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Lagged Earnings Asymmetry in a Firm-Year Measure of Accounting Conservatism

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ABSTRACT: Khan and Watts (2009) develop a firm-year measure of conditional conservatism, labeled *C_Score,* that builds on the Basu (1997) asymmetric timeliness (AT) measure. However, recent research documents an asymmetric relation between lagged earnings and current returns, indicative of bias in the Basu measure. We demonstrate that this lagged earnings asymmetry (LEA) taints *C_Score* by mimicking (i.e., overstating) *C_Score*'s relation to nearly all of the firm characteristics used by Khan and Watts (2009) as validation tests. Thus, LEA represents an alternative interpretation for hypotheses tests involving *C_Score* as a measure of conditional conservatism. We examine two very distinct explanations for LEA identified in prior research and demonstrate that controlling for both is necessary and sufficient to yield a modified *C_Score* measure that is uncorrelated with LEA. We conclude that while LEA identifies a threat to the usefulness of *C_Score* as a firm-year measure of conservatism, the underlying causes of LEA can be adequately addressed.

JEL Classifications: M41; M44; G34; G38; K22; D82.

Data Availability: Data are available from public sources identified in the text.

Keywords: conditional conservatism; firm-year measure; lagged earnings asymmetry; bias.

INTRODUCTION

Khan and Watts (2009; hereafter, KW) introduce a popular firm-year measure of conditional conservatism, labeled *C_Score,* that builds upon the pooled asymmetric timeliness (AT) model developed in Basu (1997). Recently, Patatoukas and Thomas (2011, 2016; hereafter, PT 2011 and PT 2016, respectively) and Ball, Kothari, and Nikolaev (2013; hereafter, BKN) identify an asymmetric relation between *lagged* earnings and current returns and conclude that this lagged earnings asymmetry (LEA) is a symptom of significant bias in Basu's (1997) AT measure of conservatism. In fact, PT (2011) conclude that researchers should avoid using or relying on inferences based on the Basu (1997) AT estimates of conditional conservatism. In light of this research, we first assess whether LEA represents a similar threat to the construct validity of *C_Score*. We then explore whether the distinct causes of LEA suggested by PT (2011) and BKN relate to LEA in *C_Score*.[1] Finally, we investigate whether addressing these underlying factors yields a version of *C_Score* that avoids any LEA-related bias.[2]

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[1] In their analysis of the Basu (1997) AT model, PT (2011) suggest but tabulate no evidence that *C_Score* is affected by LEA.
[2] We acknowledge that LEA-related bias is but one threat to AT measures of conservatism. However, the recent interest generated by BKN and PT (2011) suggests that further examination of this empirical regularity is warranted.

Evaluating bias in *C_Score* is important given the numerous studies that incorporate *C_Score* either as the principal measure of conservatism (e.g., Beatty and Liao 2011; Tan 2013; García Lara, García Osma, and Penalva 2016) or as a test of robustness of results relative to another measure of conservatism, such as the Basu (1997) AT measure (e.g., Ettredge, Huang, and Zhang 2012; Ahmed and Duellman 2013).[3] However, if LEA taints *C_Score* in a manner similar to the Basu measure, then it represents an alternative explanation for results of hypothesis tests based on *C_Score,* including tests used by KW to validate *C_Score*. Thus, LEA could signal structural problems that potentially negate the advantages of *C_Score* and render it invalid as a firm-year measure of conditional conservatism.[4]

Ex ante, there is no clear theoretical basis for predicting how LEA might impact the estimation of *C_Score*. *C_Score* itself is a firm-specific extension of the pooled Basu (1997) AT measure, so it is plausible that LEA demonstrated by PT (2011) and BKN in the Basu model simply extends to *C_Score*. However, unique to the estimation of *C_Score* is the inclusion of three firm characteristics—size, the market-to-book ratio, and financial leverage—both as main effects and good and bad news interactions. While the main effects (i.e., direct effects of firm size, market-to-book, leverage, and several interactions) could essentially "control" for the causes of LEA and attenuate any bias induced by it, the interactions of these same firm characteristics with bad news flow directly into the *C_Score* measure. If these interaction terms effectively proxy for the drivers of LEA, then any bias induced by LEA will be reflected in *C_Score*.

After confirming that our model estimation procedures replicate those in KW, we assess whether *C_Score* reflects LEA by comparing the original parameter estimates with those estimated with lagged earnings as the dependent variable. For the lagged earnings model, the coefficient on bad news returns is positive and approximately 70 percent of the corresponding coefficient for the current earnings model, consistent with evidence in PT (2011) and BKN regarding the Basu (1997) AT metric. However, unique to *C_Score,* the coefficients on the interactions of bad news returns with size, market-to-book equity, and leverage for the lagged earnings model are also consistent in sign and approximately half of the corresponding coefficients for the current earnings model. Thus, the cross-sectional and time-series variation in the causes of LEA are embedded in *C_Score* via these interaction terms.

Given this evidence, we develop a firm-year measure of LEA, labeled *C_ScoreLE,* which captures nonlinearity in the relation between *lagged* earnings and positive and negative returns.[5] We document that a wide range of firm characteristics proposed by KW to be related to conservatism (e.g., return on assets, investment cycle, the probability of informed trading, or "PIN") and used by KW to validate *C_Score* exhibit very similar associations with *C_ScoreLE*. In fact, with the exception of the market-to-book ratio and bid-ask spreads, we fail to reject the null that coefficients relating each firm characteristic to *C_ScoreLE* and *C_Score* are equal. We conclude that LEA in *C_Score* represents a structural problem with *C_Score* that confounds any interpretation of empirical results relying on *C_Score* as a measure of conditional conservatism.

We next evaluate potential contributors to LEA in *C_Score*. Explanations for LEA in the pooled Basu (1997) model proposed by PT (2011) and BKN represent natural starting points. PT (2011) propose that LEA could be driven by lower-priced firms that experience both a higher frequency of losses and greater return variance. In contrast, BKN propose that LEA arises from a failure to control for expected components of earnings and returns, with lagged earnings proxying for expected current earnings. After estimating several versions of *C_Score* that control for varying combinations of expectations in earnings and returns, as well as return volatility (to account for PT's (2011) scale-driven variance effect), and assessing their relations with *C_ScoreLE,* we conclude that each explanation for LEA has incremental descriptive validity. Controlling for either alternative alone fails to purge LEA from *C_Score*. However, controlling for both scale (return volatility) and expectations effects yields a modified *C_Score* estimate that is statistically unrelated to LEA. Importantly, our results indicate that the underlying causes of bias evidenced by LEA in *C_Score* can be attenuated.[6]

Focusing on the two modified measures of *C_Score* that best control for LEA, we assess their construct validity as measures of conditional conservatism by relating each to the firm characteristics originally used by KW to validate *C_Score*. Regression coefficients are of the expected sign and significant, confirming that our modified *C_Score* measures continue to represent conditional conservatism.

[3] As of May 2018, Google Scholar identifies 954 citations of KW. Alternatively, Google Scholar suggests 155 and 149 citations of BKN and PT (2011), respectively. Thus, researchers appear to be frequently relying on KW's measure of conservatism without considering the implications of LEA.

[4] Observing that LEA taints *C_Score* is necessary but not sufficient evidence to invalidate *C_Score*. Rather, demonstrating that LEA represents a component of *C_Score* unrelated to conditional conservatism that contributes to rejecting the null (i.e., Type I errors) or failing to reject the null (i.e., Type II errors) in testing relations between *C_Score* and measures hypothesized to be related to conditional conservatism is also essential. We conduct these tests.

[5] PT (2011) and BKN conclude that nonlinearity in the relation between lagged earnings and current returns is indicative of bias. PT (2016) criticize BKN for failing to incorporate this nonlinearity in their solution for the bias. Our estimation of *C_ScoreLE* incorporates the nonlinearity.

[6] As described later, we also evaluate several alternative approaches for purging LEA from *C_Score,* which are agnostic to the underlying cause, including differencing *C_Score* and *C_ScoreLE,* using firm fixed effects (Ball et al. 2013), and estimating *C_Score* using current accruals rather than current earnings (Collins, Hribar, and Tian 2014). Our evidence suggests that these fail to adequately address LEA in *C_Score*.

Our primary results show that LEA can inflate the significance of *C_Score*'s predicted relations with a wide range of firm characteristics (i.e., Type I error). Finally, we develop a hypothesis test to demonstrate that the underlying causes of LEA could also work against observing a predicted relation (i.e., Type II error). We argue that greater conditional conservatism is associated with a higher likelihood of reporting a goodwill impairment. In brief, conditional conservatism identifies firms with more timely recognition of losses. However, smaller firms are less likely to report an impairment (Francis, Hanna, and Vincent 1996; Beatty and Weber 2006). Since PT (2011) argue, and our evidence suggests, that LEA is more pronounced for smaller firms with lower share prices, any scale-related bias in *C_Score* could work against finding the predicted positive relation between *C_Score* and the probability of reporting a goodwill impairment. Consistent with this conjecture, our results demonstrate that LEA in *C_Score* significantly reduces the likelihood of finding a positive relation between conditional conservatism and reporting a goodwill impairment.

Our study makes several important contributions to the conservatism literature. While prior research identifies bias in the pooled AT measures of conservatism based on the Basu (1997) model, we document bias in the popular firm-year measure of conservatism developed by Khan and Watts (2009). Our evidence also indicates that LEA inflates the magnitude of *C_Score* as a measure of conservatism and overstates its relation with a wide range of firm characteristics associated with conservatism. However, we also demonstrate that, in some circumstances, LEA works against finding a relation with a suspected conservatism outcome (i.e., goodwill impairment). Thus, our study serves to caution researchers about the potential for either Type I or Type II errors in hypothesis tests using *C_Score,* both of which could lead to invalid conclusions.

In contrast to PT (2011) and BKN, who propose distinct (and exclusive) explanations for LEA in the pooled Basu (1997) model, our study demonstrates that BKN's expectations effect and PT's (2011) variance effect incrementally contribute to the LEA regularity in *C_Score*. As a result, addressing only one of those explanations (i.e., expectations effect or variance effect alone), as in Kravet (2014), Ramalingegowda and Yu (2012), and Erkens, Subramanyam, and Zhang (2014), is likely inadequate. In contrast to conclusions in BKN about LEA in the Basu (1997) AT measure, we find that controlling for both explanations is necessary and sufficient to yield a firm-year AT measure that does not exhibit LEA yet retains the ability to represent conditional conservatism in its predicted relations with various attributes of conservatism. The modified *C_Score* measure we propose is more effective than other less-targeted estimation approaches (e.g., firm fixed effects) and should be of interest to future researchers.

In the next section, we briefly discuss recent studies that infer bias in the Basu (1997) AT measure and how those concerns might extend to KW's firm-year conservatism measure. We discuss our research design and results in the third section, followed by our conclusion in the fourth section.

BACKGROUND LITERATURE AND EXPECTATIONS

Prior Literature

In the commonly used Basu (1997) model of conservatism, current earnings are regressed on contemporaneous stock returns, and the coefficient is allowed to vary with the sign of the returns as follows:

$$Earn_{it} = \alpha_0 + \alpha_1 D_{it} + \beta_0 Ret_{it} + \beta_1 D_{it} Ret_{it} + e_{it} \tag{1}$$

The dependent variable in this model ($Earn_{it}$) is a firm's current earnings per share deflated by beginning of period price per share. Ret_{it} is the firm's contemporaneous annual stock return, a proxy for the economic news in year *t*. D_{it} is an indicator variable that equals 1 if Ret_{it} is negative, and 0 otherwise. A positive β_1 coefficient captures the differential timeliness of earnings to bad news relative to good news and is commonly used as a measure of conditional conservatism.[7]

Khan and Watts (2009) point out that Equation (1) can be estimated (1) across firms and time in a pooled model, (2) for a given period *t* using a cross section of firms, or (3) for a given firm *i* using a time series of data. Each involves substantial tradeoffs in terms of flexibility and data availability. In particular, Equation (1) does not readily allow for a firm-year measure of conservatism (i.e., β_{1it}). This limits research directed at studying how period-specific events lead to firm-specific changes in conservatism.[8] Accordingly, KW modify Equation (1) by allowing the coefficients to vary with firm-year characteristics that they expect to be associated with conservatism. They argue that firm size, market-to-book equity, and leverage are related to the four factors that Watts (2003a) claims drive the demand for conservatism: contracts, litigation, taxation, and regulation. They propose and estimate the following annual cross-sectional model (*t* subscripts on the coefficients are suppressed):

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[7] Some studies have used the ratio of bad news to good news timeliness, $(\beta_0 + \beta_1)/abs(\beta_0)$, or the relative explanatory power of the model (R^2) when returns are negative as compared to periods when returns are positive as measures of conditional conservatism (Givoly and Hayn 2000; Givoly, Hayn, and Natarajan 2007).

[8] Khan and Watts (2009) cite LaFond and Watts (2008) as a study that is hampered by the lack of a firm-year measure of differential timeliness. In that study, the authors are interested in testing whether conservatism leads to information asymmetry, or whether it is a rational response to reduce the agency costs of information asymmetry.

American Accounting Association

$$Earn_{it} = \alpha_0 + \alpha_1 D_{it} + Ret_{it}(\mu_1 + \mu_2 Size_{it} + \mu_3 MB_{it} + \mu_4 Lev_{it}) + D_{it}Ret_{it}(\lambda_1 + \lambda_2 Size_{it} + \lambda_3 MB_{it} + \lambda_4 Lev_{it}) + \delta_1 Size_{it} + \delta_2 MB_{it} + \delta_3 Lev_{it} + D_{it}(\delta_4 Size_{it} + \delta_5 MB_{it} + \delta_6 Lev_{it}) + e_{it} \quad (2)$$

where $Size_{it}$ is the natural log of market value of equity, MB_{it} is the market-to-book ratio, and Lev_{it} is long-term debt plus short-term debt divided by market value of equity. All other variables are as previously defined. Combining the cross-sectional coefficients from Equation (2) and the values of the respective firm-year variables, KW obtain the following measure of conservatism:

$$C\_Score_{it} = \lambda_{1t} + \lambda_{2t} Size_{it} + \lambda_{3t} MB_{it} + \lambda_{4t} Lev_{it} \quad (3)$$

Thus, the firm-year measure of conservatism (C_Score_{it}) derives from the three firm-year characteristics weighted by the annual cross-sectional λ coefficients.

KW provide supporting evidence for this approach by showing a positive relation between *C_Score* and the contemporaneous cross-sectional Basu (1997) model. KW also show that *C_Score* predicts Basu's (1997) differential timeliness up to three years into the future. As further validation, KW link *C_Score* to several manifestations of conservatism, such as return on assets (*ROA*) and non-operating accruals (Basu 1997; Givoly and Hayn 2000; Watts 2003b). Generally speaking, conservatism should be associated with less profitable earnings, which would be most evident in non-operating accruals. KW report that *C_Score* is inversely related to ROA and directly related to the standard deviation of non-operating accruals, as predicted.

KW also examine *C_Score* correlations with factors that likely impact the demand for conservatism, including the probability of litigation, information asymmetry, firm age, and firm-specific uncertainty. They expect that firms facing a greater likelihood of litigation will respond with greater conservatism (Basu 1997; Watts 2003a). In addition, greater information asymmetry between managers and outside investors could prompt greater levels of conservatism as a corporate governance mechanism (LaFond and Watts 2008; Louis, Sun, and Urcan 2012). Finally, KW test whether the greater uncertainty associated with younger firms and longer investment cycles could be mitigated by increased conservatism. In general, KW report significant relations between *C_Score* and several proxies for information asymmetry and uncertainty, consistent with their hypotheses. Based on this supporting analysis, numerous empirical studies have subsequently employed *C_Score* as a firm-specific measure of conditional conservatism (see, for example, Francis and Martin 2010; Nikolaev 2010; Beatty and Liao 2011; Ettredge et al. 2012; Jayaraman 2012; Tan 2013; García Lara et al. 2016).

Despite the widespread use of the Basu and KW models, other research warns that the traditional Basu approach to measuring conservatism lacks power or has serious econometric flaws (Givoly et al. 2007; Dietrich, Muller, and Riedl 2007).[9] More recently, PT (2011, 2016) and BKN report an empirical regularity related to the levels version of Basu's (1997) model. When $Earn_{it}$ is replaced by $Earn_{it-1}$ in Equation (1), β_1 remains significantly positive indicating lagged earnings asymmetry, or LEA. These studies find that LEA is roughly 50–60 percent of the coefficient using current earnings.[10] Given the autocorrelation in earnings levels, the same factors that drive LEA could account for the asymmetric relation in current earnings, leading to an inflated measure of conditional conservatism. As a result, PT (2011) argue that future researchers should avoid using the AT approach altogether. PT (2016) similarly advocate "caution" when using the AT approach, encouraging researchers to use alternative approaches to measure conditional conservatism.

Although the PT (2011) and BKN studies agree that LEA affects the Basu (1997) model, they disagree on the underlying cause. PT (2011) argue that lagged earnings and current earnings are related to scale. Specifically, relatively low-priced firms exhibit larger percentage price changes for both good and bad news (a return variance effect). These same firms also typically have lower scaled earnings and a greater frequency of losses (a loss effect). PT (2011) graphically illustrate how the combination of these two scale effects contributes to an asymmetric relation between the level of earnings and returns.[11] Importantly, while they document factors that relate to the asymmetry, they do not propose these factors as remedies. Alternatively, BKN argue that lagged earnings proxy for the expected components in current earnings that are also asymmetrically related to expected returns. Specifically, a positive effect arises because expected returns and expected earnings both reflect common underlying economic factors. A second negative effect results from certain accounting rules for revenue

[9] We are unaware of any studies that investigate whether *C_Score* is affected by the specific concerns raised by Givoly et al. (2007) or Dietrich et al. (2007) about the Basu (1997) AT measure. Such an analysis is beyond the scope of our study. As a result, our study is limited to addressing only LEA in *C_Score*, and we make no claims about whether the procedures we employ have the potential to address any other specific concerns that may exist with *C_Score* as a measure of conditional conservatism.

[10] PT (2011) report β_1 equal to 0.185 (0.116) using current (lagged) earnings, while BKN report β_1 equal to 0.234 (0.135) using current (lagged) earnings. Both studies also report a substantial decrease in explanatory power (i.e., an adjusted R^2 decline of nearly 80 percent) after substituting lagged earnings for current earnings.

[11] Further empirical analysis supports the existence of these two proposed effects. PT (2016) advance this line of reasoning by linking an alternative "placebo" (the inverse of lagged price) to AT in current returns.

and expense recognition that correspond to fundamental firm characteristics that are correlated with expected returns. For example, greater investment in R&D, which investors generally view as good news, contributes to greater expected stock returns but lower earnings, thus depressing the relation between short-run expected earnings and expected returns. These two offsetting effects contribute to nonlinearity in the relation between expected earnings and expected returns. While these alternative explanations for LEA remain the subject of debate and additional research is necessary, both studies infer model misspecification (i.e., correlated omitted variables) as accounting for the confounding relation with lagged earnings.[12]

Expectations

Given evidence that the Basu (1997) AT measure is tainted by LEA, and since that model forms a fundamental building block in estimating *C_Score,* it is reasonable to expect that LEA might similarly affect *C_Score*. PT (2011) suggest this is the case (although they provide no tabulated evidence). However, features unique to the model used to estimate *C_Score* have the potential to mitigate LEA in *C_Score*. In particular size, market-to-book, and leverage are included as separate independent variables in Equation (2), conditional on the sign of the news, but their parameters (δ_1 through δ_6) are not included in *C_Score*. Thus, the estimation model directly controls for their effects on earnings. In fact, Ball et al. (2013, Equation (10)) propose controlling for *ex ante* determinants of earnings, including size, the market-to-book ratio, and leverage, in their paper and find that this approach removes much of the bias in the pooled AT measure, especially related to the variance effect identified in PT (2011).[13] Thus, the fact that KW's model includes these same determinants may mitigate LEA in *C_Score*.

On the other hand, the firm-year advantage of *C_Score* results from estimating the variation in timely bad news recognition associated with firm size, market-to-book equity, and leverage by including each as an interaction with good and bad news returns. These incremental effects (λ_2 through λ_4) flow directly into *C_Score*. While these incremental effects are expected to capture the cross-sectional and time-series variations in conditional conservatism, they may also capture the variation in LEA that remains after including all three as main effects. Supporting this conjecture, BKN observe that LEA remains in the Basu (1997) AT measure, albeit significantly attenuated, after including these variables as main effects to control for earnings expectations (as natural proxies).[14] Meanwhile, PT (2011) show that LEA in the Basu (1997) AT model is strongly correlated with *Size* and *MB*. To the extent that the remaining LEA in *C_Score* varies with these characteristics, it will be reflected in the bad news interaction terms and embedded in *C_Score*.

To summarize, research argues that LEA identifies a serious concern with respect to AT-based measures of conservatism, including *C_Score*. Whether LEA represents bias that invalidates *C_Score* as a viable measure of conditional conservatism is an empirical question that we address. In the following section, we conduct three primary analyses. First, we assess the degree to which LEA affects *C_Score*. We then evaluate whether any presence of LEA confounds the descriptive evidence used by KW to validate *C_Score* as a measure of conditional conservatism. Finally, we identify likely sources of LEA in *C_Score* and evaluate whether these underlying causes can be adequately addressed to create a modified *C_Score* that is uncorrelated with LEA but that still reflects conditional conservatism.

SAMPLE SELECTION, DESCRIPTIVE STATISTICS, AND RESULTS

Sample Selection and Descriptive Statistics

Our sample selection procedures generally merge those in KW with those in PT (2011) and BKN. We draw our data from the CRSP-Compustat merged file for the years 1963 to 2013. For each observation, we require current and lagged earnings, monthly CRSP data sufficient to compute annual returns ending three months following fiscal year-end, lagged market value of equity, and variables necessary to compute *C_Score* from KW. We also require sufficient daily returns to compute annualized return volatility over the fiscal year. We restrict our analyses to firms with stock price greater than \$1. Following PT (2011) and BKN, we compute expected returns using size and book-to-market matched portfolios. Specifically, we use the monthly 5×5 ($Size \times MB$) portfolio returns, as well as the portfolio break points available on Ken French's website.[15] Monthly returns are compounded over the 12 months beginning four months after the prior fiscal year-end.

To address outliers, we truncate observations with values in the top or bottom percentile of any variable distribution, except for variables with a large number of lower-bound values such as 0 (e.g., leverage) where we only truncate at the top 1

[12] Collins, Hribar, and Tian (2014) offer a third explanation for LEA. Specifically, they argue that LEA is due to asymmetry in the cash flow component of earnings, and estimates of asymmetric timeliness using only the accrual component eliminates LEA, but PT (2016) provide evidence challenging this result. Nonetheless, we consider whether a measure of *C_Score* derived from accruals (rather than earnings) associates with LEA in a later analysis.

[13] These parameters would presumably capture the loss effect that PT (2011) attribute to smaller firms as well.

[14] Among others, Penman (1991), Fama and French (1995), and Brown (1998) empirically link firm size and market-to-book equity to current and future earnings, while Harris and Raviv (1991) observe a relation between leverage and firm size.

[15] See, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

TABLE 1

Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Q1	Median	Q3
Earn	133,368	0.053	0.136	0.023	0.065	0.109
Ret	133,368	0.166	0.542	−0.147	0.088	0.364
Size	133,368	5.316	2.082	3.748	5.205	6.759
MB	133,368	2.189	2.310	0.974	1.543	2.545
Lev	133,368	0.712	1.157	0.067	0.309	0.854
ROA	129,829	0.027	0.089	0.008	0.037	0.070
NOAcc	63,359	−0.017	0.062	−0.034	−0.010	0.006
InvCyc	111,278	0.043	0.029	0.024	0.039	0.056
PIN	26,560	0.199	0.069	0.148	0.189	0.237
Spread	85,073	0.024	0.029	0.003	0.014	0.032
RetVol	133,368	0.462	0.247	0.284	0.402	0.575
ProbLit	85,479	0.004	0.005	0.001	0.002	0.004
Age	128,836	17.042	14.198	7.000	12.000	22.000

Table 1 shows descriptive statistics for firm-years between 1963 and 2013. The mean, standard deviation (Std. Dev.), median, and first (Q1) and third (Q3) quartiles are reported.

Variable Definitions:
Earn = net income before extraordinary items, scaled by lagged market value of equity;
Ret = annual returns;
MB = the market-to-book ratio;
Lev = leverage, defined as long-term and short-term debt deflated by market value of equity;
Size = the natural log of market value of equity;
ROA = earnings before extraordinary items, deflated by lagged assets;
NOAcc = non-operating accruals, scaled by lagged assets;
InvCyc = a decreasing measure of the length of the investment cycle;
PIN = the probability of informed trading from Easley et al. (2002);
Spread = the average daily bid-ask spread, scaled by the midpoint of the spread;
RetVol = the standard deviation of daily firm-level returns;
ProbLit = the probability of litigation from Shu (2000); and
Age = the age of the firm in year *t*.

percent. As reported in Panel A of Table 1, applying these restrictions and sample screens results in a sample size of 133,368 firm-year observations corresponding to 13,708 unique firms for the period 1964 to 2013; data from 1963 are used to obtain lagged earnings and market value of equity. Panel A reports descriptive statistics for our primary variables. The sample sizes for tests involving certain of these variables used in a later analysis are much smaller due to additional data requirements and time-period limitations. For instance, estimating *ProbLit* based on Shu's (2000) model further limits our sample size to 85,479; including *PIN* from Easley, Hvidkjaer, and O'Hara (2002) reduces our sample size to 26,560 firm-year observations. Overall, our sample statistics are similar to those in KW, PT (2011), and BKN. For example, our mean earnings and returns (0.053 and 0.166, respectively) are very similar to those reported in KW (0.054 and 0.157). Our sample firms appear to be roughly the same size and of similar age to those in KW. Overall, we are confident that we are working with comparable data.

C_Score Estimation: Does LEA Affect *C_Score*?

In Table 2, Panel A, we report coefficients from estimating the KW model used to construct *C_Score* (Equation (2)). The first column reports coefficients as reported in Khan and Watts (2009, Table 3) to facilitate comparison with our estimates. For presentation purposes, Table 2 reports estimates from a pooled model using all available observations. Columns 2 and 3 report our coefficient estimates and t-statistics with current earnings ($Earn_t$) and lagged earnings ($Earn_{t-1}$), respectively, as the dependent variable in Equation (2). Reported t-statistics are based on robust standard errors clustered at the firm and year level (Petersen 2009).[16]

[16] Estimation results in Table 2 are from a pooled model for simplicity and because reporting statistical significance using t-statistics derived from annual cross-sectional models (i.e., Fama-MacBeth) fails to correct for the serial correlation in error terms. All *C_Score* measures used in this paper are derived from first-stage annual, cross-sectional models, as in KW.

TABLE 2

***C_Score* Estimation Results and Correlations**

Panel A: Coefficients from Estimating Equation (2)

		Khan and Watts (2009, Table 3)		Dependent Variable				
				$Earn_t$		$Earn_{t-1}$		
Variable	**Pred. Sign**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Diff.**
Intercept		0.083	7.53	0.101	6.33	0.095	5.44	
D		−0.024	−3.56	−0.040	−4.25	−0.021	−3.42	***
Ret	+	0.031	1.84	0.016	0.52	−0.042	−3.26	***
Ret × *Size*	+	0.005	2.25	−0.003	−0.83	0.001	1.01	
Ret × *MB*	−	−0.006	−2.00	−0.001	−0.69	0.001	1.72	***
Ret × *Lev*	−	0.005	0.77	−0.011	−1.20	−0.008	−3.75	
D × *Ret*	+	0.237	10.78	0.248	6.26	0.172	5.66	***
D × *Ret* × *Size*	−	−0.033	−7.42	−0.013	−2.56	−0.007	−1.65	
D × *Ret* × *MB*	+	−0.007	−0.93	−0.011	−3.32	−0.005	−1.79	***
D × *Ret* × *Lev*	+	0.033	1.86	0.031	2.70	0.012	2.47	*
Size		0.005	4.83	−0.000	−0.08	0.001	0.44	
MB		−0.017	−7.93	−0.010	−7.77	−0.010	−8.12	
Lev		−0.008	−3.61	0.005	2.01	0.004	2.02	
D × *Size*		0.003	3.45	0.004	4.12	0.002	2.55	**
D × *MB*		−0.001	−0.42	−0.001	−0.52	−0.002	−1.46	
D × *Lev*		−0.002	−0.88	−0.006	−1.53	−0.001	−0.75	
Adjusted R^2		0.24[a]		0.11		0.06		

[a] Average of annual cross-sectional regressions.

Panel B: Descriptive Statistics for *C_Score* and *C_ScoreLE*

	Mean	Std. Dev.	Q1	Median	Q3
From Khan and Watts (2009, Table 4):					
	0.105	0.139	0.022	0.097	0.180
Based on Current Earnings (*C_Score*):					
	0.104	0.112	0.039	0.104	0.170
Based on Lagged Earnings (*C_ScoreLE*):					
	0.078	0.099	0.021	0.065	0.121

Panel C: Correlation Coefficients

	C_Score	*C_ScoreLE*	*Size*	*MB*	*Lev*	*RetVol*	*Earn*
C_Score		0.545	−0.409	−0.313	0.276	0.236	−0.098
C_ScoreLE	0.569		−0.137	−0.057	0.105	0.130	−0.181
Size	−0.385	−0.121		0.412	−0.101	−0.389	−0.008
MB	−0.201	0.027	0.249		−0.483	*0.003*	−0.188
Lev	0.374	0.214	−0.136	−0.245		−0.140	0.157
RetVol	0.212	0.104	−0.372	0.093	0.011		−0.350
Earn	−0.138	−0.169	0.041	−0.126	−0.028	−0.358	

***, **, * Denote two-tailed significance at the $p < 0.01$, 0.05, and 0.10 levels, respectively.

Table 2 presents results from estimating KW's *C_Score* model. Panel A shows coefficients from first-stage estimation of the KW model using either $Earn_t$ or $Earn_{t-1}$ as the dependent variable for the full sample of 133,368 firm-year observations from 1963 to 2013. *D* is a dummy variable equal to 1 if returns (*Ret*) are negative, and 0 if returns are positive. The final column of Panel A reports the significance of a test of difference between the *C_Score* estimation model using earnings and the estimation model using lagged earnings. Panel B shows descriptive statistics of *C_Score* based on annual cross-sectional regressions with current or lagged earnings as the dependent variable, as described in the text. The mean, standard deviation (Std. Dev.), median, first quartile (Q1), and third quartile (Q3) are reported. Panel C reports Pearson (Spearman) correlations in the left lower (right upper) quadrant. All correlations except those in italic are highly significant ($p < 0.01$).

(continued on next page)

TABLE 2 (continued)

Variable Definitions:
Earn = net income before extraordinary items, scaled by lagged market value of equity;
Ret = annual returns;
MB = the market-to-book ratio;
Lev = leverage, defined as long-term and short-term debt deflated by market value of equity;
Size = the natural log of market value of equity;
C _ScoreLE = our proxy for LEA in *C_Score*; and
C _ScoreLE = derived from applying the coefficient estimates from the first-stage model (Equation (2)) with lagged earnings as the dependent variable to Equation (3).

TABLE 3

Relating Firm Characteristics Associated with Conservatism to *C_Score* and *C_ScoreLE*

Dependent Variable	Pred. Sign	Coefficient *C_Score*	Coefficient *C_ScoreLE*	Test of Equality p-value	Adj. R^2	Obs.
Size	−	−10.774***	−11.011***	0.90	38.0%	133,368
		(−11.12)	(−5.70)			
MB	−	−6.287***	−2.474	0.02	10.4%	133,368
		(−5.18)	(−1.17)			
Lev	+	5.238***	5.858***	0.63	22.1%	133,368
		(6.70)	(5.44)			
ROA	−	−0.193***	−0.208***	0.63	7.9%	129,829
		(−11.76)	(−7.01)			
NOAcc	−	−0.005	−0.014*	0.26	1.4%	63,359
		(−0.77)	(−1.68)			
InvCyc	−	−0.033***	−0.032***	0.84	3.4%	111,278
		(−7.96)	(−6.10)			
PIN	+	0.255***	0.250***	0.93	14.2%	26,560
		(5.06)	(3.11)			
Spread	+	0.100***	0.062***	0.04	35.1%	85,079
		(6.40)	(3.22)			
RetVol	+	0.495***	0.480***	0.89	19.2%	133,368
		(6.25)	(4.44)			
ProbLit	+	−0.012***	−0.011***	0.89	17.2%	85,479
		(−5.61)	(−3.09)			
Age	−	−22.041***	−24.282***	0.58	3.3%	128,842
		(−6.72)	(−5.18)			

***, * Indicate two-tailed significance at the < 0.01 and < 0.10 levels, respectively. Tests of equality p-values are two-tailed. This table reports mean coefficient estimates, t-statistics (in parentheses), and tests of equality p-values from estimating the following stacked regression: $\begin{pmatrix} FC_{it} \\ FC_{it} \end{pmatrix} = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \beta_1 \end{pmatrix} \begin{pmatrix} C\_Score_{it} & 0 \\ 0 & C\_ScoreLE_{it} \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \end{pmatrix}$ where *FC* = *Size, MB, Lev, ROA, NOAcc, InvCyc, PIN, Spread, RetVol, ProbLit,* or *Age*.

Variable Definitions:
Size = the natural log of market value of equity;
MB = the market-to-book ratio;
Lev = leverage, defined as long-term and short-term debt deflated by market value of equity;
ROA = earnings before extraordinary items, deflated by lagged assets;
NOAcc = non-operating accruals, scaled by lagged assets;
InvCyc = a decreasing measure of the length of the investment cycle;
PIN = the probability of informed trading from Easley et al. (2002);
Spread = the average daily bid-ask spread, scaled by the midpoint of the spread;
RetVol = the standard deviation of daily firm-level returns;
ProbLit = the probability of litigation from Shu (2000); and
Age = the age of the firm in a given year.

With current earnings ($Earn_t$) as the dependent variable, the coefficients for bad news returns ($D \times Ret$) and the interactions of *Size, MB,* and *Lev* with bad news returns ($D \times Ret$) in Column 2 are 0.248, −0.013, −0.011, and 0.031, respectively, and are significant and similar in sign and magnitude to those reported in KW. With lagged earnings ($Earn_{t-1}$) as the dependent variable, results in Column 3 indicate a fairly similar pattern. There is a strong positive coefficient of 0.172 on the basic bad news interaction term, consistent with evidence in PT (2011) and BKN regarding the Basu (1997) model. Additionally, the bad news interactions with *Size, MB,* and *Lev* are consistent in sign and between 39 (*Lev*) and 54 (*Size*) percent of the magnitude of those in the model based on current earnings. We test whether the coefficients based on $Earn_t$ differ from those based on $Earn_{t-1}$. Focusing on the four terms used to generate *C_Score* ($D \times Ret$ and its interactions with *Size, MB,* and *Lev*), the coefficients on $D \times Ret$ and on its interaction with *MB* are each significantly smaller ($p < 0.01$) in the $Earn_{t-1}$ estimation model. However, the other two interaction terms used to estimate *C_Score* are very similar between models. The *Size* interaction with $D \times Ret$ is insignificantly different across the two sets of results, and the *Lev* interaction is only marginally different. These results confirm that LEA taints *C_Score,* and two of the inputs to *C_Score* could be driven by LEA.

Using the estimates of Equation (2), we apply Equation (3) to generate *C_Score* measures for each firm-year observation. The mean of *C_Score* reported in Panel B, based on current earnings (0.104), is very similar to the mean reported in Khan and Watts (2009, Table 4) (0.105), providing further assurance that our estimation procedures mirror those in KW. Interestingly, the sample mean for *C_Score* obtained from estimating Equation (2) with lagged earnings is 0.078. This measure is approximately 75 percent [0.078/0.104] of the contemporaneous *C_Score* measure. We label this measure, based on lagged earnings, *C_ScoreLE* and use it to represent LEA in *C_Score*.[17]

Panel C of Table 2 provides Pearson (Spearman) correlations in the left lower (right upper) quadrant between select variables to provide preliminary evidence about the extent of LEA in *C_Score*. The positive correlations between *C_Score* and *C_ScoreLE* of 0.569 (Pearson) and 0.545 (Spearman) suggest the presence of LEA in *C_Score*. We also observe significantly positive (negative) coefficients between *RetVol* (*Earn*) and both *C_Score* and *C_ScoreLE*. The correlations between *C_Score* and both *RetVol* and *Earn* are consistent with PT's (2011) scale effects (LEA is more pronounced for firms with more volatile returns and past negative earnings). Collectively, these results provide compelling evidence that LEA represents a considerable portion of the AT captured in *C_Score*.[18]

Consequences of LEA for *C_Score*

Evidence that LEA taints *C_Score* is necessary but not sufficient to implicate this regularity as a threat to *C_Score* in hypotheses tests. Sufficiency requires evidence that LEA is also correlated with the firm characteristics predicted to be related to conditional conservatism, which implies an increased risk of Type I (if correlated in the same direction) or Type II (if correlated in the opposite direction) errors. To validate *C_Score* as a measure of conservatism, KW link their firm-year measure to a number of other conservatism proxies and firm characteristics expected to be related to conservatism. KW report that *C_Score* is negatively related to firm size (*Size*), market-to-book equity (*MB*), return on assets (*ROA*), investment cycle (*InvCyc*), and firm age (*Age*) and positively related to leverage (*Lev*), the variability of non-operating accruals (*NOAcc*), information asymmetry (*PIN* and *Spread*), return volatility (*RetVol*), and the probability of litigation (*ProbLit*).[19] However, many of these conservatism proxies have been linked to other properties of earnings besides conservatism. Notably, BKN identify firm size, market-to-book equity, and leverage as natural determinants of expected earnings. Jiang, Xu, and Yao (2009) document that stock return volatility reflects information about future earnings, and Barth, Cram, and Nelson (2001) relate depreciation (i.e., the investment cycle) to future operating cash flows. PT (2011) empirically link LEA to return variance and the frequency of losses, both of which KW relate to *C_Score*. Further, Khan and Watts (2009, Table 2) report significant correlations between earnings and each firm characteristic. Thus, there is considerable prior evidence to suspect that LEA arises from a correlated omitted variable that could also influence the results of hypothesis tests involving *C_Score*.

Therefore, we next directly investigate whether the conservatism proxies that KW link to *C_Score* are in fact related to the LEA in *C_Score*. We utilize a stacked regression framework to simultaneously but independently estimate the relations

[17] The degree of LEA in *C_Score* appears to be somewhat larger than that observed in the Basu (1997) model as reported in Ball et al. (2013, Table 3), where the association between bad news returns and lagged earnings is about 58 percent [0.135/0.234] of the association between bad news returns and current earnings. This may reflect the added contribution of LEA to *C_Score* resulting from inclusion of the *Size, MB,* and *Lev* interactions with bad news returns.

[18] We also investigate whether *C_Score* is correlated with LEA in the Basu (1997) AT measure. We form 20 portfolios based on the rank of *C_Score,* and within each portfolio we estimate the Basu (1997) AT coefficient based on lagged earnings as the dependent variable. We observe a rank correlation coefficient of 0.805 (significant at < 0.001) between the portfolio rank of *C_Score* and LEA in the Basu (1997) pooled measure, consistent with considerable overlap in LEA between measures. This supports our choice to consider contributors to LEA in the Basu (1997) measure proposed in PT (2011) and BKN as potential contributors to LEA in *C_Score*.

[19] KW predict that *C_Score* will be negatively related to the level of *NOAcc,* but they do not find a significant relation.

TABLE 4

Coefficients (t-statistics) from Estimating Alternative Versions of Equation (5) That Include Controls for Lagged Earnings Asymmetry (LEA)

	Model											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
$X_t =$	*Earn*	*Earn*	*Earn*	*Earn*	*Earn*	*Earn*	*Earn*	*Earn*	*ΔEarn*	*ΔEarn*	*ΔEarn*	*ΔEarn*
$R_t =$	*Ret*	*Ret*	*Ret*	*Ret*	*ARet*	*ARet*	*ARet*	*ARet*	*Ret*	*Ret*	*ARet*	*ARet*
$Earn_{t-1}$ Included?	—	Yes	—	Yes	—	Yes	—	Yes	—	—	—	—
$RetVol_t$ Included?	—	—	Yes	Yes	—	—	Yes	Yes	—	Yes	—	Yes
D	−0.040***	−0.028***	−0.018	−0.009	−0.045**	−0.025*	−0.075***	−0.037***	−0.020***	0.005	−0.004	0.008
	(−4.25)	(−4.31)	(−1.43)	(−1.07)	(−2.30)	(−1.74)	(−3.56)	(−2.63)	(−2.91)	(0.68)	(−0.39)	(0.50)
R	0.016	0.037*	0.133***	0.118***	0.023	0.052***	0.125***	0.128***	0.057***	0.113***	0.083***	0.134***
	(0.52)	(1.72)	(4.35)	(4.84)	(1.38)	(3.48)	(6.97)	(7.26)	(2.89)	(5.82)	(4.76)	(8.35)
R × *Size*	−0.003	−0.004	−0.008**	−0.007**	−0.003	−0.006***	−0.007***	−0.009***	−0.004	−0.007***	−0.008***	−0.011***
	(−0.83)	(−1.42)	(−2.21)	(−2.42)	(−1.45)	(−2.99)	(−4.86)	(−5.44)	(−1.61)	(−2.81)	(−3.75)	(−6.38)
R × *MB*	−0.001	−0.001	0.000	−0.000	−0.001	−0.001	0.000	−0.000	−0.002***	−0.001	−0.002***	−0.001
	(−0.69)	(−1.34)	(0.35)	(−0.17)	(−0.76)	(−1.56)	(0.37)	(−0.35)	(−3.47)	(−1.16)	(−3.90)	(−1.43)
R × *Lev*	−0.011	−0.006	−0.005	−0.003	−0.004	0.000	−0.002	0.001	−0.002	−0.001	0.004	0.005
	(−1.20)	(−0.77)	(−1.03)	(−0.64)	(−0.67)	(0.05)	(−0.54)	(0.19)	(−0.30)	(−0.19)	(0.50)	(0.94)
R × $Earn_{t-1}$		0.088***		0.033**		0.057***		0.003				
		(6.76)		(2.07)		(3.37)		(0.20)				
R × *RetVol*			−0.091***	−0.073***			−0.077***	−0.070***		−0.065***		−0.062***
			(−5.16)	(−5.08)			(−4.71)	(−5.04)		(−5.09)		(−4.82)
D × *R*	0.248***	0.168***	0.145***	0.096**	0.172***	0.137***	0.010	0.024	0.076***	0.011	0.102***	0.046*
	(6.26)	(5.69)	(2.79)	(2.38)	(6.44)	(6.44)	(0.30)	(0.96)	(2.75)	(0.28)	(5.34)	(1.89)
D × *R* × *Size*	−0.013**	−0.010**	−0.016***	−0.011**	−0.014***	−0.014***	−0.004	−0.007**	−0.006	−0.002	−0.015***	−0.012***
	(−2.56)	(−2.40)	(−2.80)	(−2.39)	(−3.83)	(−4.68)	(−1.07)	(−2.29)	(−1.43)	(−0.43)	(−4.69)	(−4.12)
D × *R* × *MB*	−0.011***	−0.008***	−0.009***	−0.008***	−0.006**	−0.005***	−0.005**	−0.005***	−0.006***	−0.008***	−0.004**	−0.005***
	(−3.32)	(−3.28)	(−3.38)	(−3.33)	(−2.23)	(−2.63)	(−2.13)	(−2.61)	(−2.67)	(−3.01)	(−2.31)	(−2.74)
D × *R* × *Lev*	0.031***	0.024**	0.024**	0.021**	0.032***	0.026**	0.033***	0.027***	0.018*	0.017**	0.021**	0.020**
	(2.70)	(2.48)	(2.45)	(2.39)	(2.67)	(2.47)	(3.73)	(3.27)	(1.91)	(2.11)	(1.97)	(2.35)
D × *R* × $Earn_{t-1}$		−0.032		−0.013		−0.033		0.003				
		(−0.33)		(−0.14)		(−0.46)		(0.05)				
D × *R* × *RetVol*			−0.008	0.023			0.071**	0.070***		0.083*		0.069**
			(−0.21)	(0.69)			(2.14)	(2.69)		(1.83)		(2.09)
Size	−0.000	−0.000	−0.007***	−0.004***	−0.000	−0.001	−0.010***	−0.006***	−0.001	0.001	−0.001	−0.000
	(−0.08)	(−0.24)	(−3.55)	(−2.60)	(−0.25)	(−0.77)	(−4.66)	(−4.37)	(−0.98)	(1.03)	(−1.58)	(−0.35)
MB	−0.010***	−0.006***	−0.007***	−0.005***	−0.010***	−0.006***	−0.007***	−0.005***	−0.000	−0.001**	−0.001**	−0.002***
	(−7.77)	(−7.11)	(−6.51)	(−5.61)	(−8.24)	(−7.86)	(−6.88)	(−6.45)	(−0.10)	(−2.18)	(−2.23)	(−3.84)
Lev	0.005**	0.003	0.002	0.001	0.001	0.000	0.000	0.000	0.001	0.001	−0.000	0.000
	(2.01)	(1.37)	(1.02)	(0.84)	(0.32)	(0.28)	(0.07)	(0.09)	(0.31)	(0.33)	(−0.07)	(0.09)

(continued on next page)

TABLE 4 (continued)

	Model											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
$Earn_{t-1}$		0.434***		0.399***		0.474***		0.424***				
		(9.71)		(9.75)		(9.88)		(9.66)				
RetVol			−0.169***	−0.084***			−0.200***	−0.106***		0.046**		0.023
			(−9.32)	(−5.50)			(−9.93)	(−6.27)		(2.37)		(1.21)
$D \times Size$	0.004***	0.003***	0.003**	0.002*	0.003	0.001	0.007***	0.003	0.002**	0.001	−0.002	−0.003*
	(4.12)	(3.51)	(2.32)	(1.87)	(1.37)	(0.41)	(2.97)	(1.62)	(2.44)	(0.52)	(−1.41)	(−1.81)
$D \times MB$	−0.001	0.000	0.000	0.001	0.000	0.001	0.001	0.002*	0.001	0.002***	0.002***	0.003***
	(−0.52)	(0.56)	(0.44)	(1.51)	(0.26)	(1.02)	(0.88)	(1.67)	(1.57)	(2.71)	(2.90)	(2.71)
$D \times Lev$	−0.006	−0.005	−0.004	−0.004	−0.000	−0.000	0.002	0.001	−0.004	−0.004	−0.000	−0.001
	(−1.53)	(−1.55)	(−1.29)	(−1.48)	(−0.02)	(−0.08)	(0.54)	(0.28)	(−1.30)	(−1.58)	(−0.13)	(−0.20)
$D \times Earn_{t-1}$		0.022		0.006		−0.008		−0.017				
		(0.99)		(0.30)		(−0.18)		(−0.44)				
$D \times RetVol$			−0.010	−0.017			0.037*	0.010		−0.031***		−0.020
			(−0.70)	(−1.61)			(1.95)	(0.63)		(−3.38)		(−0.80)
Intercept	0.101***	0.056***	0.187***	0.101***	0.103***	0.062***	0.226***	0.131***	0.006	−0.028**	0.017**	0.002
	(6.33)	(5.95)	(9.26)	(7.35)	(5.55)	(5.34)	(10.45)	(9.24)	(0.80)	(−2.19)	(2.41)	(0.15)
Observations	133,368	133,368	133,368	133,368	133,368	133,368	133,368	133,368	133,368	133,368	133,368	133,368
Adjusted R^2	0.114	0.318	0.208	0.346	0.109	0.321	0.212	0.354	0.047	0.051	0.061	0.064

***, **, * Indicate two-tailed significance at the < 0.01, < 0.05, and < 0.10 levels, respectively.

This table shows coefficient estimates and t-statistics (in parentheses) from estimating alternative versions of the first-stage KW estimation model (Equation (5)): $X_{it} = \alpha_0 + \alpha_1 D_{it} + R_{it}(\mu_1 + \mu_2 Size_{it} + \mu_3 MB_{it} + \mu_4 Lev_{it} + \mu_5 Earn_{it-1} + \mu_6 RetVol_{it}) + D_{it}R_{it}(\lambda_1 + \lambda_2 Size_{it} + \lambda_3 MB_{it} + \lambda_4 Lev_{it} + \lambda_5 Earn_{it-1} + \lambda_6 RetVol_{it}) + \delta_1 Size_{it} + \delta_2 MB_{it} + \delta_3 Lev_{it} + \delta_4 Earn_{it-1} + \delta_5 RetVol_{it} + D_{it}(\delta_6 Size_{it} + \delta_7 MB_{it} + \delta_8 Lev_{it} + \delta_9 Earn_{it-1} + \delta_{10} RetVol_{it}) + e_{it}$

where X is *Earn* or $\Delta Earn$, and R is *Ret* or *ARet*. When $Earn_{t-1}$ *Included?* ($RetVol_{t-1}$ *Included?*) = Yes, then $Earn_{t-1}$ ($RetVol_{t-1}$) is included as a right-hand-side variable.

Variable Definitions:
Earn = net income before extraordinary items, scaled by lagged market value of equity;
$\Delta Earn$ = the change in net income before extraordinary items from year t–1 to t, scaled by lagged market value of equity;
Ret = annual returns;
ARet = abnormal returns;
Size = the natural log of market value of equity;
MB = the market-to-book ratio;
Lev = leverage, defined as long-term and short-term debt deflated by market value of equity; and
RetVol = the standard deviation of daily firm-level returns.

between each firm characteristic and both *C_Score* and *C_ScoreLE*.[20]

$$\begin{pmatrix} FC_{it} \\ FC_{it} \end{pmatrix} = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \beta_1 \end{pmatrix} \begin{pmatrix} C\_Score_{it} & 0 \\ 0 & C\_ScoreLE_{it} \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} \tag{4}$$

where FC_i is each firm characteristic (e.g., market-to-book, leverage, size). Within the stacked regression, we test the equality of the coefficients relating each characteristic to *C_Score* and *C_ScoreLE* (i.e., $\alpha_1 = \beta_1$).[21]

Results from estimating Equation (4) for each firm characteristic are reported in Table 3. For this analysis, sample sizes are only constrained by the data requirements for that particular model. Results show that, with the exception of *NOAcc* and *ProbLit,* all regression coefficients for *C_Score* reported in the first column are of the predicted sign and statistically significant.[22] More importantly, all regression coefficients relating each firm characteristic to *C_ScoreLE* (reported in the second column) are also of the predicted sign and statistically significant, demonstrating that LEA in *C_Score* represents a correlated omitted variable. Further, except for *MB* and *Spread,* p-values reported in the third column indicate a failure to reject the null hypothesis of no difference between each coefficient for *C_Score* and the corresponding coefficient for *C_ScoreLE*. Finding that LEA's relation to each characteristic mimics that of *C_Score*'s heightens concerns that results used to validate *C_Score* as a proxy for conditional conservatism may be fully explained by LEA in *C_Score*. Combined with our earlier observations, these results provide sufficient evidence that the underlying causes of LEA pose a serious threat to *C_Score* by representing an alternative explanation to conditional conservatism for the test results used to validate *C_Score* in KW. In particular, this evidence highlights the significant potential for a Type I error to account for the results in studies employing *C_Score,* including in KW.

LEA in *C_Score*: Contributing Factors and Remedy

Our next tests are intended to identify the underlying causes of LEA in *C_Score* and determine whether controlling for these factors yields a measure of *C_Score* that is untainted by (orthogonal to) LEA. PT (2011) argue that LEA is related to scale effects—lower-priced firms with greater return variance and a higher propensity of losses. In contrast, BKN argue that LEA stems from a failure to adjust current earnings and returns in the Basu (1997) model for their expected components, and AT in lagged earnings is because lagged earnings proxy for expected current earnings. As described earlier, features of the estimation of *C_Score,* both common with and unique to the Basu (1997) AT measure, make the PT (2011) and BKN explanations natural starting points in our assessment of the causes of LEA in *C_Score*.

To identify the potential underlying causes of LEA, we first estimate several specifications of *C_Score* that incorporate different controls for BKN's expectations effects and PT's (2011) scale effects. Specifically, we examine 12 permutations, including KW's *C_Score,* based on including or excluding alternative control variables in the estimation of Equation (2). We generically label these alternative specifications *C_ScoreMod*. Our second stage involves estimating the correlation between each version of *C_ScoreMod* and *C_ScoreLE,* our proxy for LEA in *C_Score*. A significant correlation between *C_ScoreMod* and *C_ScoreLE* would indicate that the included control variables used for estimating that specification of *C_ScoreMod* do not fully capture and control for LEA. Alternatively, failure to find a significant correlation would suggest that the included control variables represent the underlying causes of LEA and that controlling for these variables provides an effective remedy for LEA.

To control for BKN's expectations effects in our first stage, we use lagged earnings ($Earn_{t-1}$) as our measure of expected earnings, which we either deduct directly from current earnings (i.e., $\Delta Earn$ as dependent variable) or include as a separate right-hand-side (RHS) variable. For expected returns, we use size and book-to-market matched portfolio returns, which we deduct from *Ret* to estimate abnormal returns (*ARet*). For PT's (2011) scale effects, we use the standard deviation of daily stock returns (*RetVol*) as an additional control variable. When included on the RHS, $Earn_{t-1}$ and *RetVol* enter the estimation model as main effects, as well as interactions with good and bad news returns. Equation (5) presents the general form of the first-stage model, where $X_{it} = Earn_{it}$ or $\Delta Earn_{it}$, and $R_{it} = Ret_{it}$ or $ARet_{it}$.

[20] We adjust for serial and cross-sectional correlations by clustering standard errors by firm and year in calculating all regression t-statistics. Note that the estimation of Equation (4) produces identical coefficient and standard error estimates for α_1 and β_1 as estimating them in separate univariate regressions.

[21] While finding that the corresponding coefficients on *C_Score* and *C_ScoreLE* have similar signs and are significant is sufficient to raise concern, we employ tests of equality of the coefficients to assess the severity of the problem.

[22] The insignificant coefficient on *NOAcc* is consistent with KW. However, the negative coefficient for *ProbLit* is inconsistent with KW but consistent with Ettredge, Huang, and Zhang (2016), who report that conservatism estimated using *C_Score* is negatively related to the likelihood of a lawsuit for a GAAP violation. Watts (2003a, 209) argues that a policy of conservatism may reduce expected litigation costs by maintaining undervalued net assets. While the threat of litigation may increase conservative reporting, a conservative reporting policy can reduce the threat of litigation. That said, we also investigate this finding further. Descriptive statistics for our model variables are very similar to those reported in Shu (2000). We also observe a negative relation with *ProbLit* estimated from the litigation risk model in Rogers and Stocken (2005).

$$X_{it} = \alpha_0 + \alpha_1 D_{it} + R_{it}(\mu_1 + \mu_2 Size_{it} + \mu_3 MB_{it} + \mu_4 Lev_{it} + \mu_5 Earn_{it-1} + \mu_6 RetVol_{it}) + D_{it}R_{it}(\lambda_1 + \lambda_2 Size_{it} + \lambda_3 MB_{it} + \lambda_4 Lev_{it} + \lambda_5 Earn_{it-1} + \lambda_6 RetVol_{it}) + \delta_1 Size_{it} + \delta_2 MB_{it} + \delta_3 Lev_{it} + \delta_4 Earn_{it-1} + \delta_5 RetVol_{it} + D_{it}(\delta_6 Size_{it} + \delta_7 MB_{it} + \delta_8 Lev_{it} + \delta_9 Earn_{it-1} + \delta_{10} RetVol_{it}) + e_{it} \quad (5)$$

For each version of Equation (5), we estimate *C_ScoreMod* based on Equation (3). That is, *C_ScoreMod* is defined as $\lambda_{1t} + \lambda_{2t}Size_{it} + \lambda_{3t}MB_{it} + \lambda_{4t}Lev_{it}$ regardless of the variables included. Thus, by construction, *C_ScoreMod* is derived from coefficient estimates that are orthogonal to the effects of expected earnings, expected returns, and return volatility when controlled for in the model.

Table 4 reports the coefficients and t-statistics from estimating alternative versions of Equation (5). We report results for 12 different models. The first row below the model number indicates which dependent variable ($X_t = Earn_t$ or $\Delta Earn$) is used. The next three rows identify which return variable ($R_t = Ret$ or $ARet$) is used on the RHS, and whether lagged earnings ($Earn_{t-1}$) and return volatility (*RetVol*) are included as RHS control variables.[23] To facilitate comparison, Model 1 is the original *C_Score* equation with no additional controls. As before, coefficient estimates are derived from pooled models with standard errors corrected for serial and cross-sectional correlations.

For brevity, we do not discuss each set of estimation results individually but instead focus on the key variables, noting whether they are significant (either as main effects or interactions). However, as discussed above, the ultimate indicator of any particular model's ability to identify the underlying causes of and, thus, control for LEA comes in our second-stage tests, where we assess the correlation between each alternative *C_ScoreMod* and *C_ScoreLE*.

Regarding earnings expectations, Models 2, 4, 6, and 8 include $Earn_{t-1}$ as a RHS variable. The main effect of $Earn_{t-1}$ is highly significant, consistent with earnings persistence. The relation increases with news ($R \times Earn_{t-1} > 0$) in three of four models, although not asymmetrically with bad news. Specifically, the interaction of lagged earnings with bad news ($D \times R \times Earn_{t-1} < 0$) is generally negative but statistically insignificant. Alternatively, and not surprisingly, using earnings changes ($\Delta Earn$) as the dependent variable in the last four models of the table results in a significant decline in explanatory power. Importantly, the bad news parameters for those models generally exhibit patterns similar to the original *C_Score* (Column 1), consistent with AT, although they are often smaller in magnitude.

Regarding the adjustment for expected returns, inclusion of either *Ret* or *ARet* results in little difference to explanatory power based on the adjusted R^2 values. However, the size of the coefficients on the bad news interactions, $D \times R$, declines in Models 5 through 8, which measure news with *ARet,* relative to Models 1 through 4, which use *Ret*. More importantly, the bad news "intercept" ($D \times R$) terms are insignificant in Models 7 and 8.

Regarding scale effects, *RetVol* is included in Models 3, 4, 7, 8, 10, and 12. The main effect of *RetVol* is significant in most specifications. Negative coefficients on the interaction $R \times RetVol$ suggest less timely reporting of current news for firms with higher return volatility, but, more importantly, the positive coefficients on the bad news interactions ($D \times R \times RetVol$) in most columns suggest asymmetry in this sensitivity and are consistent with the return variance effect discussed in PT (2011) inflating estimates of AT.

Overall, significant coefficients on the bad news interactions and reductions to the adjusted R^2 after including proxies based on PT (2011) and BKN may be an indication that they capture underlying causes of LEA in *C_Score*. However, the evidence in Table 4 alone is not sufficient to determine whether controlling for these factors actually reduces LEA in *C_Score,* or which combination of factors might work "best" to eliminate LEA. To accomplish this, we turn to our second-stage analysis, examining whether LEA continues to explain the variation in our alternative estimates of *C_ScoreMod*. We rely on descriptive evidence from the following regression model that relates each version of *C_ScoreMod* to *C_ScoreLE*:

$$C\_ScoreMod_{it} = \alpha_0 + \alpha_1 C\_ScoreLE_{it} + e_{it} \quad (6)$$

A "better" control for LEA would be represented by α_1 and the adjusted R^2 moving closer to 0.

Table 5 reports coefficient estimates, t-statistics (in parentheses) derived from two-way clustered standard errors, and the adjusted R^2 values [in brackets] from estimating Equation (6) for the 12 different versions of *C_ScoreMod* described in Table 4. Model numbers (1, 2, 3,. . .,12) in Table 5 correspond to the model numbers in Table 4. The rows in Table 5 identify the alternative combinations of the earnings variable (LHS) and returns variable (RHS) used in estimating Equation (5). The columns in Table 5 reflect the inclusion of lagged earnings and return volatility on the RHS of Equation (5). Our benchmark (Model 1) relates the original KW *C_Score* to *C_ScoreLE* with a coefficient of 0.64, and the corresponding adjusted R^2 value suggests that *C_ScoreLE* explains a sizable 32 percent of the variation in KW's *C_Score*. Interestingly, we observe a substantial decline in α_1 to 0.29 (Model 2) and 0.44 (Model 3) after including $Earn_{t-1}$ and *RetVol,* respectively, as RHS

[23] We do not evaluate models that include both change in earnings as the dependent variable and lagged earnings as a RHS variable.

TABLE 5

Effectiveness of Alternative Specifications of *C_ScoreMod* (Reported in Table 4) at Reducing LEA Coefficients (t-statistics) [Adj. R^2] from Estimating

$$C\_ScoreMod_{it} = \alpha_0 = \alpha_1 C\_ScoreLE_{it} + e_{it}$$

Dependent (*Earn* or Δ*Earn*) and Return (*Ret* or *ARet*) Variables Included in Equation (5)	Independent Variables ($Earn_{t-1}$ and/or $RetVol_t$) Included in Equation (5) as Controls: None	$Earn_{t-1}$	$RetVol_t$	$Earn_{t-1}$ and $RetVol_t$
Earn and *Ret*	1	2	3	4
	0.643***	0.287***	0.435***	0.173
	(7.49)	(4.13)	(3.64)	(1.32)
	[32.4%]	[8.6%]	[7.9%]	[1.5%]
Earn and *ARet*	5	6	7	8
	0.486***	0.277***	0.387***	0.246***
	(6.78)	(4.28)	(3.54)	(2.74)
	[27.2%]	[11.3%]	[9.73%]	[5.1%]
Δ*Earn* and *Ret*	9		10	
	−0.139		−0.068	
	(−1.58)		(−0.37)	
	[3.3%]	NA	[0.3%]	NA
Δ*Earn* and *ARet*	11		12	
	−0.342***		−0.182	
	(−3.78)		(−0.82)	
	[11.7%]	NA	[1.1%]	NA

*** Indicates two-tailed significance at the < 0.01 level.
Model numbers (1, 2, 3,. . .,12) in this table correspond to the model numbers in Table 4. *C_ScoreMod* is derived from Equation (3) using coefficients from the 12 alternative first-stage model estimates reported in Table 4.

Variable Definitions:
C _ScoreLE = our proxy for LEA in *C_Score*;
C _ScoreLE = derived from applying the coefficient estimates from the first-stage model (Equation (2)) with lagged earnings as the dependent variable to Equation (3). Note that the upper-left cell (Model 1) in this table corresponds to KW's original *C_Score* measure;
Earn = net income before extraordinary items, scaled by lagged market value of equity;
Δ*Earn* = the change in net income before extraordinary items from year *t*–1 to *t,* scaled by lagged market value of equity;
Ret = annual returns;
ARet = abnormal returns; and
RetVol = the standard deviation of daily firm-level returns.

variables. These results indicate that both expectations effects and scale effects individually contribute to LEA in *C_Score*. Further, controlling for both as RHS variables (Model 4) yields an α_1 that is not significantly different from 0 at conventional levels, and the adjusted R^2 drops to 1.5 percent. Thus, explicit controls for expectations and return variance appear to substantially mitigate the presence of LEA in *C_Score*.

Comparing corresponding $Earn_t$ models that replace *Ret* with *ARet* to generate *C_ScoreMod* (Models 1 to 4 with 5 to 8) we observe a nominal reduction in coefficient estimates in Models 5 and 7 but an increase in explanatory power in Models 6, 7, and 8. Clearly Model 8 performs worse than Model 4 in attenuating LEA. Thus, using *ARet* alone to control for expectations in *Ret* yields some reduction in the economic magnitude of LEA in *C_Score,* but other combinations to control for expectations and scale effects appear to do a better job of purging LEA to statistically insignificant levels.[24]

[24] As BKN note, adequately controlling for expectations in either earnings or returns is sufficient to address the expectations effect. Expected returns are much more difficult to estimate than expected earnings.

The remaining Models (9 through 12) utilize $\Delta Earn$ as the dependent variable. *C_ScoreMod* derived from three of those four Models (9, 10, and 12) is not significantly related to *C_ScoreLE,* and the remaining measure (based on Model 11) is *negatively* related to *C_ScoreLE*. Note that a significantly negative relation with LEA is still problematic.

Of the various combinations we analyze, the most effective at eliminating a significant relation between *C_ScoreMod* and *C_ScoreLE* appear to be Models 10 and 12, which employ $\Delta Earn$ as the dependent variable and include *RetVol* (and associated interactions) as an additional regressor in the first-stage regression model. Model 4 (supplementing KW's *C_Score* with X_{t-1} and *RetVol*) and Model 9 (using a combination of $\Delta Earn$ and *Ret*) also substantially mitigate bias. Overall, these results suggest that LEA in *C_Score* arises from both a failure to control for expectations (as proposed by BKN) and a failure to address the variance effect (as proposed by PT [2011]). Controlling for both effects yields a version of *C_Score* that is no longer significantly related to LEA.

Does *C_Score* Absent LEA Still Reflect Conditional Conservatism?

We demonstrate that LEA undermines prior test results linking *C_Score* to firm characteristics that proxy for conditional conservatism. We also find that controlling for both expectations and scale effects are necessary and sufficient to yield a modified *C_Score* that is no longer significantly related to LEA. A necessary next step is to show that our modified *C_Score* that is purged of LEA still captures conditional conservatism. To do so, we examine the relations between *C_ScoreMod* and the firm characteristics (*FC*) examined previously that are predicted to be related to conditional conservatism. Based on results in Table 5, we set *C_ScoreMod* equal to one of the two modified measures most effective at eliminating statistical significance with *C_ScoreLE* (Models 10 and 12) and estimate the following regression model:

$$FC_{it} = \alpha_0 + \alpha_1 C\_ScoreMod_{it} + e_{it} \tag{7}$$

All variables are previously defined.

Results reported in Table 6, Panel A (Panel B) correspond to Model 10 (12). In Panel A, we observe highly significant coefficient estimates on *C_ScoreMod* that are in the expected direction (again with the exceptions of *NOAcc* and *ProbLit*).[25] Results in Panel B are similar. Overall, results in both panels confirm that both modified measures exhibit relations with a wide range of firm characteristics that are consistent with *C_ScoreMod* reflecting conditional conservatism.

Are Alternative Approaches to Address LEA in *C_Score* Also Effective?

While our prior results identify the underlying causes of LEA and demonstrate effective ways to address LEA in *C_Score* by addressing the causes (i.e., return volatility and expectations) in the first-stage estimation of *C_Score,* we also evaluate alternative approaches that either seem simpler or are suggested by prior studies evaluating LEA in Basu's (1997) AT measure. First, we considered simply subtracting *C_ScoreLE* from *C_Score*. This approach assumes a linear relation between LEA and *C_Score*. However, when we regress this difference on *C_ScoreLE,* we continue to observe a significant although negative relation, suggesting some form of overcorrection (coefficient = –0.36; t-statistic = –4.2).[26] BKN suggest that controlling for firm fixed effects sufficiently addresses LEA in the Basu (1997) AT measure. We observe that firm fixed effects explain only about 24 percent of the variation in *C_ScoreLE*. Further, we find that the residual from regressing *C_Score* on firm fixed effects remains significantly related to *C_ScoreLE* (coefficient = 0.460; t-statistic = 5.69). Thus, this approach appears ineffective in addressing LEA in *C_Score*.

Collins, Hribar, and Tian (2014) argue that LEA in the Basu (1997) AT measure of conditional conservatism is due to asymmetry in the cash flow component of earnings. They argue that cash flow asymmetry adds noise or bias to tests of conditional conservatism since it does not reflect differential verification for recognizing unrealized gains versus losses.[27] They recommend estimating the AT measure using only current accruals as the dependent variable to avoid LEA.[28] We evaluate this

[25] As expected, the signs of the correlations with *Size, MB,* and *Lev* match the signs of the coefficients attached to each in constructing *C_ScoreMod*.

[26] Another approach would be to include *C_ScoreLE* as a separate regressor in a model relating *C_Score* to some variable of interest. This approach would ensure that any association between *C_Score* and a variable of interest is incremental to LEA so long as the relation between LEA and the variable of interest is truly linear. An advantage of this approach is that it does not require an estimation of return volatility (*RetVol*). A disadvantage is that this approach does not incorporate the underlying causes of LEA. *C_ScoreLE* is an observable manifestation of this particular bias and not the bias itself. Thus, simply including *C_ScoreLE* as an additional regressor along with *C_Score* in a given model may be inferior in the sense that the researcher is only controlling for the manifestation when the remedy (i.e., controlling for the cause) is a viable option. The relative merits of each approach likely depend on the particular research setting, and a more detailed analysis is beyond the scope of this study.

[27] Schrand (2014) cautions that cash flow asymmetry captured by the Basu (1997) AT measure may not represent noise or bias. Rather, it could actually be part of a study's objective of interest in studying conditional conservatism. Therefore, a researcher should determine whether including some cash flow components in the dependent variable would be appropriate when estimating the Basu (1997) AT measure.

[28] PT (2016) report significant asymmetry in *lagged* accruals, suggesting LEA affects the accrual component of earnings. Further, they show the asymmetry in lagged accruals is related to scale effects and conclude that their evidence does not support the Collins et al. (2014) remedy.

TABLE 6

Relating Firm Characteristics Associated with Conservatism to *C_ScoreMod*

Panel A: *C_ScoreMod* Based on First-Stage Model 10 Using *Ret, ΔEarn,* and *RetVol*

Dependent Variable	Pred. Sign	Independent Variable: *C_ScoreMod*	Adj. R^2	Obs.
Size	−	−14.056***	34.9%	133,368
		(−5.97)		
MB	−	−10.748***	14.8%	133,368
		(−5.00)		
Lev	+	4.994***	12.2%	133,368
		(3.94)		
ROA	−	−0.227***	6.7%	129,829
		(−6.46)		
NOAcc	−	−0.003	1.3%	63,359
		(−0.21)		
InvCyc	−	−0.035***	3.0%	111,278
		(−5.31)		
PIN	+	0.389***	16.2%	26,560
		(5.66)		
Spread	+	0.174***	39.8%	85,079
		(5.65)		
RetVol	+	0.708***	19.4%	133,368
		(3.50)		
ProbLit	+	−0.016***	17.1%	85,479
		(−4.08)		
Age	−	−31.456***	3.2%	128,842
		(−4.60)		

(continued on next page)

approach in the context of LEA in *C_Score* by estimating the first-stage model (Equation (2)) using current accruals as the dependent variable. Using the parameters from this first-stage estimate, we construct a version of *C_Score* (*C_ScoreAcc*) based on Equation (3) and assess its relation to *C_ScoreLE,* our proxy for LEA. If cash flow asymmetry is the sole source of LEA in *C_Score,* then *C_ScoreAcc* should be uncorrelated with *C_ScoreLE*. However, we observe a significant association (coefficient = 0.165; t-statistic = 1.90). As a confirmation, we find that including *C_ScoreLE* substantially alters the coefficients relating *C_ScoreAcc* to the firm characteristics listed in Table 6, indicative of a common correlation between *C_ScoreLE, C_ScoreAcc,* and the firm characteristics. These results suggest that the approach proposed in Collins et al. (2014) to address LEA in the Basu (1997) AT measure fails to adequately address LEA in *C_Score*.

Extended Analysis: The Relation between Conditional Conservatism and Goodwill Impairment

With respect to evidence in KW that validates *C_Score* as a firm-year measure of conditional conservatism, we document that the bias associated with LEA contributes to an increased likelihood of rejecting the null of no association (i.e., Type I error). In our final analysis, we develop a hypothesis test demonstrating that failing to control for the drivers of LEA also poses a threat by reducing the likelihood of observing a predicted relation (i.e., Type II error). Prior studies argue that managers have considerable discretion in the timing of reporting a goodwill impairment (Francis et al. 1996; Beatty and Weber 2006; Beaver and Ryan 2005). Hayn and Hughes (2006) show that firms, on average, may delay recognition for three to four years, a period over which an economic recovery is reasonably possible.[29] However, greater conservatism likely arises from stronger board oversight and/or greater incentives to recognize losses immediately rather than delay in the hope of an economic recovery that

[29] They also show that some firms delay recognition for up to ten years.

TABLE 6 (continued)

Panel B: *C_ScoreMod* Based on First-Stage Model 12 Using *ARet,* Δ*Earn,* and *RetVol*

Dependent Variable	Pred. Sign	Independent Variable: *C_ScoreMod*	Adj. R^2	Obs.
Size	−	−8.070***	27.1%	133,368
		(−4.74)		
MB	−	−7.644***	13.7%	133,368
		(−4.57)		
Lev	+	3.328***	10.4%	133,368
		(2.48)		
ROA	−	−0.139***	5.8%	129,829
		(−5.07)		
NOAcc	−	0.007	1.3%	63,359
		(0.77)		
InvCyc	−	−0.022***	2.8%	111,278
		(−4.03)		
PIN	+	0.273***	16.2%	26,560
		(4.53)		
Spread	+	0.129***	39.6%	85,079
		(5.36)		
RetVol	+	0.463***	18.5%	133,368
		(3.21)		
ProbLit	+	−0.009***	15.1%	85,479
		(−3.19)		
Age	−	−16.856***	2.3%	128,842
		(−3.27)		

*** Indicates two-tailed significance at the < 0.01 level.

This table reports mean coefficient estimates and t-statistics (in parentheses) from estimating the following regression: Model: $FC_{it} = \alpha_0 + \alpha_1 C\_ScoreMod_{it} + e_{it}$ where *FC* = *Size, MB, Lev, ROA, NOAcc, InvCyc, PIN, Spread, RetVol, ProbLit,* or *Age*.

Variable Definitions:
C _ScoreMod = derived from Equation (3) using coefficients from first-stage Model 10 (Panel A) and Model 12 (Panel B) estimates described in Table 4;
Earn = net income before extraordinary items, scaled by lagged market value of equity;
Size = the natural log of market value of equity;
MB = the market-to-book ratio;
Lev = leverage, defined as long-term and short-term debt deflated by market value of equity;
ROA = earnings before extraordinary items, deflated by lagged assets;
NOAcc = non-operating accruals, scaled by lagged assets;
InvCyc = a decreasing measure of the length of the investment cycle;
PIN = the probability of informed trading from Easley et al. (2002);
Spread = the average daily bid-ask spread, scaled by the midpoint of the spread;
RetVol = the standard deviation of daily firm-level returns;
ProbLit = the probability of litigation from Shu (2000); and
Age = the age of the firm in a given year.

would make recognition unnecessary. Therefore, we predict that firms that are more conditionally conservative are more likely to report a goodwill impairment.

Prior studies document that smaller firms are less likely to report an impairment (Francis et al. 1996; Beatty and Weber 2006). Since LEA is more pronounced for small firms (as seen in Table 1, Panel B and Table 2, Panel A), the likelihood of reporting a goodwill impairment should be negatively related to the small firm effect in *C_ScoreLE*.[30] This, in turn, works against finding the expected positive relation between the likelihood of a reported impairment and conditional conservatism. To test our predictions, we estimate the following Probit regression model:

[30] Evidence that the market responds negatively to the disclosure of an impairment (Li, Shroff, Venkataraman, and Zhang 2011) indicates that investors do not fully anticipate the impairment. Under BKN's expectations effect in LEA, the unexpected portion will be unrelated to LEA, while the expected portion could mimic the relation between the impairment and conditional conservatism. Depending on an investor's ability to anticipate a goodwill impairment, the expectations effect in LEA could partially offset the firm size effect in LEA.

$$\Pr(Impairment)_{it} = \alpha_0 + \alpha_1(C\_Score_{it}, C\_ScoreLE_{it},\ or\ C\_ScoreMod_{it}) + \alpha_2 Beta_{it} + \alpha_3 ADisp_{it} + \alpha_4 AFollow_{it} + \alpha_5 ProbLit_{it} + \alpha_6 ROA_{it} + \alpha_7 Size_{it} + \alpha_8 RetVol_{it} + \alpha_9 MB_{it} + \alpha_{10} Lev_{it} + e_{it} \quad (8)$$

We expect $\alpha_1 > 0$. *Impairment* is an indicator variable equal to 1 if firm *i* reports an impairment in year *t*. Note that *Impairment* is undefined if the firm reports no balance for goodwill, thus restricting the sample for this test to observations where an impairment is at least possible. *C_ScoreMod* is again based on the two best first-stage models for addressing LEA, as described earlier. Evidence that expectations and/or scale effects work against this result will include a lower (and perhaps negative) coefficient for *C_ScoreLE* relative to both *C_Score* and *C_ScoreMod,* and a more significant coefficient for *C_ScoreMod* relative to *C_Score*. We also include control variables (all defined in Appendix A) that capture other characteristics of firms likely to report an impairment, including firms with higher risk and uncertainty (*Beta, RetVol, ProbLit, ADisp*), a richer information environment to increase transparency (*AFollow* and *Size*), lower profitability (*ROA*), lower growth options (*MB*), and greater leverage (*Lev*).

Results presented in Table 7 confirm our expectations. The coefficients for *C_Score* and *C_ScoreLE* are not significant at conventional levels, with the latter carrying a negative sign. Regarding our two *C_ScoreMod* variables, we observe coefficients that are positive for both and at least marginally significant (one-tailed p-values between 0.04 and 0.09). We conclude that the LEA-related bias masks the predicted relation between conditional conservatism and the likelihood of reporting a goodwill impairment. These and earlier results illustrate the extensive consequences of LEA for *C_Score* in testing hypotheses.

CONCLUSION

PT (2011) and BKN report an asymmetric relation between lagged earnings and current returns and conclude that the Basu (1997) model excludes correlated omitted variables that exaggerate the differential timeliness of earnings and thereby inflate estimates of conservatism. We provide evidence that LEA taints *C_Score* not only due to components common to the Basu (1997) AT measure, but also due to the more unique features that distinguish *C_Score* as a firm-year representation of conditional conservatism.

We replicate the key results in KW and estimate the bias in *C_Score* by exploiting the relation between lagged earnings and current returns. We then show that a wide range of conservatism-related firm characteristics used in KW to validate *C_Score* are correlated with LEA in *C_Score* in a manner that mimics their relations with *C_Score*. In each of these settings, LEA overstates *C_Score*'s ability to reflect conservatism, revealing that LEA represents a serious threat to interpreting test results based on *C_Score* as a representation of conditional conservatism. We explore potential causes of LEA and provide evidence that both PT's (2011) scale effects and BKN's expectations effects contribute to LEA in *C_Score*. We demonstrate that controlling for both is necessary and sufficient to produce a *C_Score* that is both insignificantly related to LEA and reflects conditional conservatism. Finally, we construct a hypothesis test relating conditional conservatism to the likelihood of reporting a goodwill impairment and demonstrate that failing to control for these effects in *C_Score* reduces the likelihood of rejecting the null and, in turn, increases the risk of Type II errors.

Our study makes several important contributions to the conservatism literature. Our results serve to caution researchers about the potential for both Type I or Type II errors with *C_Score,* both of which could lead to invalid conclusions. In contrast to PT (2011) and BKN, who propose distinct (and exclusive) explanations for LEA in the pooled Basu (1997) model, and studies that address only one explanation (i.e., Kravet 2014; Ramalingegowda and Yu 2012; Erkens et al. 2014), we observe that controlling for both is necessary and sufficient. More importantly, we identify a remedy for the bias that yields a modified *C_Score* measure that exhibits the predicted relations with various attributes of conservatism but not LEA. Further, controlling for LEA-related bias is relatively easy to implement and should be of interest to future researchers. Although *C_Score* has not been explicitly linked to other biases or shortcomings associated with the Basu (1997) AT measure in studies such as Givoly et al. (2007) and Dietrich et al. (2007), we acknowledge that the modified *C_Score* measures we propose might be subject to these other concerns. As a result, studies employing a modified version of *C_Score* that addresses LEA should continue to assess the robustness of those results to alternative proxies for conditional conservatism.

Overall, our study illustrates the importance of controlling for this particular bias in *C_Score* in order to ensure that *C_Score*'s role in empirical tests is attributed to conservatism rather than LEA. Thus, like BKN we conclude that mitigating the potential bias, rather than abandoning measures of conservatism based on differential timeliness, can enhance researchers' efforts to identify conservatism on a firm-year basis.

TABLE 7

The Probability of Goodwill Impairment and Conditional Conservatism

Variables	**Pred. Sign**	**Dependent Variable = *Goodwill Impairment Indicator*** (1)	(2)	(3)	(4)
C_Score	+	0.807			
		(1.15)			
C_ScoreLE	+/−		−0.378		
			(−0.85)		
C_ScoreMod:					
Ret, Δ*Earn,* and *RetVol*	+			0.653**	
				(1.69)	
ARet, Δ*Earn,* and *RetVol*	+				0.531*
					(1.36)
Beta	+/−	0.058	0.075	0.105	0.102
		(0.46)	(0.59)	(1.04)	(1.00)
ADisp	+	0.170**	0.174**	0.186***	0.186***
		(1.84)	(1.85)	(2.94)	(2.94)
AFollow	+	0.009*	0.009*	0.014***	0.014***
		(1.56)	(1.47)	(2.50)	(2.51)
ProbLit	+/−	−0.408***	−0.408***	−0.327***	−0.327***
		(−3.40)	(−3.43)	(−2.79)	(−2.79)
ROA	−	−2.316***	−2.354***	−1.865***	−1.866***
		(−6.06)	(−6.10)	(−5.71)	(−5.75)
Size	+	0.199***	0.162***	0.161***	0.157***
		(3.25)	(3.24)	(3.72)	(3.51)
RetVol	+	0.765*	0.697*	0.672*	0.694*
		(1.57)	(1.46)	(1.55)	(1.61)
MB	−	−0.201***	−0.199***	−0.214***	−0.212***
		(−5.78)	(−5.61)	(−5.18)	(−5.23)
Lev	+/−	0.039	0.073*	0.055**	0.063**
		(0.93)	(1.94)	(2.12)	(2.41)
Observations		19,070	19,070	19,070	19,070

***, **, * Indicate significance at the < 0.01, < 0.05, and < 0.10 levels, respectively.

This table reports results from estimating the following model using a Probit regression: $\Pr(Impairment)_{it} = \alpha_0 + \alpha_1(C\_Score_{it},\ C\_ScoreLE_{it},\ or\ C\_ScoreMod_{it}) + \alpha_2 Beta_{it} + \alpha_3 ADisp_{it} + \alpha_4 AFollow_{it} + \alpha_5 ProbLit_{it} + \alpha_6 ROA_{it} + \alpha_7 Size_{it} + \alpha_8 RetVol_{it} + \alpha_9 MB_{it} + \alpha_{10} Lev_{it} + e_{it}$

Variable Definitions:
C_ScoreLE = our proxy for LEA in *C_Score*;
C_ScoreLE = derived from applying the coefficient estimates from the first-stage model (Equation (2)) with lagged earnings as the dependent variable to Equation (3);
Beta = the market model beta;
ADisp = the standard deviation of analyst estimates reported in the report used to compute *AFollow*;
AFollow = the number of analyst estimates for fiscal year *t*'s earnings reported in the I/B/E/S summary file issued in the third month of the fiscal year (first month of return window);
ProbLit = the probability of litigation from Shu (2000);
ROA = earnings before extraordinary items, deflated by lagged assets;
Size = the natural log of market value of equity;
RetVol = the standard deviation of daily firm-level returns;
MB = the market-to-book ratio; and
Lev = leverage, defined as long-term and short-term debt deflated by market value of equity.

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APPENDIX A

Variable Definitions

Earn = net income before extraordinary items (Compustat IB) scaled by lagged market value of equity (Compustat PRCC_F × CSHO).

Ret = annual returns compounded from monthly returns (CRSP RET) beginning in the fourth month of the fiscal year.

D = indicator variable equaling 1 for periods where *Ret* is less than 0.

Size = the natural log of market value of equity (Compustat PRCC_F × CSHO).

MB = the ratio of market value of equity to book value of equity (Compustat CEQ) at year-end.

Lev = leverage, defined as long-term debt plus short-term debt deflated by market value of equity (Compustat [DLTT + DLC]/[PRCC_F × CSHO]).

RetVol = the annualized standard deviation of daily stock returns (CRSP RET). Specifically, we compute the standard deviation of daily stock returns over the fiscal year and multiply this value by the square root of 252.

Δ*Earn* = the change in net income before extraordinary items from year $t-1$ to t, scaled by lagged market value of equity.

ARet = abnormal returns, defined as the difference between the firm's annual return, *Ret,* and the matching size and market-to-book portfolio return over the same period. We obtain size and book-to-market breakpoints as well as portfolio returns (5 × 5) from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

C_Score = a proxy for conditional conservatism derived from applying the coefficient estimates from the first-stage model (Equation (2)) to Equation (3).

C_ScoreAcc = a proxy for conditional conservatism derived from applying the coefficient estimates from the first-stage model (Equation (2)) using current accruals as the dependent variable to Equation (3).

C_ScoreLE = a representation of lagged earnings asymmetry (LEA) in *C_Score* derived from applying the coefficient estimates from the first-stage model (Equation (2)) with lagged *Earn* as the dependent variable to Equation (3).

C_ScoreMod = modified versions of *C_Score* derived from applying the coefficient estimates from the first-stage model (Equation (2)) with current *Earn* as the dependent variable and excluding or including controls for scale effects and expectations effects (see Equation (5)) to Equation (3).

ROA = earnings before extraordinary items, deflated by lagged assets (Compustat IB/AT_{t-1}).

NOAcc = non-operating accruals, scaled by lagged assets. Non-operating accruals are measured as net income before extraordinary items, plus depreciation, minus cash flow from operations (CFOA), minus operating accruals, all deflated by lagged total assets. Operating accruals are measured as change in noncash current assets, minus change in current liabilities excluding short-term debt, deflated by lagged assets. CFOA is cash flow from operations (Compustat OANCF$_t$), deflated by lagged assets. CFOA is obtained from the statement of cash flows after 1987, and prior to that is measured as funds from operations minus operating accruals.

InvCyc = depreciation expense deflated by lagged assets; a decreasing measure of the length of the investment cycle.

ProbLit = the probability of litigation, fitted using the parameters and variables in Shu (2000, Table 3). Specifically, it is the inverse logit of {−10.049 + 0.276 (Size) + 1.153 (Inventory) + 2.075 (Receivables) + 1.251 (ROA) − 0.088 (Current Ratio) + 1.501 (Lev) + 0.301 (Sales Growth) − 0.371 (Stock Return) − 2.309 (Stock Volatility) + 0.235 (Beta) + 1.464 (Stock Turnover) + 1.060 (Delist Dummy) + 0.928 (Technology Dummy) + 0.463 (Qualified Opinion Dummy)}.

PIN = the probability of informed trading from Easley et al. (2002), obtained from the website of Soeren Hvidkjaer (https://sites.google.com/site/hvidkjaer/data).

Spread = the average of daily bid-ask spreads (CRSP bid minus CRSP ask scaled by the midpoint) over the fiscal year.

Age = the age of the firm in a given year, measured as the number of years with return history on CRSP.

Beta = the market model beta. Specifically, for each firm-year observation, we regress monthly CRSP returns on the value-weighted market index (CRSP VWRETD) over the same window that *Ret* is computed.

ADisp = the standard deviation of analyst estimates reported in the report used to compute *AFollow*.

AFollow = the number of analyst estimates for fiscal year t's earnings reported in the I/B/E/S summary file issued in the third month of the fiscal year (first month of the return window).

Impairment = indicator equaling 1 if a firm reports a goodwill impairment in year t (Compustat GDWLIP). *Impairment* is undefined if a firm reports a missing value for goodwill (Compustat GDWL).