THE ACCOUNTING REVIEW
Vol. 86, No. 5
2011
pp. 1765–1793

American Accounting Association
DOI: 10.2308/accr-10101

More Evidence of Bias in the Differential Timeliness Measure of Conditional Conservatism

Panos N. Patatoukas
University of California, Berkeley

Jacob K. Thomas
Yale University

ABSTRACT: Despite the conceptual appeal and popularity of the differential timeliness (DT) measure of conditional conservatism proposed in Basu (1997), Dietrich et al. (2007) and Givoly et al. (2007) have identified considerable biases associated with that measure. We renew their call to avoid using the DT measure because it is affected unexpectedly by two empirical regularities—namely, scale is negatively related to (1) deflated mean earnings and (2) variance of stock returns. Even though these regularities are unrelated to conditional conservatism, their joint effect is substantial and pervasive. More importantly, prior findings regarding time-series and cross-sectional variation in differential timeliness are confounded by corresponding variation in these regularities.

Keywords: *conservatism; differential timeliness; losses; scaling by share price.*

Data Availability: *Data are publicly available from sources identified in the article.*

I. INTRODUCTION

The measure of conditional conservatism proposed in Basu (1997), which captures the differential timeliness (DT) with which bad and good news are reported in contemporaneous earnings, has had a substantial impact on accounting research. A large body of subsequent research has used this DT measure as a dependent or independent variable in both cross-sectional and time-series analyses (Section III provides examples). Despite the measure's

We received many helpful comments and suggestions from Sudipta Basu, two anonymous referees, and Sanjay Kallapur (editor). Dick Dietrich provided invaluable assistance with specification and statistical issues. We also thank Anwer Ahmed, Jeff Callen, John Core, Patricia Dechow, Dan Givoly, Ed Kaplan, S.P. Kothari, Wayne Landsman, K. Ramesh, Bill Rees, Stephen Ryan, Senyo Tse, Jenny Tucker, Martin Walker, Paul Zarowin, Xiao-Jun Zhang, and seminar participants at the AAA Annual Meeting, AAA FARS Doctoral Consortium, University of Florida, The George Washington University, Hong Kong University of Science and Technology, University of California, Berkeley, and Yale University for their comments.

Editor's note: Accepted by Sanjay Kallapur.

Submitted: March 2009
Accepted: February 2011
Published Online: May 2011

conceptual appeal and popularity, Dietrich et al. (2007) and Givoly et al. (2007) provide considerable evidence suggesting that the DT measure is associated with a variety of substantial biases. And yet, we observe a sustained flow of research based on the DT measure, which may be partially due to: (1) the counter-arguments provided by Ball et al. (2010) in support of the DT measure, and (2) the intuitive feeling that while the estimates might be biased and noisy, cross-sectional and time-series variation in those estimates might still reflect genuine variation in conditional conservatism.

We document how two empirical regularities, related to scale, combine to cause a bias in the DT estimate of conditional conservatism that is so pervasive that the measure is rendered unreliable. Importantly, cross-sectional and time-series variation in the DT measure is affected substantially by corresponding variation in the empirical regularities. The first regularity is that scale is positively related to price-deflated earnings; we label this regularity as the *loss* effect because it is driven by the subset of firms reporting losses. The second regularity is that scale is negatively related to the variance of stock returns and is labeled the *return variance* effect. While the bias we note is anticipated by the general relation derived by Dietrich et al. (2007), it deserves separate attention because it is substantial and yet unexpected, insofar as the two regularities that create this bias are unrelated to conditional conservatism.

Our results offer two main takeaways. First, research on conditional conservatism should heed the call in Dietrich et al. (2007) and Givoly et al. (2007) to avoid the DT measure and consider other alternatives. Also, inferences from prior research, especially those based on cross-sectional and time-series variation in estimates of the DT measure, will likely need to be reevaluated. Even though the bias we document is large, pervasive, and explains a substantial amount of time-series and cross-sectional variation in estimates of the DT measure, it represents a lower bound on the total bias that might exist, as it does not consider all the sources of bias noted in Dietrich et al. (2007) and Givoly et al. (2007). As a result, future research should consider avoiding the DT measure even if solutions are devised to mitigate our bias.

Second, because the bias arises from within-sample variation in scale, our study illustrates the ever-present potential for bias due to clustering of observations drawn from different underlying populations. Because such biases are hard to foresee and detect, we reiterate the benefits of placebo tests (e.g., Choi et al. 2003), which replicate the analyses for dummy events or variables that should not exhibit predicted patterns. Observing similar results for dummy variables suggests that the original results are unreliable. In this case, we replicate the analyses with lagged earnings rather than current earnings. As last year's earnings cannot reflect news that will be revealed subsequently this year, it cannot differentially reflect the good and bad components of this year's news, and the DT estimate should therefore be zero. We find, however, that the DT estimate for lagged earnings is, on average, over 60 percent of that for current earnings.

Section II describes the two empirical regularities and how they combine to bias estimates of the DT measure. The prior literature is discussed in Section III, the sample is described in Section IV, and Section V reports results describing the impact of the two regularities. Section VI describes additional analyses, and Section VII concludes.

II. THE TWO SCALE-DRIVEN EMPIRICAL REGULARITIES AND THEIR IMPACT ON DT ESTIMATES

Before illustrating the two regularities, we review a commonly used version of the Basu (1997) regression model, described below as Equation (1). Annual earnings levels (scaled by lagged price) are regressed on annual abnormal returns, allowing for separate coefficients for good (bad) news partitions, represented by positive (negative) abnormal returns.[1] The coefficient β_1, which is the bad news slope minus that for good news, is the DT measure of conditional conservatism:

$$\frac{X_{it}}{P_{it-1}} = \alpha_0 + \alpha_1 D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \varepsilon_{it}, \tag{1}$$

where:

X_{it} = earnings per share reported by firm i in year t;
P_{it-1} = price per share for firm i at the end of year t–1;
AR_{it} = stock return for firm i in year t minus equally weighted market return for year t; and
D_{it} = 1 if $AR_{it} < 0$, which represents bad news, and 0 otherwise.

The first scale-driven empirical regularity we consider, labeled the *loss* effect, refers to the positive relation between scale and the mean value of scale-deflated earnings per share. While we find it convenient to use share price to represent scale, similar relations exist for other measures of scale. Note that the loss effect is a general effect in the sense that it is not conditional on the news reported in this period and it should be observed in adjacent periods; i.e., relative to low-price firms, high-price firms have higher mean values of scale-deflated earnings next year, last year, two years ago, and so on. To confirm this general nature of the loss effect, we illustrate it using lagged earnings (X_{it-1}) rather than current earnings (X_{it}).

The line "X_{t-1}/P_{t-1} (*full sample*)" in Figure 1, Panel A describes how the mean value of lagged earnings scaled by price increases across the ten share price deciles, from a low of about −0.05 for the lowest price decile (decile 1) to a high of about 0.07 for the highest price decile (decile 10).[2] These values are time-series averages of cross-sectional means computed over firm-years ending in each calendar year. The line labeled "LD_{t-1}" (measured against the right vertical axis) describes the first part of the loss effect. The *fraction* of loss firms decreases from just over 40 percent for decile 1 to about 3 percent for decile 10. The second part is indicated by the line "X_{t-1}/P_{t-1} (*loss*)," which shows that the average *magnitude* of price-deflated losses, for the subset of firms reporting losses in each price decile, decreases from about 20 percent of lagged price for decile 1 to about 6 percent of lagged price for decile 10.

Whereas price-deflated losses are larger for low-price shares, the line "X_{t-1}/P_{t-1} (*profit*)" in Panel A of Figure 1 indicates that price-deflated profits are similar for low- and high-price shares. Even though low-price shares are less likely to report profits than high-price shares, price-deflated profits do not vary with price for the subset of firms that report profits. Because the positive overall relation between X_{t-1}/P_{t-1} and scale is due entirely to loss firms—the probability of losses and the magnitude of losses—we refer to it as the loss effect.

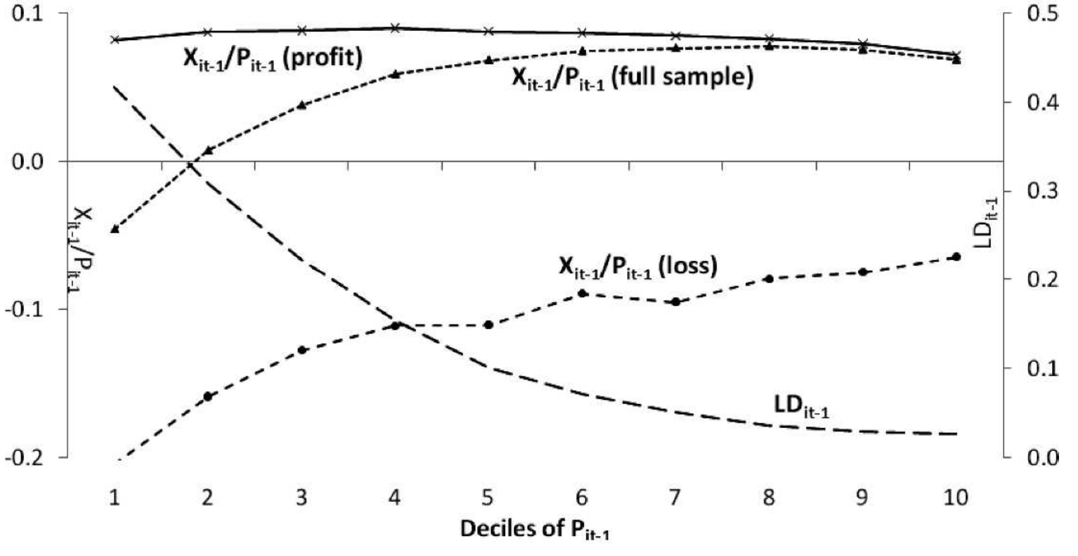
The second scale-driven empirical regularity, labeled the *return variance* effect, refers to the negative relation between scale and stock return variance. Figure 1, Panel B describes how the mean values of positive and negative abnormal returns, representing good and bad news, are negatively and positively related to price deciles. Figure 1, Panel C depicts the relevant implication of the variance effect: extreme good and bad news is more likely to be observed for low-price firms. Mean values of lagged price (P_{t-1}) for deciles of bad and good news (AR_t) increase from about \$15 for the most extreme bad and good news deciles (left and right edges of the figure) to just below \$25 for the less extreme bad and good news deciles (center of the figure).

[1] To be consistent with Basu (1997), the dependent variable in Equation (1) should be market-adjusted earnings or X_{it}/P_{it-1} minus the cross-sectional mean of X_{it}/P_{it-1}. While we use X_{it}/P_{it-1} for consistency with other research, the two specifications are essentially similar when estimated year by year; only the intercept (α_0) is affected.
[2] Details of the sample and variables underlying this discussion are provided in Section IV.

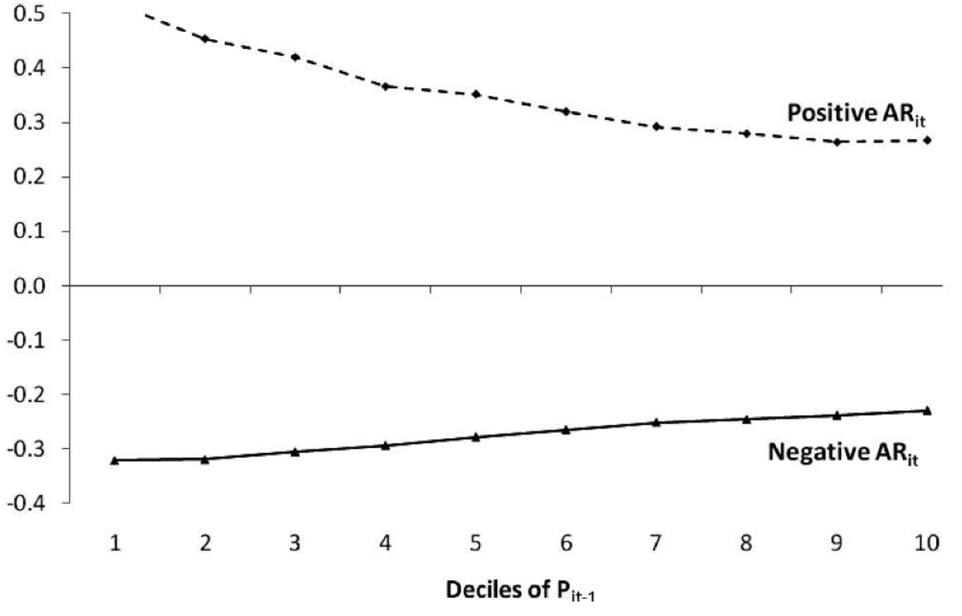
FIGURE 1
Heterogeneity across Share Price Deciles: Loss and Return Variance Effects

Panel A: Loss Effect[a]
Panel B: Return Variance Effect[b]
Panel C: Implication of Return Variance Effect[c]

A



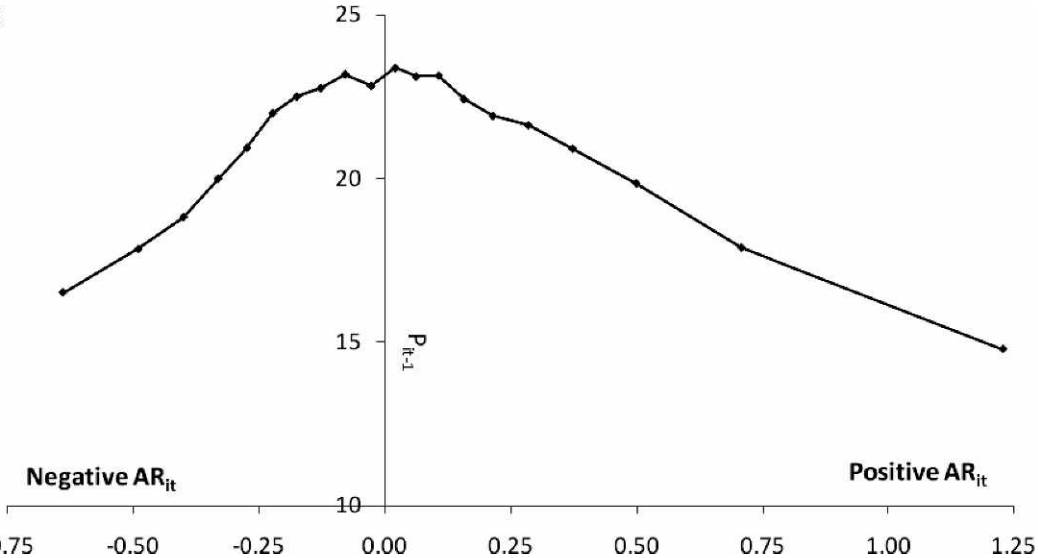
B



(continued on next page)

FIGURE 1 (continued)

C



The loss effect is that price-deflated earnings per share increases with share price because the probability of reporting a loss and the magnitude of price-deflated losses decrease with share price. The return variance effect is that magnitudes of positive and negative returns decline with share price. Variables for firm *i* and year *t* are defined as follow: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; and AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted index over the corresponding 12-month period. Additional details of all variables are provided in Appendix A. The mean values reported above are the averages of means for each annual cross-section containing firms with fiscal years ending in the same calendar year.

[a] Mean value of lagged earnings per share (X_{it-1}), scaled by lagged share price (P_{it-1}), and fraction of loss firms (LD_{it-1}) across deciles of lagged share price (P_{t-1}).

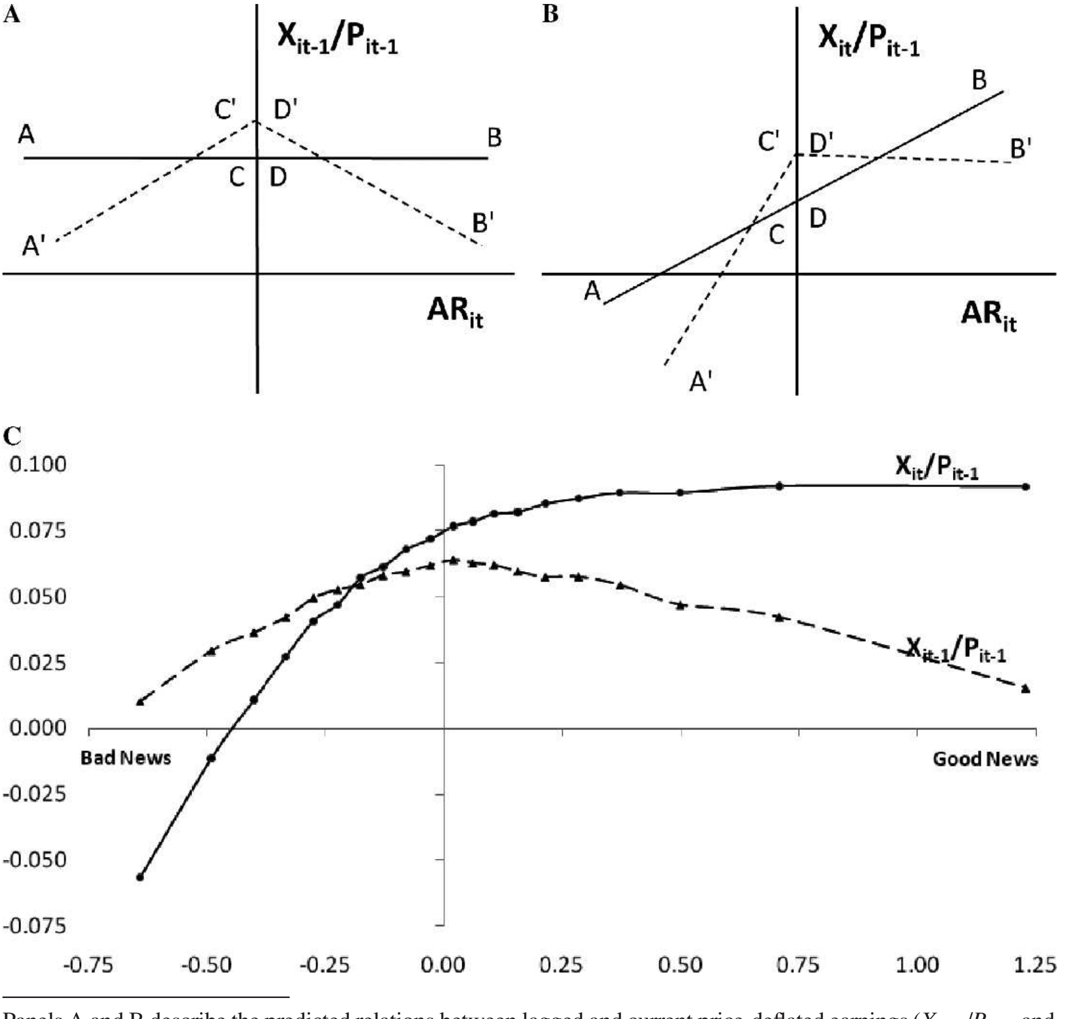
[b] Mean value of abnormal return (AR_{it}) for positive (good news) and negative (bad news) subsamples across deciles of lagged share price (P_{t-1}).

[c] Mean values of lagged price (P_{it-1}) for deciles of positive and negative abnormal return (AR_{it}).

Figure 2, Panel A illustrates the *predicted* joint impact of the return variance and loss effects on regressions of price-deflated lagged earnings (X_{t-1}/P_{t-1}) on abnormal returns (AR_t), estimated both for the overall sample and separately for good and bad news subsamples. Absent the loss and return variance effects described in Figure 1, lagged earnings should be unrelated to current abnormal returns and the overall sample regression should be represented by the flat line ACDB, corresponding to the sample mean of X_{t-1}/P_{t-1}. However, when the two effects are present separate regressions on bad and good news subsamples should be represented by the lines A′C′ and D′B′, respectively. For the bad news subsample, deciles associated with more negative news include more low-price shares (Figure 1, Panel C) and those shares have lower mean values of X_{t-1}/P_{t-1} (Figure 1, Panel A). Similarly, for the good news subsample, deciles associated with more positive news also include more low-price shares with lower mean values of X_{t-1}/P_{t-1}.

FIGURE 2
Impact of the Loss and Return Variance Effects on Earnings-Returns Regressions

Panel A: Prediction for Lagged Earnings (X_{it-1}/P_{it-1})
Panel B: Prediction for Current Earnings (X_{it}/P_{it-1})
Panel C: Mean Values of Lagged and Current Price-Deflated Earnings (X_{it-1}/P_{t-1} and X_{it}/P_{t-1}) for Deciles of Bad and Good News (AR_{it})



Panels A and B describe the predicted relations between lagged and current price-deflated earnings (X_{it-1}/P_{it-1} and X_{it}/P_{it-1}) and current abnormal returns (AR_{it}). Assuming that the full sample relation is described by ACDB, the loss and return variance effects are predicted to create an asymmetry between the separate relations for bad and good news subsamples (with $AR_{it} <$ and > 0, respectively), as described by the lines A′C′ and D′B′. Panel C describes the actual relations between X_{it-1}/P_{it-1} and X_{it}/P_{it-1} and AR_{it} by reporting mean values of lagged and current earnings for deciles of negative and positive AR_{it}. The mean values reported in Panel C are the averages of means for each annual cross-section containing firms with fiscal years ending in the same calendar year.

Variables for firm i and year t are defined as follow: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; and AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted index over the corresponding 12-month period. Additional details of all variables are provided in Appendix A.

In essence, even though abnormal returns are, on average, unrelated to lagged earnings, regressions of lagged earnings on abnormal returns estimated separately for bad (good) news subsamples will indicate a positive (negative) slope. The bad news slope (A′C′) minus the good news slope (D′B′) in Panel A of Figure 2 generates a positive β_1 coefficient when current earnings are replaced by lagged earnings in Equation (1). The joint impact of the loss and return variance effects leads to spurious evidence of differential timeliness.

Figure 2, Panel B repeats the analysis for the predicted impact of the two empirical regularities on the relation between price-deflated *current* earnings and abnormal returns. Assume that there is no conditional conservatism and that earnings are equally timely for good and bad news. That symmetric relation is described by the regression line ACDB, where the slope of the regression line represents timeliness or the sensitivity of contemporaneous earnings to news. Introducing the two effects will cause the slope of the regression line to be altered toward A′C′ (D′B′) for bad (good) news. The excess of the slope of A′C′ over that for D′B′ will erroneously be interpreted as evidence of differential timeliness due to conditional conservatism.

These predicted patterns are observed in actual data. Figure 2, Panel C reports mean values of price-deflated current and lagged earnings for deciles of positive and negative abnormal returns. The patterns reflected by these mean values in the left and right halves represent the slopes that would be reported in earnings-returns regressions estimated separately on bad and good news subsamples. The substantial asymmetric relation consistent with conditional conservatism observed for lagged earnings in Panel C confirms that the DT measure is associated with large upward bias. Observing patterns similar to those predicted in Panel A suggests that this bias is due to the loss and return variance effects. In addition, the similarity between the relation in Panel C for current earnings and the corresponding predicted relation in Panel B suggests that these two effects create substantial upward bias for estimates of β_1 from Equation (1) regressions based on current earnings.

The generality of the loss effect, which allows us to replace current earnings in Equation (1) with lagged earnings, is important for our research design. If the loss effect had only applied to current earnings, there is a potential concern that the increased likelihood of losses for low-price firms is somehow related to conditional conservatism, under which some of the losses reported this year are due to bad news disclosed this year being reflected in a more timely manner than good news this year. That concern, however, does not apply to lagged earnings, because prior-year earnings are reported before this year's news is disclosed. Given that it is not possible for news disclosed this year to be recorded in last year's earnings, it is not possible for bad news disclosed this year to be recorded in last year's earnings in a more timely manner than this year's good news.

Note that a strong correlation between lagged and current earnings does not alter this conclusion. That is, even though lagged earnings are related to current earnings, which are, in turn, related to current news, lagged earnings cannot be related to current news. This is because news can only reflect surprises, by definition, and current news must be unrelated to all lagged variables, including lagged earnings and lagged news. Therefore, any evidence of differential timeliness in the extent to which lagged earnings reflects current good and bad news must be spurious, and that same bias must also affect estimates of conditional conservatism for *current* earnings.

Because estimates of DT based on lagged earnings provide an indication of the extent to which estimates of DT based on current earnings are biased, we estimate Equation (1) separately for both current and lagged earnings in all of our analyses. An important benefit of this methodology is that it allows us to (1) show the extent to which cross-sectional and time-series variation in the DT measure estimated for current earnings is affected by cross-sectional and time-series variation in the bias associated with that measure, which is indicated by the DT measure estimated for lagged earnings, and (2) confirm that this variation in bias is caused by corresponding variation in the loss and return variance effects.

III. LINKS TO PRIOR RESEARCH ON POTENTIAL BIASES IN THE DT MEASURE

Dietrich et al. (2007) derive the general conditions under which slopes of the earnings-returns regressions differ for good and bad news samples, even when the underlying relation is similar. Their Equations (1.7a) and (1.7b) describe how each slope is potentially biased because of two effects—sample variance ratio bias and sample truncation bias—and they offer examples of conditions under which the two biases differ for good and bad news. The results in Dietrich et al. (2007, Table 2) indicate the magnitudes of the two biases and the extent to which they differ across good and bad news. As with the use of lagged earnings in this study, the regressions in Dietrich et al. (2007, Table 2) are estimated on data that should not exhibit conditional conservatism (obtained by scrambling residuals from returns-earnings regressions across firms to scrub any underlying differential timeliness).

While Dietrich et al. (2007) envision cases in which returns are related to earnings and the sample is homogeneous, the general conditions they derive apply to our case in which returns are unrelated to lagged earnings and the sample is heterogeneous. To elaborate, the sample variance ratio bias for the lagged earnings specification is zero for both good and bad news subsamples because the slope of regressions of returns on lagged earnings (represented by β in Dietrich et al. [2007]) is zero.[3] The sample truncation bias, however, which is a function of the covariance between lagged earnings and returns, estimated separately for good and bad news subsamples, is not zero. More importantly, the sample truncation bias differs across bad and good news subsamples because the slope of the X_{t-1}/P_{t-1} line in Panel C of Figure 2 is positive (negative) for bad (good) news.[4] As the loss and return variance effects combine to cause a positive (negative) covariance between abnormal returns and lagged earnings for bad (good) news, estimates of $\beta_0 + \beta_1$ (β_0) are biased upward (downward) for lagged earnings regressions based on Equation (1). The same effects will cause $\beta_0 + \beta_1$ (β_0) to be biased upward (downward) for the current earnings regression, which causes β_1 to be biased upward, thereby overstating substantially the DT measure of conditional conservatism.

One objective of Ball et al. (2010) is to minimize concerns raised by Dietrich et al. (2007). For example, they suggest that the sample variance ratio and sample truncation biases are not relevant and propose alternative estimates of good and bad news timeliness slopes in Equations (2.6a) and (2.6b), respectively. They then suggest that the DT measure is unbiased because the covariance between returns (R_t) and the expectation of earnings (I_t), conditional on returns ($E[I_t|R_t]$), is the same for good and bad news when conditional conservatism is absent.

Our evidence in Figure 2, Panel C, indicates, however, that this covariance differs across good and bad news. The mean values of X_{t-1}/P_{t-1} plotted for each decile of positive and negative abnormal returns represent the expectation of $E[I_{t-1}|R_t]$, and the covariance of those mean values with abnormal returns is clearly different for good and bad news because of the loss and return variance effects. Because the two effects carry over to current earnings, our evidence is inconsistent

[3] There is in fact a weak, nonlinear relation between price-deflated lagged earnings (X_{t-1}/P_{t-1}) and current returns, which was first documented by Basu (1977) and has spawned the E/P anomaly literature. We confirm that this weak relation can be ignored because estimates of β and the sample variance ratio bias for our sample are close to zero. Note that that the E/P anomaly literature was initiated by Sanjoy Basu, whereas the conditional conservatism literature was initiated two decades later by Sudipta Basu.

[4] In Dietrich et al. (2007), the sample truncation bias is a function of the covariance between X, the earnings variable, and η, the non-earnings information that explains returns. In our case, because returns (R) is unrelated to X (lagged earnings) it is completely explained by non-earnings information; i.e., R and η are the same.

with the presumption in Ball et al. (2010) that the covariance of $E[I_t|R_t]$ and R_t is the same across good and bad news when conditional conservatism is absent.

Given the apparent differences between the timeliness estimates derived by Ball et al. (2010) and Dietrich et al. (2007), it seems surprising that the same relations in Panel C of Figure 2, between lagged price-deflated earnings and current abnormal returns, describe why the DT measure is biased for both sets of estimates. It turns out (proof available from authors) that the estimates of timeliness in Equations (2.6a) and (2.6b) of Ball et al. (2010) are algebraically equivalent to the estimates in Equations (1.7a) and (1.7b), respectively, of Dietrich et al. (2007).

Givoly et al. (2007) provide evidence consistent with both upward and downward biases in estimates of conditional conservatism. A bias they investigate, referred to as the "aggregation effect," is caused by the difference between how information is presumed to arrive in one "chunk" in the DT model and how it actually arrives in multiple chunks over time. Because conditional conservatism is applied to the good or bad news in each piece of information, those details are lost to researchers using annual returns to generate a single measure of aggregate news. As a result, estimates of conditional conservatism are biased downward, especially for larger firms with less chunky information arrival. This aggregation effect is potentially related to the return variance effect underlying our bias, because more chunky information arrival is correlated with return variance and firm size is correlated with share price.

Beaver and Ryan (2009) offer a different reason for upward bias in the DT measure: equity returns are affected by the fact that risky debt imbeds a written put option on the firm. This put option absorbs more of the firm's economic asset returns for bad news relative to good news, yielding asymmetry in the direction of conditional conservatism. As a result, the choice of equity returns as a proxy for economic news can create spurious evidence of conditional conservatism, in the presence of risky debt. The authors support their argument by demonstrating that β_1 is higher among firms with more or riskier debt (i.e., firms with higher leverage, higher return volatility, and below investment grade credit ratings). We do not explore links between our results and those reported in Beaver and Ryan (2009).[5]

There is a vast literature based on both time-series and cross-sectional variation in conditional conservatism, but little attention is paid to corresponding variation in biases in estimates of the DT measure. Examples of studies investigating time-series variation include Basu (1997), Givoly and Hayn (2000), Holthausen and Watts (2001), Ryan and Zarowin (2003), and Shivakumar and Waymire (2003). While we document the extent to which time-series variation in the loss and return variance effects bias estimates of conditional conservatism, we do not investigate whether the bias we document affects the results in each study. Related to the loss effect, Klein and Marquardt (2006) show how time-series variation in the fraction of loss firms is explained by corresponding variation in annual estimates of β_1 from the Basu current earnings regression. Our results, however, suggest that causality can run in the opposite direction, as variation in our loss effect over time causes spurious variation in estimates of β_1.[6]

Examples of studies investigating cross-sectional variation in conditional conservatism include Giner and Rees (2001), Pae et al. (2005), Roychowdhury and Watts (2007), Ball et al. (2010), Easton et al. (2009), and Beaver and Ryan (2009). Again, while we consider some aspects of cross-sectional

[5] Another source of potential bias in estimates of the Basu measure, due to simultaneity in the earnings-returns and returns-earnings regressions, is described in Beaver et al. (2008).

[6] Note that the fraction of loss firms in the overall sample differs in important ways from our loss effect, even though the two are closely related. First, the fraction of loss firms is just one part of the loss effect (the other part relates to the magnitude of price-deflated losses) Second, the *fraction* of loss firms in the *overall* sample differs from our loss effect, which is based on the *difference* between good and bad news subsamples in the *relation* between price and the fraction of loss firms/magnitude of losses.

variation in estimates of β_1, we do not investigate the extent to which inferences in these studies are affected by corresponding variation in our loss and return variance effects. We do, however, offer some preliminary evidence on the extent to which the firm-year estimates of conditional conservatism proposed by Khan and Watts (2009) are affected by the loss and return variance effects.

IV. SAMPLE AND DESCRIPTIVE STATISTICS

We collect our sample from the intersection of Compustat annual files (including the research file) and the CRSP monthly returns file. We scan the Compustat files for firm-years ending during the period 1963 to 2006 that have non-missing values in the current and prior year for earnings per share before extraordinary items (X_{it}), common shares outstanding, and fiscal year-end stock price (P_{it}). See Appendix A for further details of variables. We note that the return variance and loss effects are higher for low-price firms, and are considerably higher for firms with share prices below \$1. We impose a minimum lagged price filter ($P_{it-1} > \$1$) to exclude the disproportionate effects of these very low-price firms; including these firm-years would cause even greater biases in our estimates of the DT measure.

Next, we match these observations to compounded "inter-announcement" 12-month returns, which begin with the fourth month of the fiscal year. We require non-missing returns on the CRSP monthly returns file for the 12 months beginning with the fourth month of the current fiscal year and ending with the third month of the next fiscal year. Compounding these monthly returns generates a buy-and-hold return (R_{it}) that proxies for the return from holding the stock between last year's earnings announcement and this year's announcement. We compute corresponding market returns based on the CRSP equally weighted market portfolio (including distributions), which are then subtracted from firm returns to generate abnormal returns (AR_{it}).

Basu (1997) considers different specifications for both the dependent variable (e.g., unadjusted and market-adjusted earnings) and the independent variable (e.g., unadjusted and market-adjusted returns, R_{it} and AR_{it}, respectively, computed over different 12-month windows). To improve comparability with key results reported in the prior literature, we report results based on unadjusted earnings and market-adjusted returns (AR_{it}) cumulated over the inter-announcement window. We confirm later that our main findings are not affected when we use the other dependent and independent variable specifications.

To be consistent with the common practice in this literature, we exclude firm-years falling in the top or bottom 1 percent of the annual cross-sections of any of the following variables: $1/P_{it-1}$, X_{it}/P_{it-1}, X_{it-1}/P_{it-1}, and AR_{it}. The resulting sample contains 124,562 firm-year observations.

Table 1, Panel A provides some statistics for the pooled distributions of the different variables. Observing a higher median than mean for X_{it}/P_{it-1} is consistent with the general findings that price-deflated earnings are left-skewed and firms reporting large losses tend to have lower prices (e.g., Durtschi and Easton 2005). Observing a higher mean than median for returns (R_{it}) indicates a right-skewed distribution, also consistent with general findings regarding the distribution of returns.[7] The negative mean and median abnormal returns (AR_{it}) are also expected, as (1) our sample firms are larger on average than the firms included in the equally weighted CRSP market index, and (2) large firm returns tend to be lower than small firm returns on average. The mean value of 0.572 for the bad news indicator variable (D_{it}) suggests that 57.2 percent of firm-years are classified as bad news firms in our sample. Similarly, the mean value of 0.179 for the loss indicator variable (LD_{it}) suggests that 17.9 percent of our sample firm-years report losses.

[7] Right skewness in returns and normally distributed error terms in the traditional linear regression model of returns on earnings would imply that earnings should be right-skewed. The fact that earnings are left-skewed is therefore anomalous, especially given that operating cash flows are also right-skewed. Conditional conservatism is one explanation for this anomaly (Basu 1995).

TABLE 1

Descriptive Statistics for Pooled Sample (124,562 Firm-Years, 1963–2006)

Panel A: Univariate Statistics

			Percentiles of Distribution				
Variable	**Mean**	**Std. Dev.**	**1st**	**25th**	**50th**	**75th**	**99th**
X_{it}/P_{it-1}	0.050	0.135	−0.493	0.022	0.063	0.107	0.339
$1/P_{it-1}$	0.119	0.136	0.014	0.037	0.066	0.140	0.667
$SIGN_{it}/P_{it-1}$	0.045	0.175	−0.571	0.022	0.045	0.092	0.615
R_{it}	0.160	0.512	−0.687	−0.145	0.089	0.365	1.894
R_{mt}	0.172	0.246	−0.251	0.032	0.158	0.310	0.888
AR_{it}	−0.012	0.466	−0.842	−0.294	−0.063	0.187	1.521
D_{it}	0.572	0.495	0.000	0.000	1.000	1.000	1.000
$D_{it} * AR_{it}$	−0.170	0.219	−0.842	−0.294	−0.063	0.000	0.000
LD_{it}	0.179	0.383	0.000	0.000	0.000	0.000	1.000

Panel B: Pair-Wise Correlations[a]

	X_{it}/P_{it-1}	$1/P_{it-1}$	$SIGN_{it}/P_{it-1}$	R_{it}	AR_{it}	D_{it}	$D_{it} * AR_{it}$	LD_{it}
X_{it}/P_{it-1}		−0.098	0.556	0.350	0.308	−0.241	0.315	−0.664
$1/P_{it-1}$	−0.209		0.405	0.000	−0.034	0.020	−0.077	0.331
$SIGN_{it}/P_{it-1}$	0.580	0.056		0.198	0.178	−0.128	0.165	−0.664
R_{it}	0.210	0.099	0.136		0.791	−0.675	0.730	−0.230
AR_{it}	0.202	0.072	0.138	0.877		−0.857	0.960	−0.234
D_{it}	−0.196	−0.005	−0.118	−0.588	−0.706		−0.893	0.166
$D_{it} * AR_{it}$	0.302	−0.069	0.177	0.553	0.732	−0.671		−0.254
LD_{it}	−0.689	0.300	−0.669	−0.154	−0.163	0.166	−0.295	

Panel C: Proportion of Firms Reporting a Loss in Year t ($X_{it} < 0$)[b]

Sample	# of Firm-Years	% of Sample	Loss Firms in t	% Loss in t
Full sample	124,562	100.00%	22,305	17.91%
Good news ($AR_{it} \geq 0$)	53,339	42.82%	5,628	10.55%
Bad news ($AR_{it} < 0$)	71,223	57.18%	16,677	23.42%
Good news ($R_{it} \geq 0$)	74,780	60.03%	8,283	11.08%
Bad news ($R_{it} < 0$)	49,782	39.97%	14,022	28.17%

[a] Pearson below the main diagonal and Spearman above. All correlations are significant at the 1 percent level, except the Pearson correlation between D_{it} and $1/P_{it-1}$ and the Spearman correlation between $1/P_{it-1}$ and R_{it}.

[b] Good and bad news is defined relative to $AR_{it} = 0$, as well as relative to $R_{it} = 0$ in the bottom two rows.

Variables measured for firm i in year t are defined as follow: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; D_{it} is a bad news indicator variable set to 1 (0) when AR_{it} is negative (otherwise), representing bad (good) news subsamples; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted market index over the 12-month period corresponding to R_{it}; $SIGN_{it}$ equals -1 when $X_{it} < 0$, and 1 otherwise; LD_{it} equals 1 when $X_{it} < 0$, and 0 otherwise. Additional details of all variables are provided in Appendix A. The sample consists of firm-years with non-missing values for the current and prior year for X_{it}, P_{it}, and common shares outstanding, non-missing values for R_{it} and P_{it-1} above \$1. Also, we exclude firm-years that fall below the first percentile or above the 99th percentile of the annual distributions of any of the following variables: $1/P_{it-1}$, X_{it}/P_{it-1}, X_{it-1}/P_{it-1}, and AR_{it}.

Table 1, Panel B reports the Pearson and Spearman correlations for different pair-wise combinations of variables. Two key correlations that are anticipated by the loss effect results reported in Figure 1, Panel A are as follows. First, the loss indicator (LD_{it}) is strongly positively related to $1/P_{it-1}$; i.e., low-price firms are more likely to report losses. Second, X_{it}/P_{it-1} is negatively related to $1/P_{it-1}$; i.e., low-price firms are more likely to have lower values of price-deflated earnings, mainly because the losses they report are larger when deflated by price.

Table 1, Panel C provides some information about the incidence of loss firm-years in our sample. Of the 17.9 percent of our sample reporting losses, the good news subsample reports losses only about 11 percent of the time, whereas the bad news subsample reports losses about 23 percent of the time. The bottom two rows of Panel C describe loss behavior for news partitions based on unadjusted or raw returns, rather than market-adjusted or abnormal returns. This alternative partition for news increases the fraction of good news firms from 43 to 60 percent. Those results show that good news firms report about 11 percent losses, similar to the news partitions based on abnormal returns. The smaller bad news subsample, however, reports losses almost 28 percent of the time.

V. RESULTS

Replicating Pooled Regressions Estimated in Basu (1997)

Although we emphasize results based on annual cross-sectional regressions, given that coefficient estimates vary substantially over time, we first report results based on pooled regressions to allow comparisons to prior research. Table 2, Panel A contains the results of estimating the Basu (1997) regression for unadjusted and market-adjusted price-deflated earnings levels for the full sample of 124,562 firm-years. The independent variable is market-adjusted abnormal returns (AR_{it}), which is also used to create the good and bad news partitions. The first row reports the coefficient estimates and associated t-statistics for unadjusted price-deflated earnings (X_{it}/P_{it-1}). The coefficient β_1, which is the Basu measure of differential timeliness or conditional conservatism, is 0.204. It is slightly lower than estimates reported in prior research, possibly because of the additional minimum price filter we impose when selecting our sample.[8]

The second row in Table 2, Panel A is based on market-adjusted earnings (X_{it}/P_{it-1} − *mean* X_t/P_{t-1}), also considered in Basu (1997). The main difference between this regression and the earlier one is that the intercept α_0 is smaller by 0.050, which corresponds to the mean level of price-deflated earnings of 0.050 reported in Panel A of Table 1. The results in Panel B of Table 2 confirm that the choice of market-adjusted returns versus unadjusted returns for the independent variable does not alter the results in a substantive way. Even though switching from abnormal returns to unadjusted returns alters substantially the good and bad news partitions (see Panel C of Table 1), the main coefficient of interest (β_1) and the associated t-statistics are similar to those reported in Panel A.

Table 2, Panel C provides the results of our efforts to replicate the results in Basu (1997) using our data sources and software code but the same sample period (from 1963 to 1990) and sample selection procedures (e.g., listed on NYSE or AMEX) as in Basu (1997). Our sample size is about 12 percent larger, possibly because we use current exchange membership, which may differ from the prevailing membership when the Basu (1997) sample was collected. The first and third rows contain the results from Panels A and B of Table 1 in Basu (1997), which correspond to regressions of unadjusted earnings on unadjusted returns and market-adjusted earnings on market-adjusted returns, respectively. The second and fourth rows present the results of our efforts to replicate those

[8] Basu (1997) and others also use the difference between R^2 for the bad and good news earnings-returns regressions as an alternative measure of conditional conservatism. We believe these R^2 values are not comparable as the variances of X/P_{t-1} may not be similar for the good and bad news subsamples.

TABLE 2

Pooled Regressions of Earnings on Returns for Good and Bad News Subsamples

Panel A: Full Sample, 1963–2006 (124,562 Firm-Years), and Return Measure (R) is AR_{it}

Earnings Variable (E)		α_0	α_1	β_0	β_1	Adj. R^2
X_{it}/P_{it-1}	Coefficient	0.085	−0.001	−0.013	0.204	9.20%
	t-statistic	112.79***	−1.18	−6.63***	59.63***	
X_{it}/P_{it-1} − *mean* X_t/P_{t-1}	Coefficient	0.035	−0.009	−0.006	0.176	9.67%
	t-statistic	48.60***	−8.22***	−3.02***	52.48***	

Panel B: Full Sample, 1963–2006 (124,562 Firm-Years), and Return Measure (R) is R_{it}

Earnings Variable (E)		α_0	α_1	β_0	β_1	Adj. R^2
X_{it}/P_{it-1}	Coefficient	0.078	−0.011	−0.001	0.236	10.64%
	t-statistic	114.06***	−9.52***	−0.52	58.57***	
X_{it}/P_{it-1} − *mean* X_t/P_{t-1}	Coefficient	0.024	−0.011	0.003	0.201	9.48%
	t-statistic	37.06***	−9.73***	1.86*	51.13***	

Panel C: Replication of Table 1, Panel A and Panel B in Basu (1997) Using the Same Sample Period 1963–1990 and Sample Selection Procedures[a]

Source and Sample Size		α_0	α_1	β_0	β_1	Adj. R^2
Table 1, Panel A, from Basu (1997);	coefficient	0.090	0.002	0.059	0.216	10.09%
43,321 firm-years	t-statistic	68.03***	0.86	18.34***	20.66***	
Our sample from the same sample period;	coefficient	0.095	0.003	0.042	0.260	14.06%
48,677 firm-years	t-statistic	90.97***	1.51	17.48***	31.04***	
Table 1, Panel B, from Basu (1997);	coefficient	0.030	0.014	0.047	0.256	12.48%
43,321 firm-years	t-statistic	22.62***	6.07***	11.03***	27.14***	
Our sample from the same sample period;	coefficient	0.032	0.007	0.025	0.235	13.82%
48,677 firm-years	t-statistic	29.25***	4.11***	7.72***	35.71***	

*, **, *** Statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, based on two-tailed tests.
[a] The earnings variable (E) is X_{it}/P_{it-1}, and return measure (R) is R_{it} in the first two rows, and the earnings measure is X_{it}/P_{it-1} − mean X_t/P_{t-1} and return measure is AR_{it} in the bottom two rows.
This table provides results of pooled regressions of two earnings variables (E) on two measures of returns (R): $E = a_0 + a_1 D_{it} + \beta_0 R + \beta_1 R * D_{it} + \varepsilon_{it}$.
The earnings and return measures are derived from the following variables for firm i in year t: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted market index over the 12-month period corresponding to R_{it}; *mean* X_t/P_{t-1} is the cross-sectional mean of X_{it}/P_{it-1} in year t; and D_{it} equals 1 when the return measure is < 0, and 0 otherwise, representing bad and good news, respectively. Additional details of all variables are provided in Appendix A.
All t-statistics are heteroscedasticity-adjusted according to White (1980).

two specifications. Because we find no major differences between the first and second rows or between the third and fourth rows, we conclude that there are no important methodological differences between Basu (1997) and our study.

Impact of Loss and Return Variance Effects on Estimates of Conditional Conservatism

The results reported in Table 3, Panel A provide empirical support for the intuition developed in Figures 1 and 2 by estimating different versions of Equation (1)-type regressions using different

TABLE 3

Annual Cross-Sectional Regressions of Earnings on Returns for Good and Bad News Subsamples (124,562 Firm-Years, 1963–2006)

Panel A: Impact of Return Variance and Loss Effects on the Basu (1997) Earnings-Returns Regression

Variable (V)		α_0	α_1	β_0	β_1	Adj. R^2
$1/P_{it-1}$	Coefficient	0.089	−0.002	0.073	−0.160	5.38%
	t-statistic	17.56***	−0.53	10.89***	−11.14***	
$SIGN_{it-1}/P_{it-1}$	Coefficient	0.051	0.000	−0.007	0.038	1.20%
	t-statistic	12.08***	0.13	−1.01	2.94***	
X_{it-1}/P_{it-1}	Coefficient	0.066	0.002	−0.035	0.116	3.09%
	t-statistic	10.12***	0.76	−8.22***	12.66***	
X_{it}/P_{it-1}	Coefficient	0.081	0.007	0.019	0.185	14.76%
	t-statistic	12.06***	3.86***	3.20***	15.33***	

Panel B: Replacing Lagged Earnings (X_{t-1}) with Earnings from the Year before (X_{t-2})

Variable (V)		α_0	α_1	β_0	β_1	Adj. R^2
X_{it-2}/P_{it-1}	Coefficient	0.071	0.000	−0.035	0.104	2.03%
	t-statistic	10.34***	0.19	−8.53***	10.86***	
X_{it-2}/P_{it-2}	Coefficient	0.070	0.000	−0.034	0.114	2.87%
	t-statistic	10.86***	0.09	−9.46***	9.90***	

Panel C: Scale by Lagged Total Assets per Share Instead of Lagged Price

Variable (V)		α_0	α_1	β_0	β_1	Adj. R^2
$1/TA_{it-1}$	Coefficient	0.077	−0.006	0.094	−0.315	2.12%
	t-statistic	12.88***	−1.13	7.42***	−8.08***	
X_{it-1}/TA_{it-1}	Coefficient	0.046	0.005	−0.030	0.121	1.21%
	t-statistic	14.53***	1.77*	−6.05***	7.08***	
X_{it}/TA_{it-1}	Coefficient	0.054	0.013	0.001	0.171	4.37%
	t-statistic	19.56***	5.41***	0.25	9.32***	

Panel D: Include $1/P_{t-1}$ as Additional Regressor to Control for Loss and Return Variance Effects

$$V = \alpha_0 + \alpha_1 D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \gamma \frac{1}{P_{it-1}} \varepsilon_{it}$$

Variable (V)		a_0	a_1	β_0	β_1	γ	Adj. R^2
X_{it-1}/P_{it-1}	Coefficient	0.091	0.001	−0.013	0.067	−0.277	12.71%
	t-statistic	16.00***	1.01	−4.91***	12.66***	−13.47***	
X_{it}/P_{it-1}	Coefficient	0.096	0.007	0.032	0.158	−0.157	18.61%
	t-statistic	15.35***	4.52***	5.74***	15.91***	−9.43***	

(continued on next page)

TABLE 3 (continued)

*, **, *** Statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, based on two-tailed tests.
This table provides results of annual regressions of different variables (V) on abnormal returns (AR_{it}): $V = a_0 + a_1 D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \varepsilon_{it}$. The variables that appear as dependent variables and AR_{it} are derived from the following variables for firm i in year t: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; TA_{it} is total assets per share; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted market index over the 12-month period corresponding to R_{it}; D_{it} equals 1 when AR_{it} is < 0, and 0 otherwise, representing bad and good news, respectively; and $SIGN_{it}$ equals -1 when $X_{it} < 0$, and 1 otherwise. Additional details of all variables are provided in Appendix A.
The annual regressions are estimated separately for firm-years with fiscal years ending in the same calendar year. The coefficients are the means of those annual coefficients and the t-statistics are derived from the time-series distributions of those coefficients.

dependent variables, each of which identifies a specific aspect of the loss and return variance effects. Unlike the pooled regressions in Table 2, the Table 3 regressions report the mean of coefficients from 44 annual regressions. Reported t-statistics are derived from the distribution of those coefficients.

The first row describes the results of replacing the dependent variable in the Basu (1997) regression (X_{it}/P_{it-1}) with $1/P_{it-1}$. Based on the return variance effect, we expect low-price firms with high return variances to be over-represented when abnormal returns are very positive and very negative. That is, the positive (negative) slopes for bad (good) news reported for lagged price in Panel C of Figure 2 should be inverted when we investigate $1/P_{it-1}$, the inverse of lagged price. As predicted, the good news slope in the first row is positive ($\beta_0 = 0.073$), and the slope for bad news firms is negative ($\beta_0 + \beta_1 = 0.073 - 0.160 = -0.087$).

The second row in Panel A of Table 3 investigates the joint impact of the variance effect and the first part of the loss effect, which is the higher frequency of losses for low-price shares. We replace $1/P_{it-1}$ in the first row with the product of $1/P_{it-1}$ and the sign of reported lagged earnings ($SIGN_{it-1}$), coded to be -1 and $+1$ when X_{t-1} is negative and positive, respectively. Given that low-price shares are over-represented when abnormal returns are very positive and negative, and given that low-price shares are more likely to report a loss, we expect more (fewer) losses for larger (smaller) magnitudes of abnormal returns. That is, we expect a positive (negative) slope for bad (good) news firms. Consistent with that prediction, the good news slope is negative ($\beta_0 = -0.007$) and the slope for bad news firms is positive ($\beta_0 + \beta_1 = -0.007 + 0.038 = 0.031$).

The third row in Panel A of Table 3 also incorporates the second part of the loss effect, which is the larger magnitude of price-deflated losses for low-price shares, by replacing $SIGN_{it-1}/P_{it-1}$ in the second row with X_{it-1}/P_{it-1}. As shown in Panel C of Figure 2, combining the loss and return variance effects should produce lower (higher) mean values of X_{it}/P_{it-1} closer to the edges (center) of the abnormal returns axis; i.e., we expect a positive (negative) slope for bad (good) news firms. Consistent with this prediction, the good news slope is negative ($\beta_0 = -0.035$) and the slope for bad news firms is positive ($\beta_0 + \beta_1 = -0.035 + 0.116 = 0.081$). In combination, the return variance effect and the two components of the loss effect create substantial spurious evidence of conditional conservatism, represented by the estimate of $\beta_1 = 0.116$. As this year's returns refer to a window that begins after last year's earnings are announced, there should be no evidence of differential timeliness and β_1 should be zero in this row of Table 2.

The bottom row in Panel A of Table 3, which is based on Equation (1), replaces lagged earnings in the third row with current earnings. Consistent with the X_{it}/P_{it-1} line in Panel C of Figure 2, there is considerable asymmetry between the slopes for the bad and good news subsamples: whereas the slope for good news firm-years is mildly positive ($\beta_0 = 0.019$) the slope for bad news firm-years is substantially positive ($\beta_0 + \beta_1 = 0.019 + 0.185 = 0.204$). Comparing this asymmetry with that for lagged earnings in the third row (β_1 of 0.185 versus 0.116) suggests that over 60 percent of the estimated DT measure is due to the bias we document. While 60 percent is a substantial level of bias, note that it represents a lower bound for the extent to which the DT measure overstates conditional conservatism. Any remaining asymmetry in the fourth row should not be viewed as evidence of conditional conservatism, as some of it is likely due to differential sample variance ratio bias between good and bad news subsamples and other sources of differential sample truncation bias not present in the lagged earnings specification (Dietrich et al. 2007).[9]

Table 3, Panel B confirms that results similar to the lagged earnings specification are obtained when we replace lagged earnings in the third row of Panel A with earnings from the year before (X_{t-2}). The first and second rows in Panel B consider deflation by price from one and two years ago (P_{t-1} and P_{t-2}), respectively. The similarity between the estimates for β_1 reported in Panel B (0.104 and 0.114) and those reported for lagged earnings in Panel A (0.116) confirm that the return variance and loss effects we document are both systematic (not unique to X_{t-1}) and robust (e.g., not driven by deflating by P_{t-1}).

Table 3, Panel C suggests that the loss and return variance effects are general scale effects, not contingent on scale being measured by share price. That is, we use lagged total assets per share (TA_{it-1}) as an alternative deflator and observe results very similar to those reported for lagged price in Panel A. Again, we find spurious evidence of differential timeliness, indicated by large and significant estimates of β_1 when the dependent variable is lagged earnings. The results in Table 3, Panel D indicate that attempts to control for scale by adding the deflator ($1/P_{t-1}$) as an additional regressor (e.g., Beaver and Ryan 2009) reduces the impact of the loss and return variance effects but does not eliminate it; the estimates for β_1 are smaller than the corresponding values in Panel A, but are still quite large.[10]

We also show that the loss and return variance effects impact both low- and high-price shares; i.e., deleting low-price shares does not eliminate spurious evidence of differential timeliness. We confirm the results in Easton et al. (2009) that estimates of β_1 for the current earnings specification are significantly positive in all price quintiles, though the magnitudes of these estimates decrease with share price. More important, we show that corresponding estimates of β_1 for the lagged earnings specification are also significantly positive in all price quintiles

VI. ADDITIONAL ANALYSES

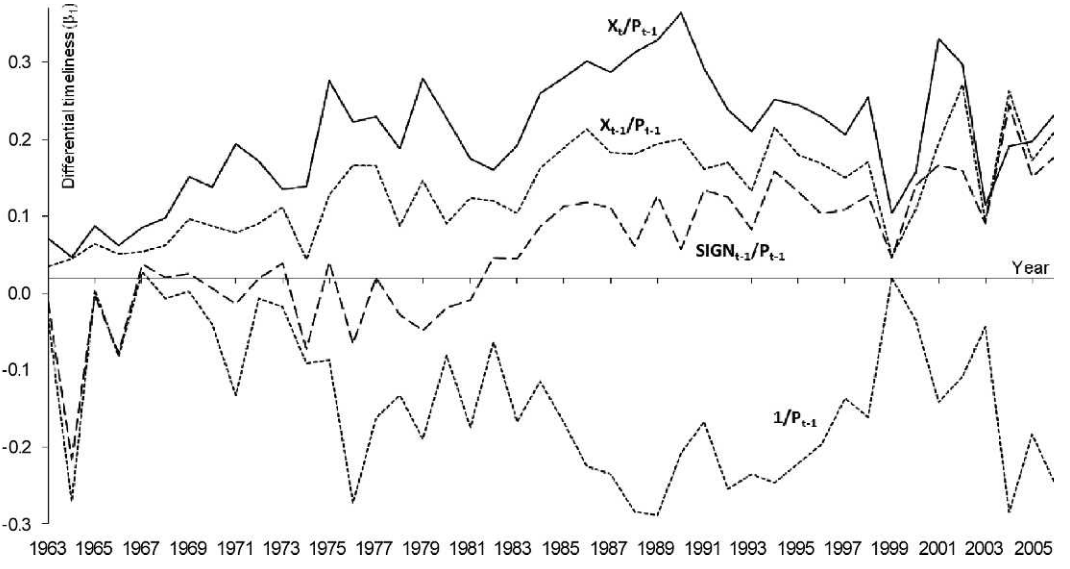
Explaining Time-Series Variation in Conditional Conservatism

The mean coefficients from annual Basu (1997) regressions reported in the bottom row of Table 3, Panel A, mask considerable time-series variation in annual coefficient estimates. The top solid line in Figure 3, labeled X_t/P_{t-1}, shows how the annual differential timeliness estimate (β_1) varies from values close to zero early in the sample period to values above 0.3 around 1990. Much of this variation must be spurious, however, and due to time-series variation in the return variance and loss effects because β_1 estimates exhibit substantial comovement with corresponding estimates

[9] One way to mitigate our bias is to subtract X_{t-1}/P_{t-1} from the left-hand side of Equation (1). Lobo et al. (2008) do so, not to mitigate our bias but because X_{t-1}/P_{t-1} serves as an expectation for X_t/P_{t-1}.

[10] We also found similar results for current and lagged earnings when we considered the following unscaled version of Equation (1): X_{it} (or X_{it-1}) $= \alpha_0 P_{it-1} + \alpha_1 D_{it} * P_{it-1} + \beta_0 * AR_{it} * P_{it-1} + \beta_1 * D_{it} * AR_{it} * P_{it-1} + \varepsilon_{it}$.

FIGURE 3
Differential Timeliness Coefficient Estimates (β_1) from Annual Regressions (124,562 Firm-Years, 1963–2006)



This figure provides differential timeliness coefficient estimates from annual regressions of four variables (V) on abnormal returns (AR_{it}): $V = a_0 + a_1D_{it} + \beta_0AR_{it} + \beta_1AR_{it} * D_{it} + \varepsilon_{it}$. Annual regressions are estimated for fiscal years ending in the same calendar year.

Variables for firm i and year t are defined as follow: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted index over the corresponding 12-month period; D_{it} equals 1 when AR_{it} is < 0, and 0 otherwise, representing bad and good news, respectively; and $SIGN_{it}$ equals -1 when $X_{it} < 0$, and 1 otherwise. Additional details of all variables are provided in Appendix A.

from the lagged earnings specification, represented by the dotted line, labeled X_{t-1}/P_{t-1}. We confirm this conjecture by investigating time-series variation in the return variance and loss effects.

The bottom dotted line in Figure 3 (labeled $1/P_{t-1}$) describes time-series variation in the return variance effect by reporting the estimated values of β_1 for annual regressions when we replace the dependent variable in the Basu (1997) regression (X_{it}/P_{it-1}) with the inverse of lagged price ($1/P_{it-1}$). The annual estimates that vary between 0 and -0.3 describe time-series variation around the mean estimate of -0.160 reported in the first row of Table 3, Panel A. The main finding is that years with greater return variance effects, as indicated by more negative values of β_1 estimates from the $1/P_{it-1}$ regressions, have more positive values of β_1 estimates for the X_{it}/P_{it-1} and X_{it-1}/P_{it-1} regressions. Even though the spurious evidence of differential timeliness in the X_{it-1}/P_{it-1} regressions is jointly determined by both the return variance and loss effects, the return variance effect appears to play a major role, as the time-series patterns for X_{it}/P_{it-1} and X_{it-1}/P_{it-1} in the top half are largely mirror-images of the return variance pattern in the bottom half. We show later that the impact of the return variance effect is muted in the early years when the loss effect is low.

As with the analyses described in Section V, we consider the loss effect in two stages. We report estimates of β_1 for annual regressions based on $SIGN_{t-1}/P_{t-1}$, which allows us to determine the joint impact of the return variance effect and the *fraction* of loss firms, which is the first part of the loss effect. We then compare those results with the estimates of β_1 for the X_{it-1}/P_{it-1} regressions to determine the incremental impact of the *magnitude* of price-deflated losses, which is the second part of the loss effect.

The middle dashed line in Figure 3, labeled $SIGN_{t-1}/P_{t-1}$, shows a pattern of time-series variation in estimates of β_1 that resembles the time-series variation exhibited by β_1 from annual DT regressions (the top solid line in Figure 3); the correlation between the two series of β_1 estimates is 0.53. That resemblance increases further when we also incorporate the magnitude of losses, represented by the middle dotted line, labeled X_{t-1}/P_{t-1}. The correlation between estimates of β_1 for the current and lagged earnings specifications is 0.81.

Because β_1 represents the difference between the separate timeliness for the bad and good news samples, $\beta_0 + \beta_1$ and β_0, respectively, we investigate next whether the high comovement between β_1 estimates from the current and lagged earnings specifications reflect high comovement between the corresponding slopes from the good and bad news subsamples. The results graphed in Figure 4 confirm that conjecture; the correlation between year-to-year changes in estimates of β_0 reported in Panel A for current and lagged earnings for the good news subsample is 0.74, and the corresponding correlation for $\beta_0 + \beta_1$ estimates for the bad news subsample reported in Panel B is 0.80.

The plots in Figure 5 confirm that time-series variation in estimates of β_1 for the lagged earnings specification is due to time-series variation in the loss and return variance effects. Whereas the evidence in Figures 3 and 4 describes time-series variation in the implications of the return variance and loss effects on Equation (1) regressions based on lagged earnings, Figure 5 documents whether those implications are supported by direct evidence on time-series variation in the original return variance and loss effects by estimating regressions of price-deflated lagged earnings (X_{t-1}/P_{t-1}) and abnormal returns (AR_{it}) on lagged price (P_{t-1}). Stated differently, whereas Figures 3 and 4 describe time-series variation in the implications of the return variance and loss effects reported in Panel C of Figure 2, Figure 5 describes time-series variation in the loss and return variance effects reported in Panels A and B of Figure 1.

Also, by reporting variation separately for the good and bad news subsamples in Panels A and B, respectively, Figure 5 provides more detail about how variation in the *difference* between the loss and return variance effects between the two subsamples reported in Figure 4 is generated by the separate time-series variation for each subsample. For purposes of comparison, we also report the Figure 4 estimates of timeliness for the good news sample (β_0) and bad news sample ($\beta_0 + \beta_1$), respectively, for the lagged earnings specification (X_{t-1}/P_{t-1}). Whereas estimates for the loss and return variance effects are measured against the left scale in each panel, the timeliness estimates are measured on the right scale.

Observing positive values in general for the line labeled "Loss Effect (GN)" in Figure 5, Panel A suggests that mean values of X_{t-1}/P_{t-1} increase with share price for the good news subsample, consistent with the overall sample results in Figure 1, Panel A. Values close to zero early in the sample period suggest that mean values of X_{t-1}/P_{t-1} are similar for low- and high-price stocks, but the higher values observed later in the sample period indicate that mean values of X_{t-1}/P_{t-1} are substantially higher for high-price stocks. The generally negative values for the line labeled "Ret. Var. Effect (GN)" suggest that mean values of AR_{it} decrease with share price for the good news subsample, consistent with the overall sample results in Figure 1, Panel B. As with the loss effect, the return variance effect for good news firms is relatively low early in the sample period, but increases substantially toward the end of that period.

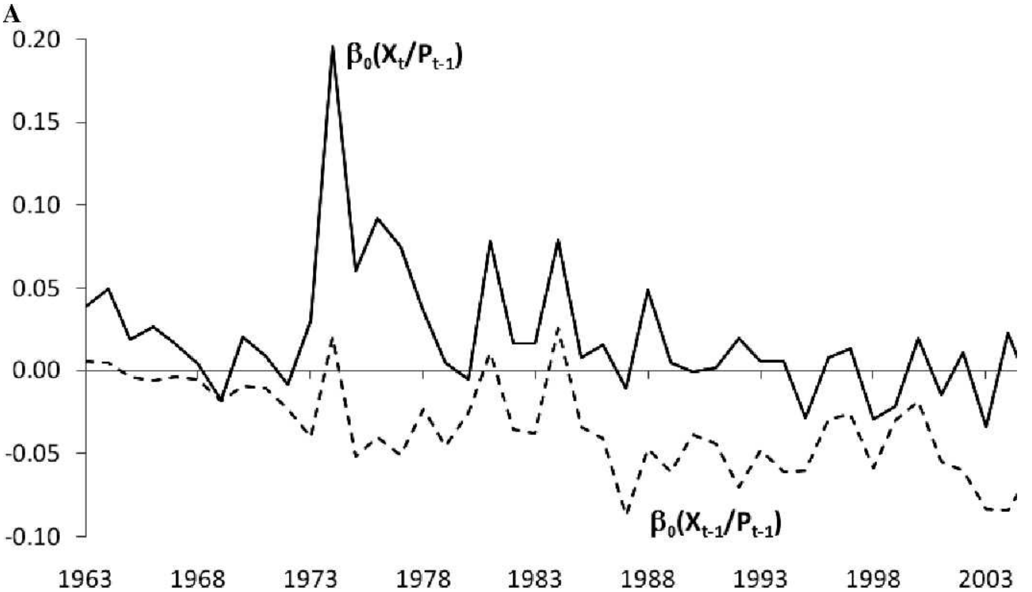
The results in Figure 5, Panel B suggest that the loss and return variance effects vary substantially through time for the bad news subsample, too. Whereas values for the loss effect are generally large and positive later in the sample period, consistent with the overall sample results in Panel A of Figure 1, they are close to zero and even negative during the early years. Note that a negative estimate for the loss effect implies that mean values of X_{t-1}/P_{t-1} decrease, rather than increase, with share price. The return variance effect is generally positive in Figure 5, Panel B, unlike the negative values in Figure 5,

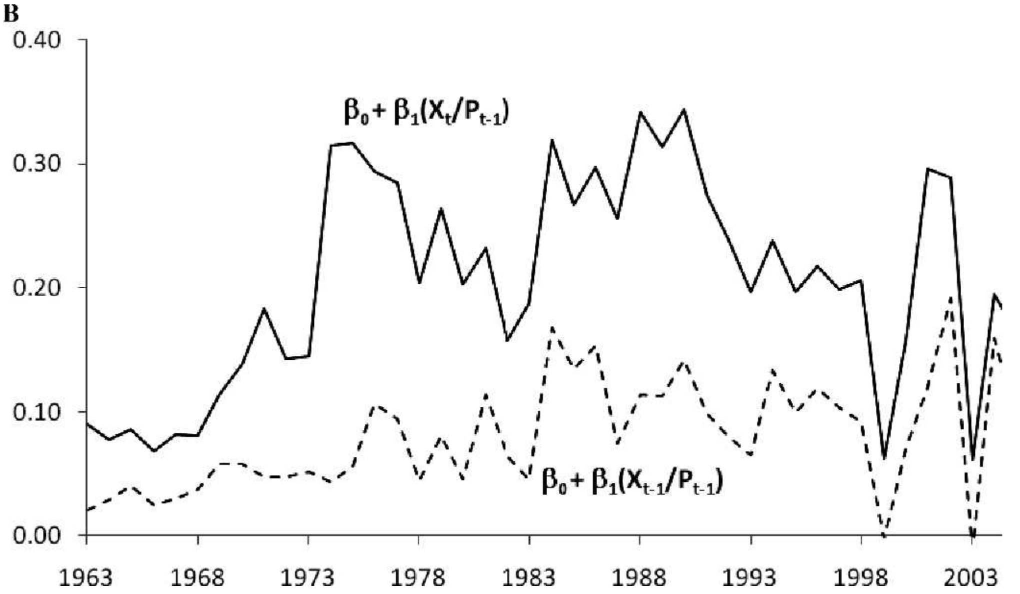
FIGURE 4

Estimates of Slopes from Annual Earnings-Returns Regressions for the Good News (β_0) and Bad News ($\beta_0 + \beta_1$) Subsamples (124,562 Firm-Years, 1963–2006)

Panel A: Slopes of Earnings-Returns Regressions for Good News Subsamples

Panel B: Slopes of Earnings-Returns Regressions for Bad News Subsamples





(continued on next page)

FIGURE 4 (continued)

This figure provides slope estimates from annual regressions of price-deflated earnings on abnormal returns (AR_{it}): $V = a_0 + a_1 D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \varepsilon_{it}$. V represents current earnings and lagged earnings X_{it}/P_{t-1} and X_{it-1}/P_{t-1}). Annual regressions are estimated for fiscal years ending in the same calendar year.
Variables for firm i and year t are defined as follow: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted index over the corresponding 12-month period; and D_{it} equals 1 when AR_{it} is $<$ 0, and 0 otherwise, representing bad and good news, respectively. Additional details of all variables are provided in Appendix A.

Panel A, because the overall results in Panel B of Figure 1 suggest that mean values of AR_{it} become less negative with share price for the bad news subsample. The return variance effect in Figure 5, Panel B, is also generally smaller (larger) in the early (late) part of the sample period. That larger variation in the later years is however negatively related to the return variance effect for good news firms in Figure 5, Panel A. For example, the return variance effect is low in Panel B for 1999 and 2003, but those years exhibit high values of the return variance effect in Panel A.

The main finding from Figure 5 is that time-series variation in the loss and return variance effects for the good and bad news subsamples is reflected in corresponding time-series variation in the estimated timeliness coefficients, represented by the lines labeled $\beta_0(X_{t-1}/P_{t-1})$ and $\beta_0 + \beta_1(X_{t-1}/P_{t-1})$ in Panels A and B, respectively. Estimates of β_0 ($\beta_0 + \beta_1$) become more negative (positive) when both effects are large, as they tend to be on average later in the sample period. As indicated by the right-hand scale used for timeliness estimates, the magnitude of upward bias for the bad news subsample in Figure 5, Panel B is much larger than the upward bias in Panel A, which implies that estimates of differential timelines (β_1) are affected mainly by the bias in the bad news subsample.

Because the bias is an interactive function of the loss and return variance effects, rather than the sum, the combined effect is small if either effect is small. Although the loss and return variance effects tend to move together in Figure 5, Panel A as well as in Panel B, there are points in time when they deviate. For example, estimates of timeliness in Figure 5, Panel B exhibit little time-series variation before 1975, despite some variation in estimates of the return variance effect. We attribute this relative lack of variation in estimates of $\beta_0 + \beta_1$ to the loss effect being close to zero during that subperiod. Similarly, estimates of $\beta_0 + \beta_1$ in Figure 5, Panel B are low during 1999 and 2005 when the return variance effect is close to zero, even though the loss effect is nonzero in those years.

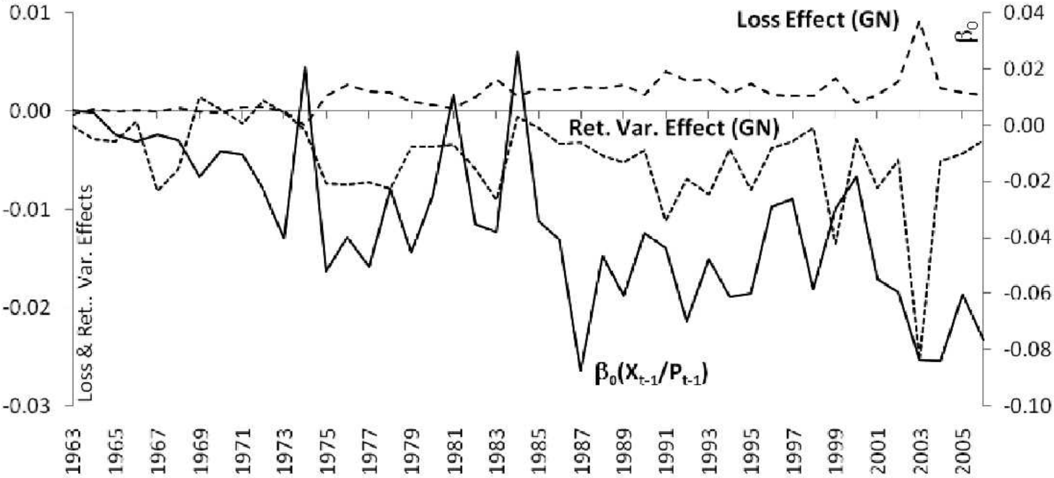
To be sure, increased conditional conservatism should be reflected in more frequent and bigger losses, and observing a positive relation between timeliness and the loss effect for bad news subsamples could be interpreted as *prima facie* evidence in support of the DT measure.[11] Under this alternative explanation, time-series variation in conservatism is explained by time-

[11] For example, Givoly and Hayn (2000) posit that left skewness of the earnings distribution is consistent with conditional conservatism. Because earnings are more (less) timely for unfavorable (favorable) events, they will contain large negative items and smaller positive items that are spread over time. If so, the observed increase over time in left skewness of the earnings distribution is consistent with an increase in conditional conservatism. See also Basu (1995) and Ball et al. (2000) for the skewness/conservatism relation.

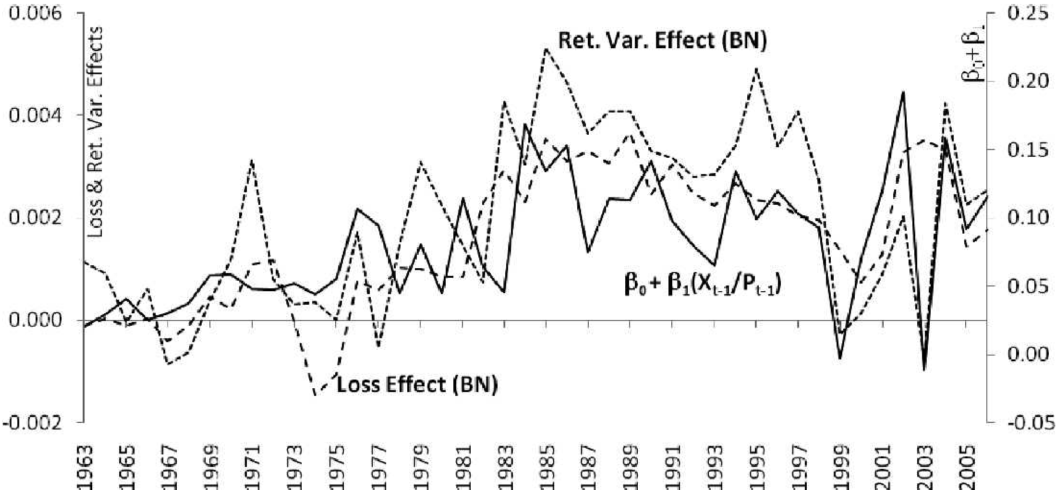
FIGURE 5
Variation in the Return Variance and Loss Effects
(124,562 Firm-Years, 1963–2006)

Panel A: Good News (GN) Subsample
Panel B: Bad News (BN) Subsample

A



B



This figure describes the impact of time-series variation in the loss and return variance effects on slope estimates from annual regressions of lagged price-deflated earnings (X_{t-1}/P_{t-1}) on abnormal returns (AR_{it}): $X_{t-1}/P_{t-1} = a_0 + a_1D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \varepsilon_{it}$. Annual regressions are estimated for fiscal years ending in the same calendar year. Variables for firm i and year t are defined as follow: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted index over the corresponding 12-month period; D_{it} equals 1 when AR_{it} is < 0, and 0 otherwise, representing bad and good news, respectively. The slopes for good news and bad news subsamples are represented by the estimates β_0 and $\beta_0 + \beta_1$, respectively. The loss (return variance) effect is the slope of a regression of X_{t-1}/P_{t-1} (AR_{it}) on P_{t-1}, estimated annually separately for good and bad news subsamples. Additional details of all variables are provided in Appendix A.

series variation in factors such as extant accounting rules, how accountants tend to interpret and apply them, and audit characteristics such as auditor liability regimes (e.g., Basu et al. 2001) and whether quarterly numbers are audited (e.g., Basu et al. 2002). This variation in conservatism levels is associated with corresponding variation in the fraction of loss firms, because increased conservatism results in more bad news being recognized in contemporaneous earnings. It is also possible that increased conservatism results in contemporaneous earnings being less timely for good news, which results in smaller positive values of β_0 for good news firms when conditional conservatism levels are high.

The evidence presented here is inconsistent with this alternative view. First, as shown in Figure 5, it is not the fraction of firms reporting losses or the magnitude of those losses that creates spurious evidence of conditional conservatism. Rather, it is the extent to which those two factors vary across share price, and the extent to which that variation differs across good and bad news firms. The alternative view does not suggest that conditional conservatism is related to variation across price in the probability of reporting a loss or the magnitude of those losses. Second, as shown in Figure 5, while the loss effect is necessary for biased estimates of conditional conservatism, it is not sufficient. The return variance effect is also necessary. Again, there is no link between conditional conservatism and the variation across price in return variances.

Third, there is considerable year-to-year variation in estimates of β_1 reported in Figure 3 for current earnings (X_t/P_{t-1}), especially after 1998. While we attribute this to time-series variation in the relation between return variance and price for the good and bad news subsamples, it appears inconsistent with the alternative view because the factors that determine conditional conservatism, such as auditor liability, are unlikely to exhibit so much volatility.[12] Finally, while conditional conservatism might result in good news firms reporting less timely earnings, which is associated with less positive values of β_0, it is hard to explain estimates of β_0 for current earnings in Panel A of Figure 4 that are close to zero and often negative.

Overall, the evidence is generally consistent with our thesis that time-series variation in the return variance and loss effects for bad (good) news firms causes timeliness estimates to be biased upward (downward), which in turn bias upward estimates of conditional conservatism (β_1).[13]

Explaining Cross-Sectional Variation in Conditional Conservatism

Our next set of analyses considers the correlation documented in the literature between conditional conservatism estimates (β_1) and (1) lagged book-to-market (B/M) ratios (e.g., Giner and Rees 2001; Pae et al. 2005) and (2) market value of equity (MV) or size (e.g., Giner and Rees 2001; Givoly et al. 2007). As in the time-series analyses, we compare cross-sectional variation in estimates of β_1 from current and lagged earnings (X_{it}/P_{it-1} and X_{it-1}/P_{it-1}) regressions. Observing similar patterns confirms our view that cross-sectional variation in the return variance and loss effects creates cross-sectional variation in the bias associated with DT estimates, as indicated by estimates of β_1 from lagged earnings regressions. Finding that cross-sectional variation in the bias substantially impacts observed cross-sectional variation in the DT measure (β_1 from current earnings regressions) raises doubts about inferences raised in prior

[12] See Givoly et al. (2007, 83–89) for a discussion of the reasons why conservatism is unlikely to vary much from year to year.

[13] The strong time-series correlation between estimates of β_1 from the lagged and current earnings specification is not contingent on using share price as the deflator. Untabulated results indicate that this correlation is 0.95 when we use total assets per share as the deflator in Equation (1).

research based on cross-sectional variation in the DT measure. For example, prior evidence on variation in conditional conservatism across *B/M* ratios has created some disagreement in the literature.[14] To the extent that this evidence reflects effects unrelated to conditional conservatism, there may not in fact be a controversy.

Table 4, Panel A provides the mean coefficients from annual Basu (1997) regressions, estimated separately for quintiles of lagged *B/M* ratios, calculated at the beginning of each year. We also provide results in the bottom row for all five quintiles combined, as the sample with available *B/M* data (122,411 firm-years) is slightly smaller than our full sample. Estimated values of β_1 are positively related to *B/M*, increasing monotonically from 0.096 for the lowest quintile to 0.320 for the highest quintile. These results are consistent with the findings of prior research, which suggest that low (high) *B/M* firms are associated with relatively low (high) levels of conditional conservatism.

Table 4, Panel B repeats the Basu (1997) regressions after replacing current earnings (X_t/P_{t-1}) with lagged earnings (X_{t-1}/P_{t-1}). The same monotonic trend is observed in Panel B: estimated values of β_1 increase from 0.078 for the lowest *B/M* quintile to 0.142 for the highest quintile. The levels of differential timeliness (β_1) in Panel B are closer to those in Panel A for lower *B/M* quintiles, but the gap increases for higher quintiles.

Table 5 repeats the analysis for quintiles based on size, measured by market capitalization. The number of firm-years with available data is the same as that for our full sample (124,562 firm-years). Table 5, Panel A indicates a monotonic negative relation between size and estimates of conditional conservatism (β_1) for current earnings. The results reported in Table 5, Panel B based on the X_{t-1}/P_{t-1} regressions exhibit the same monotonic negative relation. As in Table 4, the levels of estimated β_1 in Panel B are similar to those in Panel A for large firms in the high *MV* quintiles, but the gap increases as size declines.

While the cross-sectional patterns observed for lagged earnings in Tables 4 and 5 resemble the patterns observed for contemporaneous earnings, the extent of comovement is not as strong as that observed for time-series variation. We emphasize again that the results observed for lagged earnings represent a lower bound on the extent to which estimates of conditional conservatism (β_1) for current earnings are biased upward. Also, our estimates of timeliness for bad and good news for the lagged earnings regressions are likely to be biased toward zero because partitions based on *B/M* and size are correlated with X_t/P_{t-1}, the dependent variable in the lagged earnings-returns regressions. Given that β_0 is negative and $\beta_0 + \beta_1$ is positive for the lagged earnings specification, the effects that bias the timeliness estimates toward zero result in a downward bias for the conditional conservatism estimate (β_1). Overall, our evidence suggests that a substantial portion of cross-sectional variation in the DT measure is likely to be driven by cross-sectional variation in the loss and return variance effects.

Khan and Watts (2009) propose estimates of the DT measure that can vary both across firms and over time, by estimating cross-sectional versions of Equation (1) that include interaction terms, thereby allowing the coefficients to vary across firms based on *M/B* ratios, size, and leverage. Table 3 in Khan and Watts (2009) documents significantly positive (negative) interactions with β_1 for size (leverage), but an insignificant interaction for *M/B* ratios. We repeat the analysis with lagged rather than current earnings and find similar results (available upon request): while the size and leverage

[14] Assuming that *B/M* ratios are negatively related to *unconditional* conservatism (e.g., Beaver and Ryan 2000), is it puzzling that *B/M* ratios are positively related to conditional conservatism? Some suggest that the positive relation observed between β_1 and *B/M* is due to measurement error in both earnings and returns (e.g., Givoly et al. 2007) and that error should decline as the measurement horizon increases (e.g., Roychowdhury and Watts 2007). In contrast, others (e.g., Basu 2001; Ball et al. 2010) argue that the observed positive relation is expected as a property of income recognition in accounting, and need not be due to measurement error.

TABLE 4

Relation between Book-to-Market (*B/M*) Ratio and Conditional Conservatism (122,411 Firm-Years, 1963–2006)

Panel A: Regressions of Price-Deflated Current Earnings on Abnormal Returns

Lagged *B/M* Quintile		α_0	α_1	β_0	β_1	Sample Size	Adj. R^2
1 (Lowest)	coefficient	0.042	0.007	0.007	0.096	24,466	8.77%
	t-statistic	9.07***	3.11***	1.59	9.55***		
2	coefficient	0.071	0.011	0.014	0.126	24,490	14.29%
	t-statistic	13.24***	6.48***	2.92***	11.17***		
3	coefficient	0.089	0.010	0.016	0.176	24,492	16.43%
	t-statistic	13.58***	5.46***	3.07***	11.81***		
4	coefficient	0.100	0.013	0.028	0.234	24,490	19.91%
	t-statistic	12.98***	5.66***	4.35***	12.48***		
5 (Highest)	coefficient	0.087	0.009	0.044	0.320	24,473	20.09%
	t-statistic	9.06***	2.19**	4.83***	13.39***		
Combined sample	coefficient	0.081	0.007	0.020	0.182	122,411	14.68%
	t-statistic	12.02***	3.64***	3.19***	14.25***		

Panel B: Regressions of Price-Deflated Lagged Earnings on Abnormal Returns

Lagged *B/M* Quintile		α_0	α_1	β_0	β_1	Sample Size	Adj. R^2
1 (Lowest)	coefficient	0.028	0.001	−0.028	0.078	24,466	2.25%
	t-statistic	5.73***	0.37	−4.58***	6.81***		
2	coefficient	0.065	0.001	−0.024	0.078	24,490	3.85%
	t-statistic	12.58***	0.55	−4.36***	7.62***		
3	coefficient	0.081	0.000	−0.030	0.097	24,492	3.65%
	t-statistic	12.31***	−0.10	−6.44***	8.29***		
4	coefficient	0.085	0.004	−0.022	0.108	24,490	3.07%
	t-statistic	12.52***	1.77*	−4.46***	8.67***		
5 (Highest)	coefficient	0.058	0.001	−0.046	0.142	24,473	2.32%
	t-statistic	6.05***	0.19	−5.98***	9.35***		
Combined sample	coefficient	0.066	0.001	−0.035	0.115	122,411	3.14%
	t-statistic	10.12***	0.67	−8.14***	12.36***		

*, **, *** Statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, based on two-tailed tests.
This table provides results of annual regressions of two earnings variables (E) on abnormal returns (AR_{it}) estimated separately for lagged book-to-market (*B/M*) quintile portfolios: $E = a_0 + a_1 D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \varepsilon_{it}$. *B/M* equals the book value of common equity divided by the market value of equity. The *B/M* quintile portfolios are formed at the beginning of each year. The variables are derived from the following items for firm i in year t: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted market index over the 12-month period corresponding to R_{it}; and D_{it} equals 1 when the return measure is < 0, and 0 otherwise, representing bad, and good news, respectively. In Panel A (B), the dependent variable is X_{it}/P_{it-1} (X_{it-1}/P_{it-1}), or earnings in t (t−1) deflated by lagged price. Additional details of all variables are provided in Appendix A.
The annual regressions are estimated separately for firm-years with fiscal years ending in the same calendar year. The coefficients are the means of those annual coefficients and the t-statistics are derived from the time-series distributions of those coefficients.

TABLE 5

Relation between Firm Size (Market Value of Equity [*MV*]) and Conditional Conservatism (124,562 Firm-Years, 1963–2006)

Panel A: Regressions of Price-Deflated Current Earnings on Abnormal Returns

Lagged *MV* Quintile		α_0	α_1	β_0	β_1	Sample Size	Adj. R^2
1 (Lowest)	coefficient	0.076	0.002	0.029	0.238	24,896	15.98%
	t-statistic	8.13***	0.48	5.09***	14.80***		
2	coefficient	0.081	0.001	0.019	0.194	24,919	16.78%
	t-statistic	10.41***	0.33	2.57***	14.16***		
3	coefficient	0.083	0.007	0.013	0.178	24,923	15.74%
	t-statistic	11.33***	3.17***	3.01***	15.94***		
4	coefficient	0.082	0.006	0.012	0.137	24,918	13.05%
	t-statistic	14.02***	3.12***	1.63	11.33***		
5 (Highest)	coefficient	0.081	0.002	0.005	0.104	24,906	9.47%
	t-statistic	15.26***	1.25	0.75	8.97***		
Combined sample	coefficient	0.081	0.007	0.019	0.185	124,562	14.76%
	t-statistic	12.06***	3.86***	3.20***	15.33***		

Panel B: Regressions of Price-Deflated Lagged Earnings on Abnormal Returns

Lagged *MV* Quintile		α_0	α_1	β_0	β_1	Sample Size	Adj. R^2
1 (Lowest)	coefficient	0.033	0.004	−0.033	0.110	24,896	1.58%
	t-statistic	3.61***	0.88	−5.94***	8.81***		
2	coefficient	0.059	−0.001	−0.029	0.099	24,919	2.82%
	t-statistic	7.54***	−0.23	−5.70***	9.96***		
3	coefficient	0.068	0.005	−0.021	0.092	24,923	3.23%
	t-statistic	9.82***	1.97**	−5.58***	10.72***		
4	coefficient	0.076	0.001	−0.019	0.080	24,918	4.05%
	t-statistic	13.78***	0.35	−3.30***	8.93***		
5 (Highest)	coefficient	0.075	0.002	−0.015	0.069	24,906	3.97%
	t-statistic	15.00***	1.33	−2.64***	8.32***		
Combined sample	coefficient	0.066	0.002	−0.035	0.116	124,562	3.09%
	t-statistic	10.12***	0.76	−8.22***	12.66***		

*, **, *** Statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, based on two-tailed tests.
This table provides results of annual regressions of two earnings variables (E) on abnormal returns (AR_{it}) estimated separately for lagged size (MV) quintile portfolios: $E = a_0 + a_1 D_{it} + \beta_0 AR_{it} + \beta_1 AR_{it} * D_{it} + \varepsilon_{it}$. MV equals the market value of equity. The MV quintile portfolios are formed at the beginning of each year.
The variables are derived from the following items for firm i in year t: X_{it} is earnings per share before extraordinary items; P_{it} is price per share at the fiscal year-end; R_{it} is the return from the beginning of the fourth month of the current fiscal year to the end of the third month of the next fiscal year; AR_{it} equals R_{it} minus R_{mt}, where R_{mt} is the return for the CRSP equally weighted market index over the 12-month period corresponding to R_{it}; D_{it} equals 1 when the return measure is < 0, and 0 otherwise, representing bad, and good news, respectively. In Panel A (B), the dependent variable is X_{it}/P_{it-1} (X_{it-1}/P_{it-1}), or earnings in t (t−1) deflated by lagged price. Additional details of all variables are provided in Appendix A.
The annual regressions are estimated separately for firm-years with fiscal years ending in the same calendar year. The coefficients are the means of those annual coefficients and the t-statistics are derived from the time-series distributions of those coefficients.

interactions for lagged earnings are smaller than those for current earnings, they remain statistically significant.

VII. DISCUSSION AND CONCLUSIONS

This study probes the reliability of the differential timeliness (DT) estimates of conditional conservatism proposed by Basu (1997), by replacing current earnings with lagged earnings. Because lagged earnings are reported before current news is revealed, lagged earnings cannot reflect current news, nor can lagged earnings reflect current good and bad news in a differential way. We find, however, that lagged earnings are associated with DT measures that resemble those associated with current earnings, which suggests that the DT measure from the current earnings specification is substantially biased and unreliable. Additional investigation reveals that this substantial bias can be attributed to two empirical regularities that are related to scale but are unrelated to conditional conservatism. First, scale is negatively related to return variances (return variance effect). Second, scale is negatively related to the probability of reporting a loss as well as the magnitude of the deflated loss (loss effect).

We renew the urging of Dietrich et al. (2007) and Givoly et al. (2007) that researchers avoid use of the DT measure. In particular, it is not reasonable to assume that the different sources of bias highlighted by those studies are relatively constant in cross-sectional or time-series analysis. Both loss and return variance effects vary cross-sectionally and over time, and the patterns of spurious results observed for lagged earnings resemble substantially the patterns of cross-sectional and time-series variation documented for the DT measure.

Our study illustrates the potential for biases when samples contain observations drawn from different populations associated with different underlying relations among the variables of interest. While the results are unbiased, in the sense that they reflect a weighted average of those different underlying relations, when the different sets of observations are randomly distributed, unexpected patterns can arise if the different sets of observations cluster separately. In our setting, the unexpected patterns are caused by low- (high-) price firms with lower (higher) average price-deflated earnings, the dependent variable, being more concentrated at higher (lower) absolute magnitudes of positive and negative abnormal returns, the independent variable. Similar unexpected patterns can arise in other relationships. For example, the results in Durtschi and Easton (2009) can be characterized as explaining how combining distributions of price-deflated earnings that are different for firms of different size creates unintended discontinuities around zero.

One way to identify whether such unintended biases might creep into the analysis is to replicate the methodology for samples or variables that should not be associated with the hypothesized effects. To be sure, such replications are costly, and there is no limit to the number of samples and variables that could be considered. But some effort to replicate analyses for "dummy" samples/variables seems appropriate, especially if such replications are low cost.

To focus this study on coefficient estimate biases from the Basu (1997) regression, we have elected to ignore important issues regarding the implementation of conditional conservatism (e.g., Givoly et al. 2007). For example, we do not consider expectations or the earnings level that would be reported if no news is observed. Some part of those earnings would reflect delayed recognition of good and bad news observed in prior periods, but the remainder would be a function of each firm's assets and liabilities and the level of unconditional conservatism followed by the firm.[15] Similarly,

[15] As argued in Basu (1997), ignoring the former component should not affect estimates of β_1, as it is unrelated to current news, and the latter component should be captured *on average* by the good news intercept (α_0). But a reasonable argument could be made under certain assumptions to consider expectations of "no news" earnings that are firm-year specific.

we do not consider issues relating to how accountants measure news, given that those accounting procedures should, in principle, apply to private firms for which returns are not observed. If returns proxy for news observed by accountants, then should the "no news" benchmark be zero returns (implied when good/bad news partitions are based on positive/negative returns), or should some "normal" return be expected?[16] These and other issues have been discussed extensively in prior research.[17] Our results could be influenced by refinements proposed elsewhere.

REFERENCES

Ball, R., S. P. Kothari, and V. A. Nikolaev. 2010. *Econometrics of the Basu Asymmetric Timeliness Coefficient and Accounting Conservatism*. Working paper, University of Chicago.

Ball, R., S. P. Kothari, and A. Robin. 2000. The effect of international institutional factors on properties of accounting earnings. *Journal of Accounting and Economics* 29 (1): 1–52.

Ball, R., and L. Shivakumar. 2006. The role of accruals in asymmetrically timely gain and loss recognition. *Journal of Accounting Research* 44 (2): 207–242.

Basu, S. 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *Journal of Finance* 32 (3): 663–682.

Basu, S. 1995. *Conservatism and the Asymmetric Timeliness of Earnings*. Ph.D. thesis, University of Rochester.

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

Basu, S. 2001. Discussion of" On the asymmetric recognition of good and bad news in France, Germany, and the United Kingdom. *Journal of Business Finance and Accounting* 28 (9-10): 1333–1349.

Basu, S., L. Hwang, and C. Jan. 2001. *Differences in Conservatism between Big Eight and Non-Big Eight Auditors*. Working paper, Temple University.

Basu, S., L. Hwang, and C. Jan. 2002. *Auditor Conservatism and Quarterly Earnings*. Working paper, Temple University.

Beaver, W. H., W. R. Landsman, and E. L. Owens. 2008. *Asymmetry in Earnings Timeliness and Persistence: A Simultaneous Equations Approach*. Working paper, Stanford University.

Beaver, W. H., and S. G. Ryan. 2000. Biases and lags in book value and their effects on the ability of the book-to-market ratio to predict book return on equity. *Journal of Accounting Research* 38 (1): 127–148.

Beaver, W. H., and S. G. Ryan. 2009. *Risky Debt, Mixed Attribute Accounting, and the Identification of Conditional Conservatism*. Working paper, New York University.

Callen, J. L., and D. Segal. 2008. *An Analytical and Empirical Measure of the Degree of Conditional Conservatism*. Working paper, University of Toronto.

Choi, W., J. Gramlich, and J. Thomas. 2003. Earnings management under the AMT? The case against. *Contemporary Accounting Research* 18 (4): 571–613.

Dietrich, D., K. Muller, and E. Riedl. 2007. Asymmetric timeliness tests of accounting conservatism. *Review of Accounting Studies* 12 (1): 95–124.

[16] Should news be measured, for example, by the deviation of observed returns from expected returns based on specific risk factors? Basu (1995) considers returns adjusted for market model estimates of firm-specific betas, and Beaver et al. (2008) offer a more comprehensive set of adjustments.

[17] For example, Shroff et al. (2007) identify good/bad news from extreme positive/negative short-horizon returns, Also, Basu (1997) considers both returns accumulated over the fiscal year versus the 12 months between annual earnings announcements, with the choice between the two windows being determined by assumptions about how news is released and reflected in share prices. Ball and Shivakumar (2006) use accruals as the dependent variable (see also Table 2 in Basu 1997), Givoly et al. (2007) disaggregate long-horizon good and bad news into individual economic shocks, and Srivastava and Tse (2007) use changes in cash flows as the dependent variable. Finally, Callen and Segal (2008) model conditional conservatism within a return decomposition framework and derive a nonlinear relation between earnings shocks and return shocks.

Durtschi, C., and P. Easton. 2005. Earnings management? The shapes of the frequency distributions of earnings metrics are not evidence *ipso facto*. *Journal of Accounting Research* 43 (4): 557–592.
Durtschi, C., and P. Easton. 2009. Earnings management? Erroneous inferences based on earnings frequency distributions. *Journal of Accounting Research* 47 (5): 1249–1281.
Easton, P., V. Nikolaev, and L. van Lent. 2009. *Price-Convexity, Debt-Related Agency Costs, and Timely Loss Recognition*. Working paper, University of Notre Dame.
Giner, B., and W. P. Rees. 2001. On the asymmetric recognition of good and bad news in France, Germany, and the United Kingdom. *Journal of Business Finance and Accounting* 28 (9-10): 1285–1331.
Givoly, D., and C. Hayn. 2000. The changing time-series properties of earnings, cash flows, and accruals: Has financial reporting become more conservative? *Journal of Accounting and Economics* 29 (3): 287–320.
Givoly, D., C. Hayn, and A. Natarajan. 2007. Measuring reporting conservatism. *The Accounting Review* 82 (1): 65–106.
Holthausen, R., and R. Watts. 2001. The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics* 31 (1-3): 3–75.
Khan, M., and R. Watts. 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics* 48 (2-3): 132–150.
Klein, A., and C. A. Marquardt. 2006. Fundamentals of accounting losses. *The Accounting Review* 81 (1): 179–206.
Lobo, G. J., K. Parthasarathy, and S. Sivaramakrishnan. 2008. *Growth, Managerial Reporting Behavior, and Accounting Conservatism*. Working paper, University of Houston.
Pae, J., D. Thornton, and M. Welker. 2005. The link between accounting conservatism and the price-to-book ratio. *Contemporary Accounting Research* 22 (3): 693–717.
Roychowdhury, S., and R. Watts. 2007. Asymmetric timeliness of earnings, book-to-market and conservatism in financial reporting. *Journal of Accounting and Economics* 44 (1-2): 2–31.
Ryan, S. G., and P. Zarowin. 2003. Why has the contemporaneous linear returns-earnings relation declined? *The Accounting Review* 78 (2): 523–553.
Shivakumar, K., and G. Waymire. 2003. Enforceable accounting rules and income measurement by early 20th century railroads. *Journal of Accounting Research* 41 (2): 397–432.
Shroff, P., R. Venkataraman, and S. Zhang. 2007. *The Conservatism Principle and the Asymmetric Timeliness of Earnings: An Event-Based Approach*. Working paper, University of Minnesota.
Srivastava, A., and S. Y. Tse. 2007. *What Drives Changes in Accounting Conservation? The Effects of Accelerated Loss Recognition versus Delayed Gain Recognition*. Working paper, Texas A&M University.
White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48 (4): 817–838.

APPENDIX A

Variable Definitions and Data Sources

Variable		Description	Source
X_{it}	=	earnings per share before extraordinary items for firm i in year t;	Compustat data item 58
P_{it}	=	price per share for firm i in year t;	Compustat data item 199
LD_{it}	=	loss indicator variable equals 1 when $X_{it} < 0$, and 0 otherwise;	
$SIGN_{it}$	=	earnings sign indicator variable equals -1 when $X_{it} < 0$, and $+1$ otherwise;	
mean X_t/P_{t-1}	=	cross-sectional mean of X_{it}/P_{it-1} in year t;	

(continued on next page)

APPENDIX A (continued)

Variable		Description	Source
R_{it}	=	compounded stock return for firm i in year t, measured over the period from the beginning of the fourth month of year t to the end of the third month of year $t+1$;	CRSP monthly return file (msf), variable name RET
R_{mt}	=	compounded market return over the same period as R_{it}. The market index used is the CRSP equal-weighted index (includes distributions);	CRSP monthly index file (msi), variable name EWRETD
AR_{it}	=	R_{it} minus the corresponding R_{mt};	
D_{it}	=	bad news indicator variable equals 1 when $AR_{it} < 0$, and 0 otherwise, representing bad and good news, respectively. In Table 2, Panel B, AR_{it} is replaced by R_{it};	
MV_{it}	=	market value of equity for firm i in year t, which is the product of price per share and number of shares outstanding at year-end;	Product of Compustat data items 199 and 25
B/M_{it}	=	ratio of book value of equity to market value of equity for firm i in year t; and	Ratio of Compustat data item 60 to MV_{it}
TA_{it}	=	book value of total assets per share.	Ratio of Compustat data item 6 to Compustat data item 25