might use the available data inefficiently because of behavioral biases. For example, the anchoring effect (Tversky and Kahneman 1974) implies that accountants will disproportionately focus on current cash flow to "anchor" their cash flow forecast and will disregard other relevant indicators such as sales changes. If this effect dominates, then earnings will exhibit asymmetric timeliness with respect to operating cash flow, reproducing Ball and Shivakumar's (2005) findings; however, sales change will not have an asymmetric effect, contrary to our H1. Alternatively, accountants might mechanically lump together all available (relevant and irrelevant) indicators, because the impairment standards require use of "all available evidence" (SFAS 144, para. 17). H1 could hold in this scenario, but H2 and H3 would not hold. Thus, our predictions hinge on both accountants' effort to produce informative reports and their ability to avoid behavioral biases.

III. DATA AND EMPIRICAL MODELS

Sample Selection and Descriptive Statistics

We use the combined CRSP/Compustat annual sample from 1987 to 2007.[18] We exclude financial firms (SIC codes 6000–6999) because they have a different business model (Penman 2007; Dichev 2008) and the impairment standards that we focus on (SFAS 121, 142, and 144) do not apply to financial assets, but the results are robust to inclusion of financial firms. We discard firm-year observations with missing or invalid data for the regression variables and observations with lagged stock price below $1. We also exclude observations for which annual sales change exceeds +50 percent to eliminate "significant" mergers

[16] Even if sales change is not related to conservatism, it could have a piecewise-linear effect on earnings through gradual asymmetric adjustment of fixed costs. For example, suppose that managers hire additional workers when sales increase, but delay layoffs when sales decrease to determine whether the sales decrease is temporary (e.g., Banker, Basu, Byzalov, and Chen 2016). This would generate an asymmetric relation between sales change and earnings (through labor costs), but would not affect write-downs. Contrarily, if sales change plays a role in conservatism, then it will have an asymmetric effect on both earnings and write-downs (Lawrence et al. 2013).

[17] Accountants might use the market value of equity to estimate the total fair value of the firm, but still need to allocate this value among the individual reporting units for goodwill impairment tests. Under SFAS 142, para. 21, the fair value estimate for goodwill is the fair value of the unit (i.e., expected discounted cash flows from the reporting unit over an infinite horizon) minus the fair value of the net assets (i.e., expected discounted cash flows from the unit's net assets over their remaining life). Because the goodwill impairment estimate is primarily based on long-term cash flows, it will be associated more strongly with stock return than with the short-term indicators.

[18] Operating cash flow data reported under SFAS 95 (FASB 1987) start in 1987. Our results are robust to extending the sample period backward in time using the less accurate balance sheet method for estimating operating cash flow (e.g., Collins and Hribar 2002; Cheng, Liu, and Schaefer 1997). We end the sample in 2007 to avoid the effects of the financial crisis that started in 2008. Our results hold when we extend the sample to 2014.

TABLE 1

Variable Definitions

Variable		Definition and Data Items
$EARN_t$	=	net income (Compustat item NI) in year t, scaled by the market value of equity (PRCC_F × CSHO) at the beginning of the year;
RET_t	=	stock return for the 12-month period of fiscal year t (CRSP item RET);
DR_t	=	dummy variable that equals 1 if stock return RET_t is negative, and 0 otherwise;
ΔCF_t	=	change in operating cash flow (Compustat item OANCF) from year $t-1$ to year t, scaled by market value of equity at the beginning of the year;
DC_t	=	dummy variable that equals 1 if cash flow change ΔCF_t is negative, and 0 otherwise;
$\Delta SALES_t$	=	change in sales (Compustat item SALE) from year $t-1$ to year t, scaled by market value of equity at the beginning of the year;
DS_t	=	dummy variable that equals 1 if sales change $\Delta SALES_t$ is negative, and 0 otherwise;
WD_t	=	long-lived asset write-down (Compustat item WDP) in year t, scaled by market value of equity at the beginning of the year; and
GW_t	=	goodwill impairment (Compustat item GDWLIP) in year t, scaled by market value of equity at the beginning of the year.
Additional indicators used in robustness checks in Table 4		
$\Delta CSALES_t$	=	change in cash sales (Compustat items SALE + RECCH) from year $t-1$ to year t, scaled by market value of equity at the beginning of the year;
ΔCGM_t	=	change in cash gross margin (Compustat items SALE − COGS + RECCH + INVCH + APALCH) from year $t-1$ to year t, scaled by market value of equity at the beginning of the year;
CF_t	=	operating cash flow (Compustat item OANCF) in year t, scaled by market value of equity at the beginning of the year;
ΔOB_t	=	change in order backlog (Compustat item OB) from year $t-1$ to year t, scaled by market value of equity at the beginning of the year;
ΔEPS_F_t	=	the change in analysts' consensus EPS forecast for year $t+1$ (I/B/E/S item MEDEST, MEASURE = "EPS") that occurred from the beginning to the end of year t, scaled by the stock price at the beginning of year t;
ΔCPS_F_t	=	the change in analysts' consensus CPS (operating cash flow per share) forecast for year $t+1$ (I/B/E/S item MEDEST, MEASURE = "CPS") that occurred from the beginning to the end of year t, scaled by the stock price at the beginning of year t; and
$\Delta SALES\_F_t$	=	the change in analysts' consensus sales forecast for year $t+1$ (I/B/E/S item MEDEST, MEASURE = "SAL") that occurred from the beginning to the end of year t, scaled by market value of equity at the beginning of year t.
Additional controls used in Section V		
ΔE_t	=	change in pre-write-down earnings in year t (items PI − WDP − GDWLIP), scaled by market value of equity at the beginning of the year;
DE_t	=	dummy variable that equals 1 if $\Delta E_t < 0$, and 0 otherwise;
ΔGDP_t	=	GDP growth in year t (source: https://fred.stlouisfed.org/series/A191RL1A225NBEA);
$\Delta INDROA_t$	=	change in median industry ROA for the two-digit SIC industry of the firm in year t;
ΔMGT_t	=	dummy variable that equals 1 if any of the top three executives of the firm has changed from year $t-1$ to year t, and 0 otherwise;
$BATH_t$	=	ΔE_t if ΔE_t is below the median of the negative tail of ΔE_t, and 0 otherwise;
$SMOOTH_t$	=	ΔE_t if ΔE_t is above the median of the positive tail of ΔE_t, and 0 otherwise; and
$DEBT_t$	=	a dummy variable that equals 1 if the firm's debt is private (i.e., not publicly rated by Standard & Poor's), and 0 otherwise.

(Collins and Hribar 2002), and use a symmetric negative threshold of −50 percent to exclude large dispositions. The results hold when we retain these observations in the sample. All continuous variables are winsorized at the top and bottom 1 percent. The final sample comprises 54,910 firm-year observations for 8,028 firms. Because data for asset write-downs and goodwill impairments are available in Compustat only beginning in 2001, tests for these variables are based on a smaller sample from 2001 to 2007 that comprises 21,125 observations for 4,836 firms (after replacing missing impairment values with zeros, following Dechow and Ge 2006). The variable definitions are presented in Table 1.

The univariate descriptive statistics and the correlation matrix are presented in Panels A and B of Table 2, respectively. Net income, operating cash flow change, and sales change are scaled by the market value of equity at the beginning of the year. On average, net income is equal to −0.7 percent of lagged market value, and the median is 4.7 percent. Scaled earnings is left-

TABLE 2

Descriptive Statistics

Panel A: Univariate statistics

	Mean	S.D.	Q1	Median	Q3
EARN	−0.007	0.241	−0.016	0.047	0.081
DR	0.445	0.497	0.000	0.000	1.000
RET	0.137	0.582	−0.212	0.050	0.344
DR × *RET*	−0.128	0.198	−0.212	0.000	0.000
DC	0.449	0.497	0.000	0.000	1.000
Δ*CF*	0.010	0.181	−0.039	0.006	0.054
DC × Δ*CF*	−0.046	0.110	−0.039	0.000	0.000
DS	0.300	0.458	0.000	0.000	1.000
Δ*SALES*	0.069	0.449	−0.021	0.055	0.183
DS × Δ*SALES*	−0.091	0.302	−0.021	0.000	0.000
WD	−0.006	0.037	0.000	0.000	0.000
GW	−0.006	0.050	0.000	0.000	0.000

Panel B: Correlation Matrix

	EARN	*DR*	*RET*	*DR* × *RET*	*DC*	Δ*CF*	*DC* × Δ*CF*	*DS*	Δ*SALES*	*DS* × Δ*SALES*	*WD*	*GW*
EARN		−0.230	0.209	0.324	−0.089	0.096	0.295	−0.270	0.368	0.406	0.378	0.411
DR	−0.399		−0.633	−0.721	0.149	−0.089	−0.057	0.223	−0.169	−0.089	−0.083	−0.099
RET	0.440	−0.854		0.612	−0.145	0.149	0.009	−0.194	0.219	0.057	0.062	0.091
DR × *RET*	0.450	−0.953	0.896		−0.138	0.071	0.089	−0.270	0.193	0.139	0.128	0.158
DC	−0.151	0.149	−0.172	−0.157		−0.518	−0.442	0.172	−0.078	−0.062	−0.027	−0.032
Δ*CF*	0.160	−0.152	0.192	0.156	−0.860		0.691	−0.065	0.069	0.014	**0.009**	0.028
DC × Δ*CF*	0.176	−0.142	0.160	0.156	−0.947	0.907		−0.184	0.179	0.329	0.151	0.100
DS	−0.311	0.223	−0.249	−0.258	0.172	−0.142	−0.212		−0.508	−0.419	−0.127	−0.102
Δ*SALES*	0.381	−0.275	0.333	0.304	−0.158	0.169	0.168	−0.799		0.809	0.140	0.101
DS × Δ*SALES*	0.320	−0.215	0.240	0.253	−0.166	0.137	0.221	−0.978	0.817		0.181	0.127
WD	0.193	−0.093	0.113	0.115	−0.028	0.016	0.032	−0.102	0.102	0.109		0.126
GW	0.215	−0.115	0.136	0.144	−0.041	0.034	0.050	−0.103	0.101	0.112	0.179	

The table reports summary statistics for 54,910 firm-year observations from 1987 to 2007 (for asset write-downs *WD* and goodwill impairment *GW*, the sample comprises 21,125 observations from 2001 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. Correlations in bold in Panel B are statistically insignificant at the 5 percent level.
The variable definitions are provided in Table 1.

skewed (mean < median), consistent with the presence of conditional conservatism (Basu 1995; Ball et al. 2000). Annual stock return is 13.7 percent, on average, and the median is 5.0 percent. Stock return is negative ($DR = 1$) for 44.5 percent of the sample. Average operating cash flow change is equal to 1.0 percent of lagged market value, and average sales change is equal to 6.9 percent of lagged market value; the medians are 0.6 percent and 5.5 percent, respectively. Cash flow decreases ($DC = 1$) and sales decreases ($DS = 1$) account for 44.9 percent and 30.0 percent of observations, respectively. All of the pairwise correlations between stock return (*RET*), scaled cash flow change (ΔCF), and scaled sales change ($\Delta SALES$) are less than 30 percent, which suggests that these indicators capture different aspects of firm performance that can provide useful information. All three indicators are significantly positively correlated with earnings.

Because write-downs reduce earnings, we code them as negative values. On average, in Table 2, tangible asset write-down is equal to −0.6 percent of lagged market value; average goodwill impairment has a similar magnitude. Among firms that report a non-zero tangible asset write-down (18.8 percent of the sample), it is equal to −3.4 percent of lagged market value, on average, and the median is −0.8 percent; 6.9 percent of firms report a non-zero goodwill impairment, which is equivalent to −9.0 percent of lagged market value, on average, and the median is −2.7 percent. Both variables are significantly correlated with stock return, cash flow change, and sales change; when these indicators are unfavorable, asset write-down and goodwill impairment are larger (more negative). These correlations are driven primarily by bad news. For example, whereas the Pearson correlation of write-down with stock return is 0.062, the correlation with the negative portion of stock return ($DR \times RET$) is 0.128, or more than double. This suggests that standard impairment models (e.g., Riedl 2004), which typically do not distinguish between gains and losses for individual indicators, can be improved by incorporating asymmetric loss recognition.

These correlations differ systematically between tangible assets and goodwill. Negative stock return ($DR \times RET$) has a higher Pearson correlation with goodwill impairment than with asset write-down (0.158 and 0.128, respectively; Table 2, Panel B), whereas negative cash flow change ($DC \times \Delta CF$) and negative sales change ($DS \times \Delta SALES$) are more strongly correlated with finite-lived asset write-down. These correlations are consistent with our argument that the weights on an indicator in asset impairment tests vary with the time horizon of the expected cash flows from the asset.

Empirical Models

We start with the Basu (1997) asymmetric timeliness model:

$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \varepsilon_t \tag{1}$$

where $EARN_t$ is earnings in year t, scaled by beginning-of-year market value of equity; RET_t is stock return for the 12-month period of fiscal year t; and DR_t is a dummy variable equal to 1 if RET_t is negative, and 0 otherwise. We omit the firm index for brevity. Conditional conservatism implies that the coefficient on $DR \times RET$ is positive, i.e., bad news (negative RET) is reflected in earnings to a greater extent than good news (positive RET).

Ball and Shivakumar (2006) add the operating cash flow indicator to the Basu model:

$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + v_t \tag{2}$$

where ΔCF_t represents operating cash flow change in year t, scaled by beginning-of-year market value of equity; DC_t is a dummy variable equal to 1 if ΔCF_t is negative, and 0 otherwise; and the remaining variables were defined previously. Ball and Shivakumar (2006) predict positive coefficients on $DR \times RET$ and $DC \times \Delta CF$, which represent conservatism for both indicators.

In our main model, we incorporate sales change as a third indicator:

$$\begin{aligned} EARN_t = {} & \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t \\ & + \gamma_3 DS_t \times \Delta SALES_t + \varsigma_t \end{aligned} \tag{3}$$

where $\Delta SALES_t$ is sales change in year t, scaled by beginning-of-year market value of equity; DS_t is a dummy variable equal to 1 if $\Delta SALES_t$ is negative, and 0 otherwise; and all other variables were defined previously. H1 predicts that the coefficient on $DS \times \Delta SALES$ is positive; i.e., conditional on both stock return and operating cash flow change asymmetries, earnings displays asymmetric timeliness with respect to sales change. Similar to Ball and Shivakumar (2006), we also expect positive asymmetric timeliness coefficients on $DR \times RET$ and $DC \times \Delta CF$, because each of the included indicators likely contains useful information.[19]

We examine the interaction effects of multiple indicators using the following model:

$$\begin{aligned} EARN_t = {} & \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t \\ & + \gamma_3 DS_t \times \Delta SALES_t + \delta_1 DR_t \times DC_t + \lambda_1 DR_t \times DS_t + DC_t \times (\delta_2 RET_t + \delta_3 DR_t \times RET_t) \\ & + DS_t \times (\lambda_2 RET_t + \lambda_3 DR_t \times RET_t) + DR_t \times (\delta_4 \Delta CF_t + \delta_5 DC_t \times \Delta CF_t) \\ & + DR_t \times (\lambda_4 \Delta SALES_t + \lambda_5 DS_t \times \Delta SALES_t) + \xi_t \end{aligned} \tag{4}$$

where all variables are as defined previously. The coefficient on $DC \times RET$ captures the interaction effect of a cash flow decrease on the recognition of good news contained in stock return (i.e., the impact of $DC = 1$ on the slope for positive RET), while the coefficient on $DR \times \Delta CF$ represents the interaction effect of a negative stock return on the recognition of good news embedded in cash flow (i.e., the impact of $DR = 1$ on the slope for positive ΔCF). The coefficients on $DS \times RET$ and $DR \times \Delta SALES$ capture the interaction effects between sales change and stock return. H2a predicts that these interaction coefficients are negative. In other words, a positive RET, ΔCF, or $\Delta SALES$ (good news) is recognized in earnings to a lesser extent when the other indicators are unfavorable, as reflected in the dummy variables DC, DS, or DR.

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[19] The main coefficients on RET, ΔCF, and $\Delta SALES$ capture good news recognition, i.e., earnings response to favorable values of these indicators. These coefficients need not be (or can be) positive. Roychowdhury and Watts (2007) point out that the coefficient on RET can be negative, because value-increasing (but uncapitalized) R&D expenditures reduce reported earnings, but increase stock return. An analogous argument for advertising expenditures may lead to a negative coefficient on $\Delta SALES$. From Dechow (1994) and Ball and Shivakumar (2006), the coefficient on ΔCF may be negative due to the noise-reduction role of operating accruals. ΔCF and $\Delta SALES$ also control for the mechanical associations of earnings with concurrent cash flow and sales.

The coefficient on $DC \times DR \times RET$ reflects the interaction effect of a cash flow decrease on asymmetric loss recognition for stock return (i.e., the impact of $DC = 1$ on the incremental slope for $DR \times RET$), while the coefficient on $DR \times DC \times \Delta CF$ represents the interaction effect of a negative stock return on asymmetric timeliness with respect to cash flow changes (i.e., the impact of $DR = 1$ on the incremental slope for $DC \times \Delta CF$). The coefficients on $DS \times DR \times RET$ and $DR \times DS \times \Delta SALES$ measure the interaction effects between sales change and stock return (i.e., the impact of $DS = 1$ on the incremental slope for $DR \times RET$ and the impact of $DR = 1$ on the incremental slope for $DS \times \Delta SALES$, respectively). H2b predicts that these coefficients are positive. In other words, the extent of asymmetric loss recognition for a given bad news indicator ($DR \times RET$, $DC \times \Delta CF$, or $DS \times \Delta SALES$) is greater when this indicator is confirmed by other bad news (represented by the dummies DC, DS, or DR).

In tests for tangible asset write-downs and goodwill impairments, we replace earnings in Models (1)–(3) with the corresponding write-down. Because we code write-downs as negative numbers, the expected coefficient signs are the same as for earnings. H3a and H3b predict that the relative impact of cash flow change and sales change is greater for tangible asset write-down, whereas the relative impact of stock return is greater for goodwill impairment.

IV. EMPIRICAL RESULTS

The estimates of Models (1)–(3) are presented in Table 3. Consistent with Basu (1997), in all models, the asymmetric timeliness coefficient on $DR \times RET$ is positive and significant, i.e., bad news (negative RET) is recognized in concurrent earnings more fully than good news (positive RET), indicating conditional conservatism for stock return. Similar to Ball and Shivakumar (2005, 2006), we find a significant positive coefficient on $DC \times \Delta CF$, which indicates asymmetric timeliness with respect to concurrent operating cash flow change. When we add sales change, the coefficient on $DC \times \Delta CF$ is reduced by 41 percent, from 0.823 in the Ball and Shivakumar (2006) model (Column (2)) to 0.482 in our full three-indicator model (Column (3)). This suggests that sales change is an important correlated omitted variable in the Ball and Shivakumar (2006) model. However, this smaller asymmetry coefficient on $DC \times \Delta CF$ remains significant, consistent with our argument that unrealized gains and losses are best modeled by a vector of indicators.

As predicted in H1, in Table 3, after controlling for *both* stock return and operating cash flow change, as in Ball and Shivakumar (2006), sales change has a significant asymmetric effect on earnings (the coefficient on $DS \times \Delta SALES$ is 0.174, t $= 8.74$ in Column (3)).[20] The sales indicator plays an important incremental role in conditional conservatism. For example, while a \$1 sales increase (good news) raises earnings by just 5.9 cents, on average, a \$1 sales decrease (bad news) reduces earnings by 23.3 cents, on average ($= 0.059 + 0.174$), indicating much quicker recognition of bad news than good news for sales.

In untabulated tests, the results hold when we control for cross-sectional correlation between the expected components of earnings and stock return using the firm fixed effects model, the earnings first-difference model, and the asymmetric autoregressive earnings expectation model (Ball et al. 2013b). The estimates are robust to the scale effect of Patatoukas and Thomas (2011), which we control for using the Fama and MacBeth (1973) estimation for lagged stock price partitions, following Ball et al. (2013b). The results also hold when we discard all firm-years with material divestitures, defined as discontinued operations in excess of \$10,000, following Collins and Hribar (2002), and all firm-years with footnote codes for mergers. To ensure that the estimates are not driven by the mechanical association of earnings with concurrent operating cash flow and sales, we replace earnings with total operating accruals (Basu 1997; Ball and Shivakumar 2006; Hsu, O'Hanlon, and Peasnell 2011, 2012; Collins et al. 2014) and tax-adjusted non-sales-related operating accruals (i.e., operating accruals net of sales-related accruals, and net of tax accruals to remove the tax effects of sales); in both cases, the results are robust. These estimates are also robust to removing liability-related accruals, which should exhibit little conservatism (Ijiri and Nakano 1989). The results also hold for subsamples of manufacturing (SIC codes 2000–3999), service (SIC codes 7000–8999), and trade (SIC codes 5000–5999) firms.

In Table 4, we examine additional proxies for unrealized gains and losses. First, to ensure that the results are not driven by the accrual component of sales, we redefine the sales indicator as the change in cash sales, $\Delta CSALES$. We consider three additional indicators from Compustat: the level of current operating cash flow, CF; the change in cash gross margin, ΔCGM; and the change in order backlog, ΔOB.[21] We also examine indicators from I/B/E/S that are based on analysts' forecast revisions for future earnings per share (ΔEPS_F), future operating cash flow per share (ΔCPS_F), and future sales ($\Delta SALES\_F$),

[20] Ball and Shivakumar (2006) include sales change in one of their empirical specifications, following the Jones (1991) model. However, whereas they use sales change as a symmetric control variable (similar to $\Delta SALES$ in Table 3), we focus on the asymmetric effect of sales change ($DS \times \Delta SALES$) as a fundamental indicator in impairment tests.

[21] Operating cash flow is typically negative for young growth firms and positive for mature firms (Dickinson 2011). Therefore, the level of current cash flow is a less appropriate predictor of future cash decreases than is the change in current cash flow (our main version of the cash flow indicator). For consistency with Ball and Shivakumar (2006), we examine both specifications, despite the *a priori* limitations of the operating cash flow level. Steele and Trombley (2012) find that changes in gross margin and order backlog help predict sales.

TABLE 3

Asymmetric Timeliness Estimates for Multiple Indicators

Models (1)–(3) for Earnings:

$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \varepsilon_t$$
$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + v_t$$
$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t + \gamma_3 DS_t \times \Delta SALES_t + \zeta_t$$

		Basu (1997) Model (1)	Ball and Shivakumar (2006) Model (2)	Full Three-Indicator Model (3)
Intercept		0.038***	0.066***	0.062***
		(8.08)	(15.91)	(14.36)
DR		0.005	0.007	0.005
		(0.82)	(1.21)	(0.94)
RET		0.011	0.028**	0.015
		(1.23)	(2.34)	(1.49)
DR × RET	+	**0.378*** **	**0.326*** **	**0.284*** **
		(11.13)	**(11.03)**	**(11.39)**
DC			0.006	0.007
			(1.31)	(1.56)
ΔCF			−0.254***	−0.125***
			(−7.94)	(−5.35)
DC × ΔCF	+		**0.823*** **	**0.482*** **
			(8.90)	**(7.96)**
DS				−0.013***
				(−2.78)
ΔSALES				0.059***
				(8.79)
DS × ΔSALES	+			**0.174*** **
				(8.74)
Adj. R^2 (%)		10.3	17.2	26.3
F-statistic for the full effect of				
DR, RET, DR × RET		49.16***	49.82***	49.94***
DC, ΔCF, DC × ΔCF			75.22***	42.09***
DS, ΔSALES, DS × ΔSALES				221.43***
F-statistic for the asymmetric effect of				
DR, DR × RET		73.42***	68.23***	73.22***
DC, DC × ΔCF			70.68***	38.82***
DS, DS × ΔSALES				164.85***

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The table presents pooled regression estimates on a sample of 54,910 firm-year observations from 1987 to 2007. The t-statistics in parentheses are based on standard errors clustered by firm and year. The main coefficients of interest in our tests are in bold.
The variable definitions are provided in Table 1.

TABLE 4

Incremental Effect of Additional Indicators

$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \pi_1 DX_t + \pi_2 X_t + \pi_3 DX_t \times X_t + \varepsilon_t$$

$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \pi_1 DX_t + \pi_2 X_t + \pi_3 DX_t \times X_t + \nu_t$$

$$EARN_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t + \gamma_3 DS_t \times \Delta SALES_t + \pi_1 DX_t + \pi_2 X_t + \pi_3 DX_t \times X_t + \zeta_t$$

where X_t stands for the additional indicator, and DX_t is a dummy variable that equals 1 if X_t is negative.

		Additional Indicator (*X*)						
		ΔCSALES **(1)**	***ΔCGM*** **(2)**	***CF*** **(3)**	***ΔOB*** **(4)**	***ΔEPS_F*** **(5)**	***ΔCPS_F*** **(6)**	***ΔSALES_F*** **(7)**
Main indicator = *RET*, following Basu (1997)								
DX		−0.034***	−0.008**	−0.041***	0.007	0.015***	0.006	0.003
		(−6.83)	(−2.34)	(−3.95)	(0.94)	(3.53)	(0.26)	(0.62)
X		0.015**	−0.126***	−0.117***	−0.016*	−0.251	−0.287***	0.031***
		(2.27)	(−5.13)	(−4.20)	(−1.80)	(−1.09)	(−4.24)	(3.22)
DX × X	+	**0.184*****	**0.581*****	**0.997*****	**0.159*****	**2.155*****	**2.128***	**0.181*****
		(9.02)	**(11.44)**	**(7.65)**	**(5.70)**	**(6.27)**	**(1.96)**	**(6.64)**
Adj. R^2 (%)		23.6	19.9	20.3	11.6	23.6	15.9	16.8
Main indicators = *RET* and Δ*CF*, following Ball and Shivakumar (2006)								
DX		−0.021***	−0.001	−0.029***	0.007	0.014***	0.001	0.003
		(−6.83)	(−0.15)	(−2.64)	(1.18)	(3.44)	(0.03)	(0.56)
X		0.052***	0.002	−0.011	0.028***	−0.053	−0.190***	0.071***
		(8.06)	(0.06)	(−0.42)	(2.79)	(−0.26)	(−3.17)	(5.43)
DX × X	+	**0.111*****	**0.365*****	**0.710*****	**0.048***	**1.700*****	**1.501***	**0.082*****
		(5.85)	**(7.54)**	**(7.42)**	**(1.86)**	**(5.70)**	**(1.65)**	**(4.69)**
Adj. R^2 (%)		25.6	20.9	21.9	17.6	25.5	21.8	21.3
Main indicators = *RET*, Δ*CF*, and Δ*SALES*, following our main model								
DX		0.001	0.006*	−0.031***	0.013**	0.013***	−0.001	0.006
		(0.29)	(1.73)	(−3.33)	(2.40)	(3.80)	(−0.07)	(1.37)
X		−0.037**	−0.052*	0.058**	0.025*	−0.207	−0.198***	0.024
		(−2.15)	(−1.94)	(2.56)	(1.86)	(−0.99)	(−3.71)	(1.37)
DX × X	+	**0.100*****	**0.201*****	**0.590*****	**−0.018**	**1.594*****	**1.305**	**0.098*****
		(2.42)	**(4.72)**	**(7.12)**	**(−0.69)**	**(5.17)**	**(1.39)**	**(2.90)**
Adj. R^2 (%)		26.6	26.8	31.0	28.1	30.4	25.0	22.6

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The table presents pooled regression estimates on a sample of 54,910 firm-year observations for Δ*CSALES*, Δ*CGM*, and *CF*; 21,296 firm-year observations for Δ*OB*; 29,013 firm-year observations for Δ*EPS_F*; 5,508 firm-year observations for Δ*CPS_F*; and 12,838 firm-year observations for Δ*SALES_F*. For brevity, we only report the coefficients for the additional indicator. The t-statistics in parentheses are based on standard errors clustered by firm and year. The main coefficients of interest in our tests are in bold.
The variable definitions are provided in Table 1.

respectively. Analysts' forecasts likely embed some of the firms' forward-looking information that is not fully captured by our Compustat-based indicators (e.g., Hutton 2005; Cotter, Tuna, and Wysocki 2006). To isolate the news that arrived during the current fiscal year, we define these indicators as the change in analysts' consensus forecast for year *t*+1 that occurred from the beginning to the end of year *t*.[22] In all cases, the additional indicators have a significant asymmetric effect in the Basu (1997)

[22] In untabulated tests, the revisions in analysts' cash flow forecasts (Δ*CPS_F*) are more closely associated with concurrent sales change (Δ*SALES*) than with concurrent operating cash flow change (Δ*CF*). For example, the Pearson correlation of Δ*CPS_F* with Δ*SALES* is 16.0 percent, whereas the correlation of Δ*CPS_F* with Δ*CF* is 13.1 percent. Further, after controlling for Δ*SALES*, the effect of Δ*CF* on Δ*CPS_F* is insignificant. Sales change also has a strong association with revisions in analysts' sales forecasts (the correlation of Δ*SALES* with Δ*SALES_F* is 53.9 percent). These results are consistent with Ertimur, Mayew, and Stubben (2011) and Call, Chen, and Tong (2013), who show that analysts use sales projections as a major input to their earnings and cash flow forecasts.

and Ball and Shivakumar (2006) models. Further, even when they are added as a *fourth* indicator in our full model, all but two (ΔOB and ΔCPS_F) exhibit significant asymmetric loss recognition.

The estimates of the interaction effect Model (4) are presented in Table 5. As expected (H2a), the interaction coefficients on $DC \times RET$, $DS \times RET$, $DR \times \Delta CF$, and $DR \times \Delta SALES$ are negative and significant. This indicates that earnings is less sensitive to good news represented by a positive RET, ΔCF, or $\Delta SALES$ when this good news is contradicted by an unfavorable indicator (DC, DS, or DR). Consistent with H2b, the interaction coefficients on $DS \times DR \times RET$, $DR \times DC \times \Delta CF$, and $DR \times DS \times \Delta SALES$ are positive and significant. In other words, asymmetric loss recognition for stock return ($DR \times RET$) is greater when the bad news in stock return is confirmed by bad news in the sales indicator ($DS = 1$). Similarly, the asymmetric timeliness with respect to both operating cash flow change and sales change ($DC \times \Delta CF$ and $DS \times \Delta SALES$, respectively) is increased when the stock return is unfavorable ($DR = 1$).[23] The interaction effects imply that conservatism is stronger when more than one of the indicators is negative; however, even when any two out of the three indicators are positive, we observe conservatism for the third indicator (i.e., the coefficients on $DR \times RET$, $DC \times \Delta CF$, and $DS \times \Delta SALES$ are all positive and significant).

The interaction effects are economically significant. For example, when the sales indicator is unfavorable, the asymmetric timeliness coefficient for stock return (i.e., the full coefficient on $DR \times RET$, including all relevant higher-order interactions) increases from 0.216 to 0.395 ($= 0.216 + 0.179$), an increase of 83 percent. When the stock return is negative, the asymmetric timeliness for the cash flow indicator ($DC \times \Delta CF$) changes from 0.202 to 0.838 ($= 0.202 + 0.636$), an increase of 315 percent, and the asymmetric timeliness for the sales indicator ($DS \times \Delta SALES$) rises from 0.055 to 0.275 ($= 0.055 + 0.220$), an increase of 400 percent. Thus, as predicted in H2b, the interaction effects lead to substantial variation in asymmetric timeliness for each indicator. The Giner and Rees (2001) and Ball and Shivakumar (2006) multi-indicator conservatism models are additive and do not permit interaction effects; our findings indicate that they can be improved substantially by allowing such interactions.

As a simple illustration of the interaction effects, in Figure 1, we plot the empirical relation between each indicator and earnings after partitioning the sample based on the sign of a second indicator. For example, Panel A presents the nonlinear relation between stock return and earnings conditional on whether the operating cash flow indicator is favorable (the upper curve) or unfavorable (the lower curve). All of the curves exhibit an asymmetry that is consistent with conditional conservatism for the indicator on the horizontal axis. In all four panels, the curve for the unfavorable partitioning variable has a greater degree of asymmetry. In other words, the asymmetric loss recognition with respect to the indicator on the horizontal axis is greater when another indicator confirms the bad news, consistent with our predictions.[24]

In untabulated tests, the interaction effect estimates are robust to all of the alternative model specifications that were described earlier, such as the firm fixed effects model, the earnings first-difference model, the asymmetric autoregressive earnings expectation model, the Fama and MacBeth (1973) estimation for lagged stock price partitions, estimation for accruals-based dependent variables, and estimation for alternative sample definitions. In a further robustness check, we include the main firm-level determinants of conservatism from prior research (e.g., Ball et al. 2013b): size, book-to-market ratio, and leverage, measured at the beginning of the year. These variables are significantly correlated with the bad news dummies DR, DC, and DS (untabulated), which could distort the interaction effect estimates due to correlated omitted variable bias. Even when we include all three indicators concurrently (and control for the impact of size, book-to-market ratio, and leverage on both gain and loss recognition), all the interaction effects have the expected signs from H2a and H2b, and all but one are statistically significant (untabulated).[25] For all three indicators, conservatism decreases with firm size and increases with book-to-market ratio and

[23] The only exception is the insignificant interaction effect of cash flow decrease on asymmetric loss recognition for stock return ($DC \times DR \times RET$). This is consistent with our argument that the cash flow indicator is relatively noisy.

[24] Although Figure 1 provides a useful illustration, it only documents univariate associations, which could be influenced by the omitted indicators. Therefore, it cannot replace the comprehensive empirical Model (4), which incorporates the asymmetric main effects of all three indicators and their interaction effects. If a researcher is interested in controlling for the interaction effects, but does not need a comprehensive model, then a parsimonious reduced-form specification may suffice. In untabulated supplementary tests, we use principal component analysis to compress our three main indicators into summary scores of good and bad news, and then interact the good (bad) news score with the number of favorable (unfavorable) indicators to approximate the interaction effects. We find significant interaction effects of the expected sign. The adjusted R^2 of the principal-component model is higher than in the Basu (1997) model (25.2 percent versus 10.3 percent), but is lower than in the comprehensive interaction-effect model (29.0 percent). Thus, while the principal-component approach extracts useful information from multiple indicators and their interactions, it entails information loss relative to our comprehensive multi-indicator model. Byzalov and Basu (2016) show that because impairment tests are conducted at a low aggregation level, the relevant information is better approximated by a vector of individual indicators than by aggregate news proxies.

[25] The results continue to hold when we replace sales with cash sales and when we use additional indicators that were described earlier. The results are also robust to incorporating an alternative impairment indicator from Lawrence et al. (2013) that is equal to 1 if the book value of assets exceeds their market value, and 0 otherwise.

TABLE 5

Estimates of the Interaction Effects between Multiple Indicators

Model (4) for Earnings:

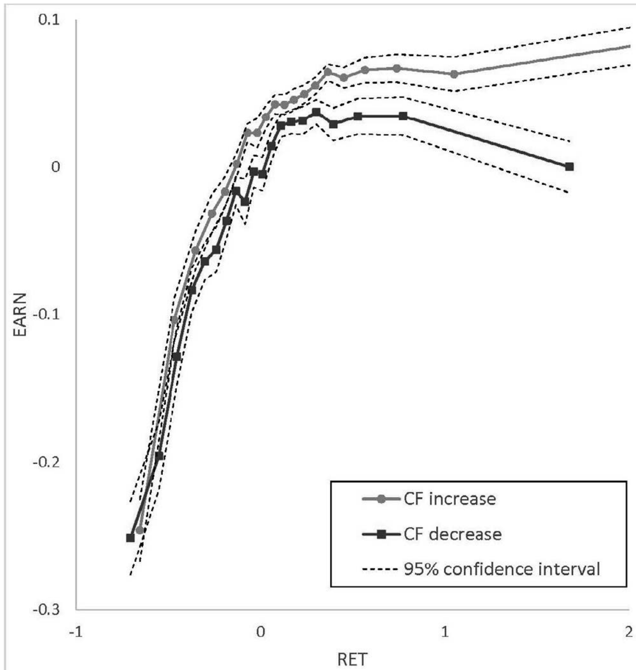
$$\begin{aligned} EARN_t = {} & \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t \\ & + \gamma_3 DS_t \times \Delta SALES_t + \delta_1 DR_t \times DC_t + \lambda_1 DR_t \times DS_t + DC_t \times (\delta_2 RET_t + \delta_3 DR_t \times RET_t) \\ & + DS_t \times (\lambda_2 RET_t + \lambda_3 DR_t \times RET_t) + DR_t \times (\delta_4 \Delta CF_t + \delta_5 DC_t \times \Delta CF_t) \\ & + DR_t \times (\lambda_4 \Delta SALES_t + \lambda_5 DS_t \times \Delta SALES_t) + \xi_t \end{aligned}$$

		Full Three-Indicator Model with Interactions	
		Estimate	**t-statistic**
Intercept		0.044***	14.95
DR		0.036***	8.56
RET		0.017**	2.44
DR* × *RET	**+**	**0.216*** **	**13.76**
DC		0.005	1.63
ΔCF		−0.007	−0.36
DC* × Δ*CF	**+**	**0.202*** **	**4.93**
DS		−0.015**	−2.52
$\Delta SALES$		0.078***	11.94
DS* × Δ*SALES	**+**	**0.055** **	**2.16**
DR × *DC*		−0.010	−1.20
DR × *DS*		0.042***	2.83
Impact of unfavorable ΔCF ($DC = 1$) on recognition of *RET*			
DC* × *RET	**−**	**−0.015*** **	**−4.13**
DC* × *DR* × *RET	**+**	**−0.024**	**−1.45**
Impact of unfavorable $\Delta SALES$ ($DS = 1$) on recognition of *RET*			
DS* × *RET	**−**	**−0.040*** **	**−3.95**
DS* × *DR* × *RET	**+**	**0.179*** **	**6.22**
Impact of unfavorable *RET* ($DR = 1$) on recognition of ΔCF			
DR* × Δ*CF	**−**	**−0.304*** **	**−7.83**
DR* × *DC* × Δ*CF	**+**	**0.636*** **	**7.20**
Impact of unfavorable *RET* ($DR = 1$) on recognition of $\Delta SALES$			
DR* × Δ*SALES	**−**	**−0.077*** **	**−5.31**
DR* × *DS* × Δ*SALES	**+**	**0.220*** **	**7.64**
Adj. R^2 (%)		29.0	
F-statistic for the interaction effects between			
DC and *RET*		10.65***	
DS and *RET*		37.87***	
DR and ΔCF		32.27***	
DR and $\Delta SALES$		30.18***	

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The table presents pooled regression estimates on a sample of 54,910 firm-year observations from 1987 to 2007. The t-statistics are based on standard errors clustered by firm and year. The main coefficients of interest in our tests are in bold.
The variable definitions are provided in Table 1.

FIGURE 1
The Relation between Each Indicator and Earnings, After Partitioning the Sample Based on Favorable and Unfavorable Values of Another Indicator

Panel A: Indicator = *RET;* Partitioning Variable = Sign of Δ*CF*



Panel B: Indicator = *RET;* Partitioning Variable = Sign of Δ*SALES*

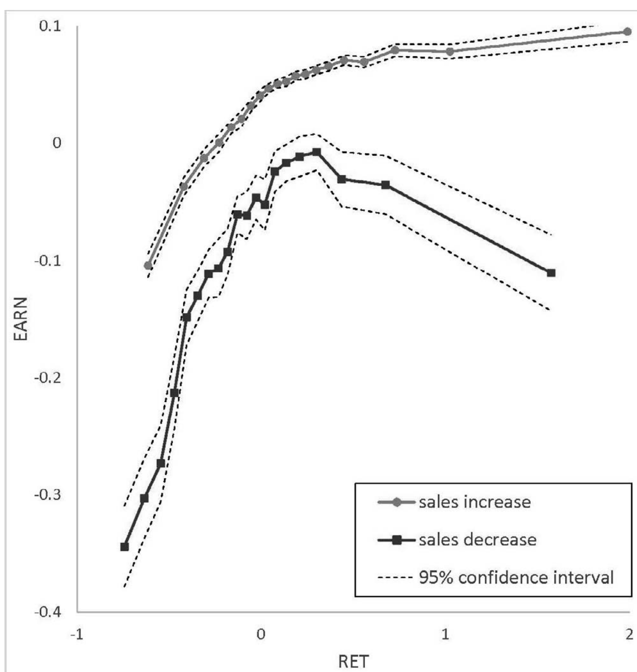


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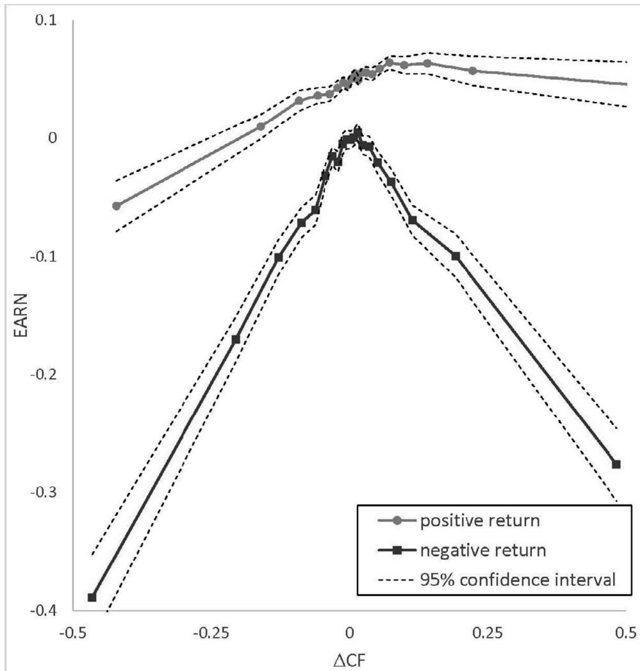
FIGURE 1 (continued)

Panel C: Indicator = ΔCF; Partitioning Variable = Sign of *RET*



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leverage, consistent with the theory. Out of the total explained variation in asymmetric timeliness for stock return, 35 percent is explained by the interaction effects of multiple indicators, and 65 percent is attributable to the combined effect of size, book-to-market ratio, and leverage.[26] Thus, the interaction effects are a first-order source of variation in conservatism, on par with the standard demand drivers of conservatism.

To test H3, we estimate Models (1)–(3) for write-downs of tangible assets and goodwill (Table 6).[27] For both tangible assets and goodwill, we find asymmetric timeliness with respect to all three indicators (i.e., the coefficients on $DR \times RET$, $DC \times \Delta CF$, and $DS \times \Delta SALES$ are all positive and significant). In untabulated tests, we also find significant asymmetric loss recognition for the additional indicators from Table 4. Because conservatism flows through write-downs while other asymmetries in earnings do not, these estimates confirm that the documented effects of multiple indicators on earnings are attributable to conservatism.

The asymmetric timeliness coefficients for goodwill impairment in Table 6, Columns (4)–(6) differ from the parallel long-lived asset write-down coefficients in Columns (1)–(3), as predicted by H3a and H3b. The coefficient on $DR \times RET$ increases significantly by 100–146 percent, whereas the coefficients on $DC \times \Delta CF$ and $DS \times \Delta SALES$ *decrease* by 17–33 percent. Thus, the relative impact of stock return, a long-term indicator that incorporates expected cash flows over an infinite horizon, is greater for impairment of (indefinite-lived) goodwill, whereas cash flow change and sales change, our short-term indicators, play a greater role in write-downs of (finite-lived) tangible assets. This evidence is consistent with our time-horizon explanation for accountants' use of multiple indicators.

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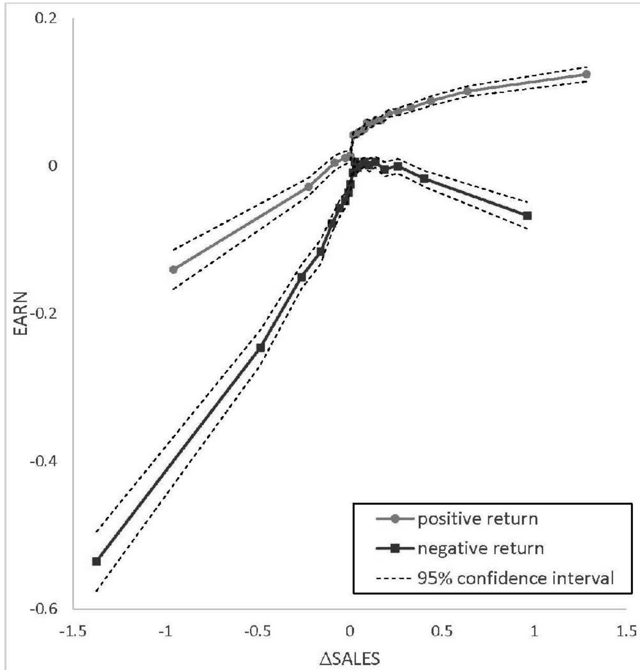
[26] For each firm-year, the predicted asymmetric timeliness for stock return (i.e., the slope on $DR \times RET$, including all relevant interaction terms) is $ASYM = \alpha_3 + \delta_3 DC + \lambda_3 DS + \pi_{DR \times RET \times SIZE} SIZE + \pi_{DR \times RET \times BM} BM + \pi_{DR \times RET \times LEV} LEV$, where $\delta_3 DC + \lambda_3 DS$ represents the interaction effects of sales decreases and operating cash flow decreases, and $\pi_{DR \times RET \times SIZE} SIZE + \pi_{DR \times RET \times BM} BM + \pi_{DR \times RET \times LEV} LEV$ captures the impact of size, book-to-market ratio, and leverage. We decompose total explained variation in asymmetric timeliness as $Var(ASYM) = Cov(ASYM, ASYM) = Cov(ASYM, \delta_3 DC + \lambda_3 DS) + Cov(ASYM, \pi_{DR \times RET \times SIZE} SIZE + \pi_{DR \times RET \times BM} BM + \pi_{DR \times RET \times LEV} LEV)$. The ratio $Cov(ASYM, \delta_3 DC + \lambda_3 DS)/Var(ASYM)$ captures the proportion of total explained variation that is attributable to the interaction effects.

[27] Because H3 focuses on the relative impact of individual indicators, we test it in models that do not include the interaction effects. The interaction effect estimates for asset write-downs and goodwill impairment are consistent with H2a and H2b (untabulated). Because write-downs are bounded from above at zero, we also test H3 using censored regression (Tobit) in Section V, yielding similar results. All of the results for goodwill impairment also hold when we restrict the sample to firms with positive beginning-of-year goodwill.

FIGURE 1 (continued)

Panel D: Indicator = Δ*SALES;* Partitioning Variable = Sign of *RET*



The graphs present the conditional mean of scaled earnings *EARN* in the sample as a function of a continuous indicator $X = RET$, ΔCF, or $\Delta SALES$ and a binary partitioning variable $PART = DC$, DS, or DR, which is based on the sign of a second indicator. We form two subsamples based on *PART*. We then divide the observations in each subsample into 20 equal-sized portfolios based on *X*, and compute average *EARN* and average *X* in each portfolio as an approximation of the conditional mean. The 95 percent confidence interval is based on the standard deviation of the mean of *EARN* within each portfolio.

In a further test of our time-horizon argument, we examine the relation between the expected life of tangible assets and the weights on different indicators in asset write-downs. Stock return should play a greater role in write-downs of longer-lived tangible assets. We approximate expected asset life using the ratio of net property, plant, and equipment (PP&E) to annual depreciation expense.[28] We partition the sample at the median of this proxy. The median asset life for the full sample is 5.2 years, and the medians for the two subsamples are 3.0 and 8.0 years, respectively. As expected, asymmetric timeliness for stock return is greater by 52 percent (significant at the 5 percent level) for the above-median sample relative to the below-median subsample (untabulated). In contrast, the change in asymmetric timeliness for the cash flow and sales indicators is smaller (11–43 percent), and is insignificant even at the 10 percent level.

In summary, Tables 3 and 4 show that conditional conservatism is driven by multiple indicators, and that sales change is a major trigger of impairment. Table 5 demonstrates that different indicators interact with each other, and each indicator has a much greater impact on earnings when it is confirmed by additional evidence, consistent with the accounting standard guidance. The estimates in Table 6 for tangible asset write-downs and goodwill impairment validate the main results for earnings and yield new insights about the information role of short-term indicators versus stock return for assets with different cash flow horizons.

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[28] We focus on beginning-of-year net PP&E (Compustat item PPENT) to identify the remaining expected life of these assets before current-period write-downs (the dependent variable), and exclude amortization of finite-lived intangible assets (Compustat item AM) from annual depreciation. Because some intangible assets, such as goodwill, have an indefinite life after SFAS 142, we do not compute the remaining asset lives for intangible or total assets.

TABLE 6

Estimates for Tangible Asset Write-Downs and Goodwill Impairment

Models (1)–(3) for Tangible Asset Write-Downs ($Y_t = WD_t$) and Goodwill Impairment ($Y_t = GW_t$):

$$Y_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \varepsilon_t$$
$$Y_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \nu_t$$
$$Y_t = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t + \gamma_3 DS_t \times \Delta SALES_t + \zeta_t$$

		Y = Tangible Asset Write-Down			Y = Goodwill Impairment		
		Basu (1997) Model (1)	Ball and Shivakumar (2006) Model (2)	Full Three-Indicator Model (3)	Basu (1997) Model (4)	Ball and Shivakumar (2006) Model (5)	Full Three-Indicator Model (6)
Intercept		−0.002***	−0.001***	−0.001***	−0.002***	−0.001***	−0.001***
		(−4.88)	(−7.47)	(−4.36)	(−5.72)	(−5.94)	(−3.10)
DR		0.001***	0.001***	0.001***	0.002***	0.002***	0.003***
		(2.84)	(4.06)	(5.08)	(3.72)	(4.03)	(4.00)
RET		−0.001*	0.000	0.000	0.000	0.001***	0.001***
		(−1.87)	(0.70)	(0.61)	(0.14)	(3.45)	(2.84)
DR* × *RET	+	**0.015*** **	**0.012*** **	**0.011*** **	**0.030*** **	**0.028*** **	**0.027*** **
		(16.66)	**(14.92)**	**(12.68)**	**(13.44)**	**(13.51)**	**(13.68)**
DC			0.000	0.000		0.000	0.000
			(0.00)	(0.96)		(0.46)	(1.16)
ΔCF			−0.023***	−0.019***		−0.014***	−0.010***
			(−6.51)	(−5.93)		(−6.37)	(−3.91)
DC* × Δ*CF	+		**0.052*** **	**0.042*** **		**0.038*** **	**0.028*** **
			(5.98)	**(5.34)**		**(4.68)**	**(3.15)**
DS				−0.002***			−0.002***
				(−4.60)			(−4.71)
$\Delta SALES$				−0.001***			−0.002**
				(−4.99)			(−2.22)
DS* × Δ*SALES	+			**0.006*** **			**0.005** **
				(25.32)			**(2.00)**
Adj. R^2 (%)		1.6	4.4	5.0	3.4	4.1	4.3
Percentage difference between the asymmetric timeliness coefficient for goodwill impairment and the parallel coefficient for tangible asset write-down							
$DR \times RET$					+100%***	+133%***	+146%***
$DC \times \Delta CF$						−27%	−33%
$DS \times \Delta SALES$							−17%

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The table presents pooled regression estimates on a sample of 21,125 firm-year observations from 2001 to 2007. The t-statistics in parentheses are based on standard errors clustered by firm and year. The percentage differences are computed as the asymmetric timeliness coefficient for goodwill from Columns (4)–(6) divided by the corresponding coefficient for tangible assets from Columns (1)–(3) minus 100 percent. To assess the statistical significance of these cross-model differences, we jointly estimate the corresponding two models for tangible assets and goodwill using stacked regression (Wooldridge 2002, 149), with two-way clustering by firm and year. The main coefficients of interest in our tests are in bold.
The variable definitions are provided in Table 1.

V. EXTENSION ANALYSIS: IMPLICATIONS FOR IMPAIRMENT RESEARCH

Unlike conservatism models, empirical models in impairment research (e.g., Elliott and Hanna 1996; Francis, Hanna, and Vincent 1996; Rees, Gill, and Gore 1996; Riedl 2004; Beatty and Weber 2006; Li, Shroff, Venkataraman, and Zhang 2011; Ramanna and Watts 2012) typically incorporate multiple measures of firm performance and use censored regression

(Tobit) in place of piecewise-linear ordinary least squares (OLS).[29] The explanatory variables in these models typically have a linear effect on the *latent dependent variable,* which is usually interpreted as the change in the value of a firm's assets (e.g., Riedl 2004, footnote 9). When the latent variable is negative, it is observed as a write-down, while positive values are censored at zero because value increases are not recognized as asset write-ups under U.S. GAAP except for some traded securities.

This literature attempts to model asymmetric loss recognition by using censored regression. However, we argue that even with censoring, impairment models should incorporate piecewise-linear effects of individual indicators on the latent variable. For example, consider a firm with two independent assets, A and B, that have unrealized value changes ΔA and ΔB, respectively. For simplicity, we treat ΔA and ΔB as directly observable. In a standard impairment model, the latent variable Y^* is defined as the change in the total value of A and B, $Y^* = \Delta A + \Delta B$, and the predicted write-down is $Y = min\{0, Y^*\} = min\{0, \Delta A + \Delta B\}$, i.e., a piecewise-linear function of Y^*. However, because each asset is tested for impairment separately, the actual write-down is $Y = min\{0, \Delta A\} + min\{0, \Delta B\}$. For example, if the firm has an unrealized gain of \$100 on asset A and an unrealized loss of \$100 on asset B (i.e., $\Delta A = 100$ and $\Delta B = -100$), then only the latter is recognized in the current period, and the total write-down is \$100 ($min\{0, 100\} + min\{0, -100\} = 0 + [-100] = -100$). In contrast, the standard model predicts a write-down of zero ($min\{0, 100 + [-100]\} = 0$) based on the total value change $\Delta A + \Delta B$. Therefore, the standard model is misspecified. Instead, the latent variable should be specified as $Y^* = min\{0, \Delta A\} + min\{0, \Delta B\}$, i.e., the sum of piecewise-linear functions of individual indicators:

H4: Stock return, operating cash flow change, and sales change have an asymmetric effect on the latent variable in censored regression models of impairment.

We test this prediction using a censored version of Model (3) for asset write-downs:

$$Y_t = \min\{0,\ Y_t^*\} \tag{5}$$

$$Y_t^* = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t + \gamma_3 DS_t \times \Delta SALES_t + \zeta_t \tag{6}$$

where Y_t stands for either tangible asset write-down WD_t or goodwill impairment GW_t; Y_t^* is the corresponding latent variable; and the remaining variables were defined previously. We also estimate an extended model that includes additional determinants of impairment from Riedl (2004): change in pre-write-down earnings (ΔE), GDP growth (ΔGDP), change in industry ROA ($\Delta INDROA$), a dummy variable for a change in senior management (ΔMGT), a proxy for "big bath" reporting ($BATH$), a proxy for "earnings smoothing" reporting ($SMOOTH$), and a dummy variable for private debt ($DEBT$); all variable definitions are provided in Table 1. H4 implies that the coefficients on $DR \times RET$, $DC \times \Delta CF$, and $DS \times \Delta SALES$ are positive; i.e., even after controlling for the piecewise-linear transformation of the latent dependent variable in Model (5), each indicator has a piecewise-linear effect on the latent dependent variable in Model (6).

The estimates are presented in Table 7. As expected, for both tangible asset and goodwill impairment, the coefficients on $DR \times RET$, $DC \times \Delta CF$, and $DS \times \Delta SALES$ are positive and significant (Column (2) in Panels A and B), i.e., each of the three indicators has an asymmetric effect. Compared to the standard prior specification in Column (1), in which the latent variable is a linear function of the indicators and the only source of asymmetry is censoring, the pseudo R^2 improves from 0.7 to 5.0 percent for tangible assets and from 2.6 to 4.6 percent for goodwill. The results continue to hold when we include both economic and reporting controls from prior literature (Columns (4) and (5)).[30] Thus, standard impairment models can be improved by recognizing the asset-specific nature of impairment tests, which manifests as asymmetric loss recognition for individual indicators.

As a broad theme, impairment research examines whether the observed write-downs reflect the firm's economic performance or managers' opportunistic reporting behavior. A typical research design (e.g., Francis et al. 1996; Riedl 2004; Ramanna and Watts 2012) tests the "economic null hypothesis" of unbiased write-downs that reflect the economic substance of events against an alternative hypothesis of earnings management through write-downs. Ball (2013) emphasizes that earnings management tests require an accurate benchmark model of the "normal" process under the null hypothesis. When the benchmark model is misspecified, this normal process can be mistaken for "abnormal" or "discretionary" behavior. Because

[29] Censored regression is estimated using maximum likelihood, which assumes that the error term is independently and identically Normally distributed, and can lead to inconsistent estimates when this strong assumption is violated. A piecewise-linear OLS regression is more robust because it provides a valid piecewise-linear projection of the conditional expectation without making strong assumptions about the error term (e.g., Wooldridge 2002, 53). We use censored regression in this section for consistency with prior impairment research.

[30] In untabulated robustness checks, we separately model the incidence and magnitude of impairment (Beaver and Ryan 2005) using the Heckman (1979) selection model. The results continue to hold, but the improvement in explanatory power relative to the simpler Tobit models from Table 7 is statistically insignificant, consistent with untabulated results (for a linear specification of the latent dependent variable) in Riedl (2004, footnote 10).

TABLE 7

Asymmetric Effects of Multiple Indicators in Censored Regression Models of Impairment

Models (5)–(6) for Asset Write-Downs ($Y_t = WD_t$) and Goodwill Impairment ($Y_t = GW_t$):

$$Y_t = \min\{0,\ Y_t^*\}$$

$$Y_t^* = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t + \gamma_3 DS_t \times \Delta SALES_t + \zeta_t$$

Panel A: Censored Regression Estimates for Asset Write-Downs

		Three-Indicator Models		Riedl (2004) Model	Three-Indicator Models with the Controls from Riedl (2004)	
		Linear Effects (1)	Piecewise-Linear Effects (2)	Linear Effects (3)	Linear Effects (4)	Piecewise-Linear Effects (5)
Intercept		0.053***	0.065***	0.041***	0.040***	0.047***
		(38.17)	(42.34)	(27.07)	(19.06)	(17.59)
DR			0.003			0.001
			(1.52)			(0.67)
RET		0.011***	0.004**		0.009***	0.001
		(7.07)	(2.35)		(4.43)	(0.28)
DR × RET	+		**0.042*** **			**0.034*** **
			(10.08)			**(4.99)**
DC			−0.001			−0.001
			(−0.57)			(−0.89)
ΔCF		−0.001	−0.044***	0.012**	0.009	−0.038***
		(−0.14)	(−5.35)	(2.17)	(0.96)	(−3.24)
DC × ΔCF	+		**0.089*** **			**0.091*** **
			(6.60)			**(4.31)**
DS			−0.010***			−0.007***
			(−6.86)			(−4.09)
ΔSALES		0.008***	−0.004*	0.008***	0.006**	−0.002
		(3.50)	(−1.92)	(4.14)	(2.15)	(−0.60)
DS × ΔSALES	+		**0.014*** **			**0.011* **
			(3.97)			**(1.71)**
DE						−0.003
						(−1.34)
ΔE				0.254***	0.215***	0.021
				(4.90)	(3.22)	(0.28)
DE × ΔE						0.089
						(0.66)
ΔGDP				0.533***	0.215***	0.198
				(4.83)	(3.82)	(1.59)
ΔINDROA				−0.094**	−0.102**	−0.076*
				(−2.24)	(−2.48)	(−1.80)
ΔMGT				−0.005***	−0.005***	−0.004***
				(−3.52)	(−3.52)	(−3.30)
BATH				−0.168***	−0.132*	−0.096
				(−3.15)	(−1.87)	(−0.93)
SMOOTH				−0.293***	−0.267***	−0.036
				(−5.67)	(−4.12)	(−0.48)
DEBT				0.007***	0.007***	0.007***
				(4.95)	(5.17)	(5.63)
Log-likelihood		−144.13	100.93	674.36	691.18	760.61
Pseudo R^2 (%)		0.7	5.0	4.5	4.5	7.6

(continued on next page)

TABLE 7 (continued)

	Three-Indicator Models		Riedl (2004) Model	Three-Indicator Models with the Controls from Riedl (2004)	
	Linear Effects (1)	**Piecewise-Linear Effects (2)**	**Linear Effects (3)**	**Linear Effects (4)**	**Piecewise-Linear Effects (5)**
Incremental pseudo R^2 (%)					
economic factors			1.5	1.4	4.5
reporting factors			3.6	3.3	1.9
χ^2 tests					
(1) versus (2)	637.04***				
(4) versus (5)				145.22***	

Panel B: Censored Regression Estimates for Goodwill Impairment

		Three-Indicator Models		Riedl (2004) Model	Three-Indicator Models with the Controls from Riedl (2004)	
		Linear Effects (1)	**Piecewise-Linear Effects (2)**	**Linear Effects (3)**	**Linear Effects (4)**	**Piecewise-Linear Effects (5)**
Intercept		0.240***	0.282***	0.190***	0.177***	0.206***
		(32.84)	(25.85)	(23.15)	(18.38)	(19.55)
DR			0.005			0.007
			(0.91)			(1.01)
RET		0.080***	0.025***		0.069***	0.011
		(10.11)	(3.29)		(7.45)	(1.24)
DR* × *RET	+		**0.167*** **			**0.167*** **
			(11.17)			**(8.18)**
DC			−0.007			−0.007
			(−1.26)			(−1.25)
ΔCF		0.017	−0.092***	0.048**	0.025	−0.108***
		(0.67)	(−3.36)	(2.39)	(1.05)	(−2.88)
DC* × *ΔCF	+		**0.198*** **			**0.233*** **
			(4.63)			**(4.20)**
DS			−0.028***			−0.026***
			(−4.79)			(−3.28)
ΔSALES		0.024***	−0.017**	0.025***	0.015*	−0.005
		(3.11)	(−2.50)	(3.50)	(1.68)	(−0.31)
DS* × *ΔSALES	+		**0.040*** **			**0.005**
			(3.34)			**(0.31)**
DE						−0.021**
						(−2.55)
ΔE				1.099***	0.823***	0.040
				(5.07)	(3.81)	(0.11)
DE × *ΔE*						−0.060
						(−0.11)
ΔGDP				0.216	−0.676	−1.548***
				(0.48)	(−1.50)	(−4.12)
ΔINDROA				−0.039	−0.124	−0.053
				(−0.24)	(−0.88)	(−0.36)
ΔMGT				−0.023***	−0.023***	−0.022***
				(−4.30)	(−4.02)	(−4.36)
BATH				−0.698***	−0.460**	0.155
				(−3.19)	(−2.16)	(0.41)
SMOOTH				−1.185***	−0.986***	−0.092
				(−5.45)	(−4.63)	(−0.26)

(continued on next page)

TABLE 7 (continued)

	Three-Indicator Models		Riedl (2004) Model	Three-Indicator Models with the Controls from Riedl (2004)	
	Linear Effects (1)	**Piecewise-Linear Effects (2)**	**Linear Effects (3)**	**Linear Effects (4)**	**Piecewise-Linear Effects (5)**
DEBT			0.028***	0.032***	0.035***
			(5.12)	(6.24)	(6.33)
Log-likelihood	−2,685.14	−2,518.68	−932.89	−881.19	−812.02
Pseudo R^2 (%)	2.6	4.6	3.1	5.1	8.5
Incremental pseudo R^2 (%)					
economic factors			0.2	2.2	5.6
reporting factors			2.2	2.4	3.8
χ^2 tests					
(1) versus (2)	214.49***				
(4) versus (5)				100.29***	

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The table presents censored regression (Tobit) estimates, which are based on a sample of 21,125 firm-year observations from 2001 to 2007 in Columns (1) and (2), and a smaller sample of 7,190 observations in Columns (3) through (5) due to additional data requirements for the control variables. The t-statistics in parentheses are based on bootstrapped standard errors. Write-downs are coded as negative numbers. The computation of pseudo R^2 follows Wooldridge (2002, 529). The economic factors are *RET*, *ΔCF*, *ΔSALES*, *ΔE*, *ΔINDROA*, and *ΔGDP*, and the reporting factors are *ΔMGT*, *BATH*, *SMOOTH*, and *DEBT*, following Riedl (2004). The main coefficients of interest in our tests are in bold.
The variable definitions are provided in Table 1.

the normal process for write-downs must incorporate conservatism, the standard symmetric models from prior research are (by construction) inconsistent with the economic null hypothesis. Therefore, these misspecified models are likely to reject the null hypothesis when true, leading to spurious findings of earnings management. In contrast, our asymmetric model incorporates the conservative nature of write-downs, providing an improved benchmark.

To illustrate the importance of this improved benchmark, we examine the incremental explanatory power of the "economic factors" (*RET*, *ΔCF*, *ΔSALES*, *ΔE*, *ΔINDROA*, and *ΔGDP*) relative to the "reporting factors" (*ΔMGT*, *BATH*, *SMOOTH*, and *DEBT*) following Riedl (2004). When we use the symmetric model as in prior research (Column (4) in Table 7), the economic factors seem less informative than the reporting factors. For tangible asset write-downs, the incremental pseudo R^2s of the economic and reporting variables are 1.4 versus 3.3 percent, respectively; for goodwill impairment, they are 2.2 versus 2.4 percent. These results suggest low-quality write-downs that are primarily attributable to managers' opportunistic behavior, consistent with Riedl (2004). However, when we incorporate conservatism (Column (5) in Table 7), the results are very different. The economic factors now have much greater explanatory power than the reporting factors (for tangible asset write-downs, the incremental pseudo R^2s are 4.5 versus 1.9 percent, respectively; for goodwill impairment, they are 5.6 versus 3.8 percent). These results for the asymmetric benchmark indicate that the observed write-downs reflect the economic substance of events to a much greater extent than they reflect opportunistic behavior, leading to markedly different inferences about the drivers of write-downs.

We next examine what levels of bad news trigger loss recognition in asset write-downs. The standard conservatism models distinguish positive and negative stock return, i.e., the impairment trigger is usually set to zero.[31] Ball and Shivakumar (2006) use an analogous distinction between positive and negative operating cash flow change. However, the impairment trigger likely differs from zero. First, a positive stock return can indicate bad news if it is lower than the cost of equity. Similarly, a positive operating cash flow change or sales change can be an unfavorable indicator if it is lower than expected. Second, because internal and external auditors distinguish temporary and permanent (or other-than-temporary) impairments under U.S. GAAP (Basu 2005), they can use a "loose" impairment trigger (Beaver and Ryan 2005), which implies that only material bad news

[31] Basu (1997) uses market-adjusted and market model-adjusted returns in robustness checks, while Ball et al. (2013b) examine an adjustment for expected returns. However, the impairment trigger for adjusted returns in these papers continues to be zero. Shroff et al. (2013) explore extreme bad news thresholds of three-day market-adjusted returns less than (1) −10 percent, or (2) firm-specific mean − 2.58 standard deviations of market-adjusted returns.

leads to write-downs (Shroff, Venkataraman, and Zhang 2013). These two effects imply that the impairment trigger can be either positive or negative, but is unlikely to be exactly zero:

H5a: The impairment trigger for stock return, operating cash flow change, and sales change differs from zero.

The impairment trigger likely differs across indicators. Because managers can manipulate the timing of operating cash flow (e.g., Dechow 1994; Ball and Shivakumar 2006), even a small operating cash flow decrease in the current period (which managers were unwilling or unable to avoid through manipulation) likely indicates significant bad news, triggering asset write-downs.[32] Therefore, operating cash flow change likely has a "tighter" trigger than stock return and sales change, which are likely more difficult to manipulate (e.g., Ertimur et al. 2003):

H5b: The impairment trigger for operating cash flow change is "tighter" than those for stock return and sales change.

The impairment triggers likely differ between tangible assets and goodwill. When goodwill and another asset are tested for impairment at the same time, the other asset should be tested, and written down if impaired, before the test for goodwill (SFAS 142, para. 29). Therefore, goodwill impairment likely has a "looser" impairment trigger than tangible asset write-downs:

H5c: Goodwill impairment has a looser impairment trigger than tangible asset write-downs.

To model the implicit impairment triggers, we set the dummy variable *DR* (*DC, DS*) to 1 if stock return *RET* (cash flow change ΔCF, sales change $\Delta SALES$) is in the bottom p^{RET} ($p^{\Delta CF}$, $p^{\Delta SALES}$) percent of the distribution, and 0 otherwise. We extend the spline regression approach advocated by Basu (2005) and estimate these triggers in Table 8 as the values of p^{RET}, $p^{\Delta CF}$, and $p^{\Delta SALES}$ that maximize the log-likelihood in Models (5)–(6).

For tangible asset write-downs (Column (1) of Table 8), the implicit impairment triggers differ significantly from the standard definitions of bad news (Vuong Z = 2.33), consistent with H5a. Pseudo R^2 improves from 5.0 to 5.2 percent. We find "loose" impairment triggers for stock return and sales change, which correspond to the 29th percentile ($RET = -0.140$) and 19th percentile ($\Delta SALES = -0.026$) of the respective distribution. As predicted in H5b, the cash flow indicator has a much "tighter" trigger (58th percentile, $\Delta CF = 0.016$).

Consistent with H5a, the impairment triggers for goodwill impairment in Table 8, Column (2) differ significantly from zero (Vuong Z = 3.09). Pseudo R^2 improves from 4.6 to 5.0 percent. Similar to tangible asset write-downs, we find very "loose" impairment triggers for stock return (18th percentile, $RET = -0.291$) and sales change (15th percentile, $\Delta SALES = -0.060$); the impairment trigger for operating cash flow change is "tighter" (42nd percentile, $\Delta CF = -0.002$), consistent with H5b. As expected (H5c), the triggers for goodwill impairment are "looser" than those for tangible asset write-downs. For example, the kink in the piecewise-linear effect of stock return on asset write-downs occurs at the 29th percentile of the return distribution, corresponding to a stock return of −14.0 percent, while the kink for goodwill impairment is at the 18th percentile, corresponding to a more extreme return of −29.1 percent.[33]

In summary, the results suggest two avenues for improvement in impairment models. First, because different assets are impaired separately, censored regression models of impairment should incorporate piecewise-linear effects of individual indicators. This modification leads to a better-specified model and changes inferences about the drivers of impairment. Second, the implicit impairment triggers (i.e., the estimates of the kink in the piecewise-linear relation between each indicator and asset write-downs) vary predictably across both indicators and asset types, further improving model specification and yielding new insights into accounting judgment.

VI. CONCLUSION

We examined the differential effects of multiple impairment indicators in conservative financial reporting. We argued that while stock price efficiently combines information about future cash flows to estimate overall firm value, this information is weighted differently in asset impairment tests. Because these tests are conducted for individual assets or asset groups, the breakdown of total gains and losses across different asset types is relevant, and cannot be summarized by a one-dimensional measure of total "bookable" value changes. Therefore, additional indicators that predict cash flow over shorter time horizons have an incremental effect. We proposed sales change as a major new indicator that arises from the standard cash flow forecasting

[32] Additionally, a firm's shareholders might "anchor" on a current-period cash flow decrease as an indicator of future decreases (Tversky and Kahneman 1974). Therefore, the firm and its external auditor might prefer to record a write-down even for moderate cash flow decreases to avoid shareholder lawsuits.

[33] Goodwill impairments occur less frequently in our sample than asset write-downs (6.9 percent of firm-year observations versus 18.8 percent, respectively), but when they occur, they are larger (9.0 percent of lagged market value, on average, versus 3.4 percent for asset write-downs). This further confirms that goodwill impairment is triggered by more extreme bad news. In untabulated tests, we add a second kink for each indicator to distinguish between moderate and extreme bad news; however, the improvement in log-likelihood is insignificant.

TABLE 8

Estimates of the Implicit Impairment Triggers

Models (5)–(6) for Tangible Asset Write-Downs ($Y_t = WD_t$) and Goodwill Impairment ($Y_t = GW_t$):

$$Y_t = \min\{0,\ Y_t^*\}$$
$$Y_t^* = \alpha_0 + \alpha_1 DR_t + \alpha_2 RET_t + \alpha_3 DR_t \times RET_t + \beta_1 DC_t + \beta_2 \Delta CF_t + \beta_3 DC_t \times \Delta CF_t + \gamma_1 DS_t + \gamma_2 \Delta SALES_t + \gamma_3 DS_t \times \Delta SALES_t + \zeta_t$$

where the dummy variables DR_t, DC_t, and DS_t are defined as follows:

$DR_t = 1$ if RET_t is in the bottom p^{RET} percent of the distribution, and 0 otherwise;

$DC_t = 1$ if ΔCF_t is in the bottom $p^{\Delta CF}$ percent of the distribution, and 0 otherwise; and

$DS_t = 1$ if $\Delta SALES_t$ is in the bottom $p^{\Delta SALES}$ percent of the distribution, and 0 otherwise.

		Asset Write-Downs (1)	Goodwill Impairment (2)
Impairment triggers that maximize the log-likelihood			
RET	percentile p^{RET}	29	18
	[value]	[−0.140]	[−0.291]
ΔCF	percentile $p^{\Delta CF}$	58	42
	[value]	[0.016]	[−0.002]
$\Delta SALES$	percentile $p^{\Delta SALES}$	19	15
	[value]	[−0.026]	[−0.060]
Log-likelihood		115.40	−2,493.30
Improvement in log-likelihood		14.47	25.37
Pseudo R^2 (%)		5.2	5.0
Improvement in pseudo R^2 (%)		0.2	0.4
Vuong *Z*-statistics		2.33**	3.09***

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.
The table presents the impairment thresholds p^{RET}, $p^{\Delta CF}$, and $p^{\Delta SALES}$, which maximize the log-likelihood in the censored regression model. Because the bad news indicators *DR, DC,* and *DS* are discontinuous functions of p^{RET}, $p^{\Delta CF}$, and $p^{\Delta SALES}$, we cannot use standard gradient-based maximization. Instead, we determine the optimal thresholds using grid search from the 5th to the 95th percentile in each of the three dimensions. The regression estimates are based on a sample of 21,125 firm-year observations from 2001 to 2007. The Vuong (1989) test and the improvement in log-likelihood and pseudo R^2 are relative to the model in Column (2) in Panels A and B of Table 7, which uses the standard definitions of the dummies *DR, DC,* and *DS*.
The variable definitions (except for the modified definitions of *DR, DC,* and *DS*) are provided in Table 1.

procedures. We further predicted that each indicator is recognized to a greater extent when it is confirmed by additional indicators (i.e., the combined effect of several consistent indicators is stronger than the sum of their standalone effects), and that the relative weight of an indicator also varies across asset types, such as tangible assets and goodwill. We also grounded our predictions in the U.S. impairment standards (FASB 1995, 2001a, 2001b, SFAS 121, 142, and 144 [now included in ASC 350 and ASC 360]), which we view as codifying preceding best accounting practices (e.g., Waymire and Basu 2011).

The results for Compustat/CRSP data support our predictions and are robust. The results indicate that multiple impairment indicators are combined with weights that vary systematically with the time horizon of the assets and the degree of consistency among the indicators.

We also examined the implications of conservative accounting practice for empirical models in impairment research. We showed that these models should incorporate asymmetric loss recognition for individual indicators, which provides an improved benchmark of the "normal" accounting process in tests of opportunistic behavior by managers. We also showed that the implicit impairment triggers vary predictably across both indicators and asset classes.

Our theoretical predictions and refined empirical specifications arise from modeling accountants' decision process as outlined by accounting standards. We show that studying asset impairment practice yields new insights into how earnings is determined. Earnings is the primary output of the accounting system that is used in both contracting and valuation. By providing a better understanding of how various data sources are combined to construct earnings, our results can enrich the theoretical models that seek to explain how and why earnings is informative (relative to cash flows and returns). Additionally, our analysis highlights the deep connection between cost and financial accounting. Because accountants use internal forecasts in impairment tests, external financial reports are influenced by the internal budgets and forecasting models from cost accounting. Studying the implications of this fundamental link is likely to contribute both new insights and improved empirical models of financial reporting.

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