Many conflicting theoretical claims have been levied, and much conflicting empirical evidence have been provided, about Basu’s measure of asymmetric timeliness (AT). These claims and evidence are difficult to evaluate individually and to collectively synthesize. In Sections OA.1-OA.5 of this Online Appendix, we intuitively explain the main potential biases in Basu’s measure identified by the prior literature, critically evaluate these biases based on logic and empirical evidence, and thereby offer a coherent set of recommendations for future empirical researchers to consider in using this measure. While we emphasize the importance of some studies and downplay the importance of others, our goal is to move the literature forward or, at least, to frame the debate clearly. This purpose updates Ryan [2006] for the extensive research conducted over the intervening years, and it lays the groundwork for our second and primary purpose. In Section OA.6 of this appendix we develop a firm-year measure of conditional conservatism based on our modified Basu model.
The literature refers to regressions of earnings on returns—such as Basu’s piecewise linear regression, equation (1)—as reverse regressions, as opposed to traditional forward regressions of returns on earnings. The reverse regression approach, first employed by Beaver, Lambert, and Ryan [1987], reflects a measurement perspective, that is, earnings incorporates news with timeliness that depends on accounting rules and other factors. It would be cumbersome at best to estimate the timeliness of earnings using the forward regression approach, which reflects the information content perspective that has dominated accounting research since Ball and Brown [1968], that is, earnings provide market participants with information upon which they trade or that otherwise finds its way into returns. Dietrich et al. [2007] posit that equation (1) produces biased AT estimates to the extent that earnings has information content incremental to other available information, so that returns (the regressor) are endogenously determined by earnings,\footnote{Ryan [2006] recommends several simple approaches to reduce endogeneity bias, such as filtering returns to remove the portion attributable to the public disclosure of earnings and identifying alternative news proxies that are not determined by earnings. Such alternative proxies are most likely to be available in certain industries and other specific contexts. For example, Badia, Duro, Penalva, and Ryan [2017] use oil price index changes as the proxy for news in the oil and gas industry, and Lin, Ryan, and Tseng [2019] use industry output volume changes as the proxy for news in manufacturing industries. Even in restricted settings, however, alternative proxies may not be available that come close to capturing the breadth of the information reflected in returns, and they may introduce unknown biases. Banker et al. [2017] show empirically that the use of multiple indicators of news improves the specification of the Basu model. In untabulated analysis, we verify that our inferences are robust to including the change in sales and innovation in cash flow from operations as additional news proxies. For parsimony, and given the amount of noise in the innovation in cash flow from operations as a news proxy, and the small improvement in adding the change in sales (untabulated), we use returns as the measure of news.} or to the extent that the distribution of earnings (the regressand) is effectively truncated by the piecewise linear structure of the model.

Dietrich et al. [2007] characterize the first of these sources of bias by comparing the corresponding bivariate forward and reverse regressions:

\[
R_{i,t} = \alpha X_{i,t} + \mu_{i,t} \tag{OA.1}
\]
In the forward regression, equation (OA.1), Dietrich et al. [2007] assume that $R_{i,t}$ is a linear function of $X_{i,t}$ and uncorrelated other information $\mu_{i,t}$—empiricists typically omit this other information, which thus passes through to the residual—so that this equation is well specified and OLS estimates of the slope coefficient $\alpha$ are unbiased. They further assume that $X_{i,t}$ and $\mu_{i,t}$ are each drawn from a single distribution. Under these assumptions, Dietrich et al. [2007] argue that the reciprocal of the slope coefficient $\beta$ in the reverse regression, equation (OA.2), is an upwardly biased estimator of the slope coefficient $\alpha$ in the forward regression, because $R_{i,t}$ is endogenously determined by $X_{i,t}$ and thus correlated with the error term $\epsilon_{i,t}$, in the reverse regression.

Dietrich et al. [2007] refer to the probability limit of the difference of $1/\beta$ and $\alpha$, which equals $\frac{\sigma_{X}^{2}}{\alpha \sigma_{X}^{2}} - \alpha$, as the sample variance ratio bias, where $\frac{\sigma_{X}^{2}}{\sigma_{X}^{2}}$ is the sample variance ratio. However, $1/\beta$ (which also equals $\alpha/R^{2}$) and $\alpha$ differ whenever the common $R^{2}$ in the two bivariate equations is greater than 0 and less than 1. Hence, this difference is attributable to the omission of the other information, which reduces the $R^{2}$ below one, not to returns being endogenously determined by earnings, which increases the $R^{2}$ toward one all else being equal. In fact, when returns are determined solely and linearly by earnings (i.e., the case of complete endogeneity), the $R^{2}$ equals one and this difference is zero. Hence, this difference is not properly viewed as an endogeneity bias. Moreover, as Ball et al. [2013a] emphasize, this difference is irrelevant if the researcher’s objective is not to estimate the inverse earnings response coefficient, but rather to assess the

\[ X_{i,t} = \beta R_{i,t} + \epsilon_{i,t}. \]  

(OA.2)

\[ X_{i,t} = \beta R_{i,t} + \epsilon_{i,t}. \]  

(OA.2)
accounting rules-induced timeliness with which earnings incorporate available information, i.e.,
the objective of essentially all research on conditional conservatism.³

Dietrich et al.’s [2007] second source of bias, which they refer to as sample truncation bias,
may arise because Basu’s piecewise linear regression, equation (1), effectively partitions the
overall sample into subsamples with positive and negative values of \( R_{i,t} \). On average, observations
with positive (negative) values of \( R_{i,t} \) have positive (negative) values of both \( X_{i,t} \) and the (typically
omitted) other information \( \mu_{i,t} \) in equation (OA.1).⁴ This partitioning yields bias if it induces
differential correlations between \( X_{i,t} \) and \( \mu_{i,t} \) in the subsamples of positive and negative \( R_{i,t} \). Such
differential correlations may result from the incremental information content of earnings being
different for good news and bad news (i.e., from returns being asymmetrically endogenous with
respect to earnings across the range of returns) or from essentially any other source of
misspecification in the reverse regression. To illustrate this point, Dietrich et al. [2007] (figure 3,
panels B and C) depict two small-sample examples in which AT results from the variance of the
omitted other information \( \mu_{i,t} \) in equation (OA.1) rising with earnings and from left skewness in
the earnings distribution. These examples provide highly limited support for this point; the former
example is inconsistent with the empirical fact that the variance of returns is U-shaped with respect
to earnings, and the latter example is consistent with conditional conservatism.⁵

³ Despite Dietrich et al.’s [2007] framing of the sample variance ratio bias using linear models, it may be argued that
sample variance ratio bias arises in Basu’s piecewise linear model because the sample variances are truncated sample
variances. However, as explained below, Dietrich et al.’s [2007] analysis shows that returns-earnings endogeneity is
neither necessary nor sufficient for truncation bias to exist, and that the more endogenous returns are to earnings, the
weaker is the truncation bias.

⁴ Beaver et al. [1987] is the first accounting paper to make this point. The authors show that partitioning on the
dependent variable \( R_{i,t} \) in a forward regression yields bias in the slope coefficient owing to the induced association
between the average values of \( R_{i,t} \) and \( \mu_{i,t} \) for the partitions.

⁵ Dietrich et al. [2007] (section 1.6) state three general conditions (a symmetric earnings distribution, a mean zero and
symmetric distribution of other information, and formation of the good and bad news samples at the mean of returns)
under which they claim that AT estimates are not biased. They argue that, if these conditions are not met, bias in AT
estimates “likely would result”. However, conditional conservatism itself would violate the first of these conditions.
Dietrich et al.’s [2007] equations (1.7a) to (1.9) indicate, however, that absent additional assumptions they cannot sign the sample truncation bias, which depends on the joint distribution of $X_{i,t}$ and $\mu_{i,t}$. Moreover, returns being endogenous with respect to earnings is neither necessary nor sufficient for this bias to exist. Dietrich et al.’s [2007] Section 1.7.4 implies that the more endogenous returns are with respect to earnings, the weaker the truncation bias. In our view, for the possibility of sample truncation bias to have meaningful implications for whether, and if so how, researchers should use reverse regression models to investigate conditional conservatism, researchers must specify aspects of the joint distribution of $X_{i,t}$ and $\mu_{i,t}$ that give rise to this bias. In the following section, we discuss the first study that does something akin to this, Patatoukas and Thomas [2011].

Based on the discussion above, we conclude that the sample variance ratio bias is of insufficient concern and the sample truncation bias is of insufficient specificity to contradict the use of Basu’s model and AT measure given their accounting centrality, straightforward intuition, and empirical simplicity.

OA.2. The loss and return variance effects (Patatoukas and Thomas [2011])

Relaxing Dietrich et al.’s [2007] assumption that earnings and other information are each drawn from a single distribution, Patatoukas and Thomas [2011] examine two empirically

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6 Forward regressions of returns on earnings also suffer from endogeneity bias, because earnings are influenced by returns (Beaver, McAnally, and Stinson [1997], Beaver, Landsman and, Owens [2012]) for various reasons. For example, goodwill impairments are triggered by share price declines (Comiskey and Mulford [2010]; Chen, Shroff and, Zhang [2019]). More generally, managers of firms whose stock prices decline (rise) likely make economic and earnings management decisions to mitigate these declines (exploit these increases) (Bond, Edmans and, Goldstein [2012], Badia, Duro, Jorgensen and, Ormazabal [2020]). Hence, it is not obvious that endogeneity bias is a larger consideration in the reverse regression than in the forward regression. In addition, Dietrich et al.’s [2007] assumptions for equation (B.1) ignore the well-known and sizeable biases in forward regressions attributable to white-noise or serially correlated measurement errors in earnings. White-noise measurement errors in earnings are eliminated (i.e., pass through to the residual) in reverse regressions. Other types of measurement errors (e.g., lags) in earnings are more readily modeled in reverse regressions than in forward regressions. In practice, it is not clear that any sample truncation bias in Basu’s piecewise linear regression is more severe than the biases in forward regressions.
pervasive scale-related forms of cross-sectional heterogeneity that affect Basu’s AT measure. First, smaller firms have higher losses and with higher frequency (the “loss effect”, see their Figure 1, Panel A). Second, smaller firms have higher return variability (the “return variance effect”, see their Figure 1, Panels B and C). These effects are not directly related to conditional conservatism and, according to Patatoukas and Thomas, they do not individually yield bias in Basu’s AT measure, but together they have direct and strong effects on this measure. These effects apply in some fashion to all of the AT measures based on firm-specific news proxies in the literature (e.g., Dutta et al. [2020]), not just to Basu’s AT measure. For example, conditionally conservative accruals are more negative and innovations in cash flow from operations are more variable for smaller firms.

The following example depicted in Figure 1, Panels C-D illustrates the loss and return variance effects and how they interact. Assume that firms have one of two scales, large or small, that no AT exists for either scale group, and more generally that the simple linear reverse regression of earnings on returns, equation (OA.2), is well specified for each scale group. Under this assumption, equation (OA.2) explains earnings just as well as Basu’s more expansive piecewise linear reverse regression, equation (1), for each scale group. However, owing to the loss effect, equation (OA.2) for the large-firm group lies above this equation for the small-firm group. Owing to the return variance effect, the observations of returns tend to take more central (extreme negative and positive) values for the large-firm (small-firm) group. When Basu’s piecewise linear

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7 More generally, the loss effect involves smaller firms having lower average scaled earnings than larger firms. However, Patatoukas and Thomas [2011] (Figure 1, Panel A) show that the average of positive earnings scaled by beginning market value does not vary with lagged price, so the loss effect is driven by firms with negative earnings. Patatoukas and Thomas [2011] proxy for scale using price, but there is a strong correlation between price and other measures of firm size, such as market value, so we frame our discussion in terms of size. 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.
regression is estimated on the pooled sample containing the two scale groups, the estimation weights the small-firm group more than the large-firm group in both tails of returns, and it weights the large-firm group more than the small-firm group for central values of returns, yielding AT that is unrelated to conditional conservatism in either group, i.e., bias. It is the combination of the loss effect, which involves vertical shifts in equation (OA.2) across the scale groups, and the return variance effect, which involves distinct clustering of returns for the scale groups, and the fact that these effects are both scale related, that yields bias.

Patatoukas and Thomas [2011] conduct several analyses that demonstrate the existence of the loss and return variance effects and the magnitude of the resulting bias in Basu’s AT measure. Most of these analyses are placebo tests in which the dependent variable in Basu’s linear piecewise regression, equation (1), is replaced with a variable for which any observed AT with respect to current returns cannot plausibly be ascribed to conditional conservatism. First, primarily to demonstrate the loss effect, Patatoukas and Thomas [2011] estimate equation (1) replacing the numerator of the dependent variable with lagged earnings, which should not reflect current returns. Despite this fact, they find significant AT (see their Table 3, Panels A and B). This finding reflects the fairly high positive serial correlation in earnings. A firm with a loss rather than a gain in the current year is more likely to have a loss in prior years, causing the loss effect to also be present in lagged earnings. Second, to demonstrate the return variance effect, Patatoukas and Thomas [2011] estimate equation (1) replacing the dependent variable with the reciprocal of lagged price. They find a V-shaped relationship between the reciprocal of lagged price and returns, i.e., a negative association between the reciprocal of lagged price and negative returns and a positive association between the reciprocal of lagged price and positive returns (see their Table 3, Panel A). This finding reflects low-price firms tending to have more extreme returns. Third, they
document that annual cross-sectional estimates of Basu’s AT measure are strongly positively
(negatively) correlated over time with annual cross-sectional estimates of AT using lagged
earnings (the reciprocal of lagged price) as the dependent variable in equation (1) (see their Figure
3). The findings for lagged earnings (the reciprocal of lagged price) are consistent with the
variation in Basu’s AT measure over time being attributable at least in substantial part to variation
in the bias attributable to the loss effect (return variance effect) over time, rather than to variation
in conditional conservatism over time.

To see how the accrual component of earnings manifests the loss effect, Figure OA.1
depicts, for each decile of lagged price, the means and frequencies of negative lagged earnings and
negative lagged cash flow from operations, with both variables scaled by lagged market value.
Inspection of this figure shows that scale is more strongly negatively related to the mean and more
positively related to the frequency of negative earnings than it is to the mean and frequency of
negative cash flow from operations.

Patatoukas and Thomas [2011] (Table 3, Panel D) find that estimating an expansion of
equation (1) that includes the reciprocal of price as a control for scale, as suggested by Beaver and
Ryan (2009), mitigates but does not eliminate the bias. Ball et al. [2013a], which we discuss in the
following section, emphasize that this finding does not imply that the bias cannot be mitigated
further by better controls for scale. As we explain in Section OA.3 and show empirically in Section
3.2, Patatoukas and Thomas’ [2011] scale-related biases are largely eliminated by the use of
unexpected earnings ($UX_{i,t}$), unexpected returns ($UR_{i,t}$), and the inclusion of firm fixed effects and
interactive $VarR_{i,t}$ and $MTB_{i,t-1}$ controls in our modified Basu model, equation (2).

Patatoukas and Thomas [2011] (p. 1772) attempt to relate their loss and return variance
effects, which involve scale-related sample heterogeneity, to Dietrich et al.’s [2007] modeling of
sample truncation bias in an assumed homogenous sample; we discuss this modeling in detail in Section OA.1. In our view, this attempt is strained, although we agree that sample heterogeneity can affect the joint distribution of earnings and other information in a fashion that yields a bias akin to sample truncation bias in a homogeneous sample. We also agree with Patatoukas and Thomas’ [2016] (p. 627) overall conclusion that bias may arise whenever earnings is associated with the second or higher moments of the distribution of returns.

OA.3. The conditional covariances of the expected and unexpected components of earnings and returns (Ball et al. [2013a], Patatoukas and Thomas [2016])

Ball et al. [2013a] suggest that the bias in Basu’s AT measure documented by Patatoukas and Thomas [2011] is attributable to the covariance between expected earnings and expected returns depending on the sign of returns. Ball et al. [2013a] provide evidence that this bias can be substantially mitigated but not eliminated by estimating and removing the expected components of earnings and returns in one of three alternative ways: (1) the linear (i.e., non-interactive) inclusion of scale-related control variables in the model (their Table 3), (2) the use of first-stage expectations models for earnings and returns (their Table 4), or (3) the inclusion of firm fixed effects in panel data models (their Table 5).

However, Patatoukas and Thomas [2016] (Table 4, row 1) provide evidence that the conditional covariance of the expected components of earnings and returns does not vary with the sign of returns, suggesting that this covariance does not yield substantial bias in Basu’s AT measure. In contrast, Patatoukas and Thomas [2016] (Table 4, rows 2 and 4) provide evidence that the conditional covariances of both expected and unexpected earnings with unexpected returns vary with the sign of returns, suggesting that these covariances yield upwardly biased AT

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8 Following prior research, we refer to the covariance between an earnings variable and a returns variable conditional on the sign of the returns variable as a “conditional covariance”.

OA-9
estimates. Moreover, they provide evidence that controlling for expected earnings and expected returns does not remove the bias in Basu’s AT measure (Patatoukas and Thomas [2016], Tables 1 and 2). We are largely able to replicate Patatoukas and Thomas’ [2016] findings.

We explain the divergent findings and conclusions of Ball et al. [2013a] and Patatoukas and Thomas [2016] as follows. Ball et al.’s [2013a] various approaches to removing the mean of earnings remove a sizeable portion of the loss effect. However, because none of their approaches allows the mean of earnings for a firm to vary as its scale varies over time, some of the loss effect likely remains. In addition, Ball et al.’s [2013a] approaches to removing the mean of returns do essentially nothing to mitigate the return variance effect. Since Patatoukas and Thomas [2011] claim that the loss and return variance effects do not individually yield bias in AT estimates, there are two possible non-mutually exclusive explanations for Patatoukas and Thomas’ [2016] findings that scale-related bias remains after applying Ball et al.’s [2013a] approaches. The first is that Ball et al.’s [2013a] approaches to removing the mean of earnings are imperfect, and a sufficiently large portion of the loss effect remains that interacts with the unchanged return variance effect.

The second explanation is that at least one other scale-related effect exists that interacts with the return variance effect. In this respect, the case presented in Figure 1, Panel C1, is a simplification of economic reality. A more realistic case is to assume that the association between earnings and returns is not the same across firms of different scale. Figure 1, Panel D2, presents such a case in a pooled sample comprised of two scale groups, large and small, each of which does not exhibit AT and for which the association between earnings and returns is different (i.e., the

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9 Because Patatoukas and Thomas [2016] scale each conditional covariance by the conditional variance of returns rather than by the applicable conditional variance of expected or unexpected returns, their analysis cannot provide evidence regarding whether these conditional covariances yield bias in Basu’s AT measure.
slope is different). Even in the absence of the loss effect, estimating Basu’s model on the pooled sample yields a biased AT that is unrelated to conditional conservatism in either group.

In addition, prior research, the bulk of which predicts and finds that conditional conservatism decreases with firm size (e.g., Watts and Zimmerman [1986], Ball [2001], Watts [2003a], Ball and Shivakumar [2005], Khan and Watts [2009]), provides a likely complementary scale-related effect that shows that even the return variance effect by itself can bias AT estimates when groups of different scale exhibit differential nonlinearities in the relationship between earnings and returns (i.e., different real ATs). Because groups of different scale exhibit differential nonlinearity in the relationship between earnings and returns, the problem in estimating equation (1) on the pooled sample of the groups discussed in Section OA.2 in the context of the loss effect remains—i.e., the estimation weights smaller-scale groups more than larger-scale groups in both tails of returns and larger scale groups more than smaller scale groups for central values of returns—albeit with subtler implications. These shifting weights on the observations in the different scale groups for different values of returns yields an estimate of AT in the pooled sample that is not a meaningful weighted-average of the estimates of AT for the two groups, i.e., bias.

Figure OA.2 depicts this bias for a simple numerical example with two groups, one in Panel A with large scale (and thus low return variance) and low AT and the other in Panel B with small scale (and thus high return variance) and high AT. Specifically, returns, the explanatory variable, takes three possible values (−10%, 0%, 10%). The large-firm group has 60% (20%) of its observations with 0% (both −10% and 10%) returns, and the small-firm group has 20% (40%) of its observations with 0% (both −10% and 10%) returns. The two groups have equal numbers of observations and AT is six times larger for the small-firm group (1.05) than for the large-firm group (0.17). To portray this bias as distinct from the one arising from the interaction of a constant
loss effect with the return variance effect, we remove the scale-group mean of earnings, the
dependent variable, to suppress the loss effect. For central values of returns, mean-adjusted
earnings is considerably higher for the small-firm group than for the large-firm group. In contrast,
for extreme values of returns, mean-adjusted earnings is fairly similar for the two groups. Primarily
because there are more observations with central values of returns in the large-firm group, as
depicted in Panel C the estimate of AT in the pooled sample (0.40) is well below the simple average
estimate of AT in the two scale groups, i.e., the coefficient absent the return variance effect [0.61
= (1.05 + 0.17)/2].

OA.4. AT in non-conditionally conservative earnings components (Basu [1997], Collins et al.
[2014], Dutta et al. [2020])

Earnings contains both cash flow from operations and accruals. Accounting-rules-driven
conditional conservatism naturally does not apply directly to cash flow from operations, which
incorporates operating receipts and expenditures as they occur, i.e., symmetrically. However,
replacing earnings with cash flow from operations in equation (1), Basu finds evidence that cash
flow from operations exhibits AT, a finding confirmed by subsequent studies (e.g., Ball et al.
[2000] and Collins et al. [2014]). Hence, when AT is measured using earnings as the dependent
variable, not all of the observed AT is attributable to conditional conservatism.

The post-Basu literature quickly recognized that AT in cash flow from operations likely is
attributable to economic phenomena, such as economic success coming slower for firms than
decline or failure (e.g., Watts [2003a,b]) and the business cycle (Khurana, Martin, Pereira and,
Raman [2005]). More recently, Collins et al. [2014] show that this AT depends on firms’ life-cycle
stage. For young firms, the association between cash flow from operations and unfavorable returns
is strongly positive, but the association of cash flow from operations with positive returns is weaker
because these firms are usually valued based on their growth prospects. In contrast, Collins et al.
[2014] find minimal AT in cash flow from operations for mature firms.

Similarly, Dutta et al. [2020] distinguish three components of accruals: (1) short-term operating accruals, such as accounts receivable, that primarily smooth intertemporal fluctuations in cash flow from operations; (2) conditionally conservative accruals, such as impairment write-downs of inventory and long-lived tangible and intangible assets; and (3) depreciation and amortization expense, which is largely a deterministic allocation of prior investing cash or non-cash outflows. Using the innovation in cash flow from operations from a first-order autoregressive process as the news proxy, Dutta et al. [2020] predict and provide evidence that (1) short-term operating accruals do not exhibit AT; (2) conditionally conservative accruals exhibit AT; and (3) depreciation and amortization expense exhibit AT. They provide evidence that the last finding is attributable to financing frictions leading firms to increase their investing cash outflows, and thus subsequent depreciation and amortization expense, when they experience positive innovations in cash flow from operations.10

Collins et al. [2014] (Dutta et al. [2020]) recommend estimating AT using (conditionally conservative) accruals instead of earnings as the dependent variable in equation (1).11 We view these recommendations as unnecessary. They are unnecessary because the drivers of AT in cash flow from operations and depreciation and amortization expense are largely firm specific and thus readily captured by the inclusion of firm fixed effects and interactive $VarR_{t,t}$ controls. Specifically,

10 In untabulated analysis, we find evidence that the AT of depreciation and amortization expense with respect to the innovation in cash flow from operations is attributable to a version of the loss effect (i.e., depreciation and amortization expense is higher for smaller firms) rather than to financing frictions. Employing a placebo test as in Patatoukas and Thomas [2011], we find the AT in lagged depreciation and amortization expense (which is unaffected by current investing cash outflows) has similar sign and significance as the AT in current depreciation and amortization expense.

11 Collins et al. [2014] further claim that the use of accruals as the dependent variable in the Basu model mitigates most of the other biases in Basu’s AT measure identified in the literature, in particular, the bias associated with loss and return variance effects documented by Patatoukas and Thomas [2011]. However, Patatoukas and Thomas [2016] demonstrate that substantial bias remains when accruals are so used.
Collins et al. [2014] find that the inclusion of firm fixed effects eliminates AT in cash flow from operations, a finding that we replicate. We find that the inclusion of firm fixed effects eliminates about two-thirds of the AT in depreciation and amortization expense and that the additional inclusion of interactive $VarR_{i,t}$ controls renders this AT insignificant. Moreover, depending on the research context, these recommendations can potentially reduce statistical power, because the use of accruals can obscure or even remove firms’ application of conditional conservatism owing to the interrelationships between accruals and cash flow from operations (Collins et al. [2014], Dutta et al. [2020]) and because firms’ incentives are often contractually or noncontractually related to earnings (Collins et al. [2014], Schrand [2014]). In addition, the measurement of “conditionally conservative” accruals requires the researcher to make judgmental choices regarding measurement that can have non-trivial effects on empirical results. Nevertheless, we estimate our modified Basu model using accruals, conditionally conservative accruals, and accruals before depreciation and amortization expense as the dependent variable and obtain essentially identical inferences.

In the next two remaining sections, we discuss one other known source of statistical bias that affect Basu’s measure of asymmetric timeliness (AT), returns aggregation (Givoly et al.

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12 The interrelationships between accruals and cash flow from operations include accruals smoothing time-series volatility in cash flow from operations as well as various forms of economic interplay, such as this one described by Collins et al. [2014] (pp. 197−198): “Management is more likely to have control over when cash outflows are realized than when cash inflows are realized. Consequently, firms that experience bad news and accrue losses are more likely to take actions that result in realization of cash outflows in the same accounting period that losses are accrued…This could result in cash flow asymmetry that mirrors the accrual asymmetry and both would contribute to asymmetric timeliness of earnings. Under this scenario, cash flow asymmetric timeliness is not directly affected by differential verification thresholds for recognizing the cash flows, but the differential verification thresholds for accruals and the actions that management may take in response to these accruals cause cash flows to exhibit the asymmetric patterns in good and bad news environments. Therefore, the cash flow component of earnings could be viewed as an important component of the timely signal about bad news imposed by conservative accounting rules.”

13 The measurement of conditionally conservative accruals involves non-trivial difficulty. For instance, the measures developed by Larson et al. [2018] and Dutta et al. [2020] have a Pearson (Spearman) correlation of only 0.61 (0.33), suggesting that one or both of these measures capture these accruals with substantial error. Thus, even under a narrower definition of conditional conservatism, there is a measurement error trade-off between using unexpected earnings with fixed effects (which in our sample remove asymmetric timeliness due to cash flows and non-conditionally conservative accruals effectively) and using conditionally conservative accruals (which have the challenge of separating which part of accruals are conditionally conservative).
and we also develop a firm-year measure of conditional conservatism based on our modified Basu model following the procedures of Khan and Watts [2009].

OA.5. Effect of returns aggregation on the AT estimate (Givoly et al. [2007])

Under the assumption that firms apply conditional conservatism to individual news events, Givoly et al. [2007] show that the aggregation of multiple individual news events during a period in firms’ periodic earnings and returns attenuates Basu’s AT measure relative to individual-news-event AT (which is unobservable given periodic reporting). Intuitively, individual good and bad news events of equal absolute magnitude offset perfectly in periodic returns but only partially in periodic earnings, which reflects the bad news more than the good news. This aggregation of good and bad news events during a period thus effectively creates measurement error in periodic returns as a predictor of conditionally conservative earnings. Moreover, this measurement error typically should be greater for larger firms with richer information environments and thus more frequent news events that move share price less, yielding a negative association between Basu’s AT measure and firm size. This association is in the same direction as predicted by certain economic theory discussed in Section 3.6 of the paper, i.e., large firms report less conservatively because they have richer information environments and thus less information asymmetry between firms and their stakeholders, as well as greater diversification of news across business units (Easley et al. [2002], LaFond and Watts [2008], Khan and Watts [2009]).

To assess the impact of aggregation on Basu’s AT measure, Givoly et al. [2007] develop a proxy for the extent to which periodic returns are dominated by a few large price-moving events, which they refer to as “dominance” ($DOM_{t,i}$). Givoly et al. [2007] find that controlling for $DOM_{t,i}$ eliminates the negative association between AT and firm size. They conclude that the aggregation of individual news events, rather than the economic theory mentioned above, explains this
association. Basu [2009] (p. 11) contests this conclusion, and more generally the assumption underlying Givoly et al.’s [2007] analysis, positing that “accountants do not apply conditional conservatism event by event; rather write-downs are typically based on a comparison of fair values and book values at the end of the reporting period. The relevant information that could change the impairment decision from the previous period is the entire change in fair value in the current period. I am unaware of any accounting or auditing standard or interpretation that conditions the write-down on whether the price fell steadily (“uniformly”) or sharply (“extreme”) or in any other manner during the period.”

Collins et al. [2014] replicate Givoly et al.’s [2007] tests using accruals rather than earnings as the dependent variable, and they find that the attenuating effect of controlling for $DOM_{it}$ on the negative association between firm size and Basu’s AT measure disappears. Table OA1 reports similarly motivated replications estimating our modified Basu model, equation (2), first as expressed in Table 6, Panel C of the paper and then adding interactive controls for $DOM_{it}$, for partitions of the sample into size quintiles. Column (1) confirms that mean $DOM_{it}$ decreases monotonically with size quintile. Column (2) reports the AT estimates from equation (4), which decline strongly with size quintile. Column (3) reports the AT estimates including interactive $DOM_{it}$ controls, which decrease more strongly and monotonically with size quintile than those reported in column (2). Intuitively, the modest effect of including interactive $DOM_{it}$ controls to our modified Basu model reflects the high Pearson (Spearman) correlation of $VarR_{it}$ and $DOM_{it}$ of 0.46 (0.64), so that the interactive $VarR_{it}$ controls largely subsume the effect of the interactive $DOM_{it}$ controls. Based on these results and those of Collins et al. [2014], we conclude that it is not necessary to control for $DOM_{it}$.
OA.6. Firm-year measure of conditional conservatism (Khan and Watts [2009])

Paralleling Khan and Watts’ [2009] firm-year measure of conditional conservatism, C_Score, in this section we develop and validate a firm-year measure of conditional conservatism based on our modified Basu model, equation (2). To enable annual estimation, we exclude firm fixed effects. As in Khan and Watts [2009], we include additional interactive controls for firm size (Size_{i,t-1}) and financial leverage (Lev_{i,t-1}). The resulting model is

\[ UX_{i,t} = \beta_0 + \beta_1 D_{i,t} + \beta_2 Size_{i,t-1} + \beta_3 MTB_{i,t-1} + \beta_4 Lev_{i,t-1} + \beta_5 D_{i,t} Size_{i,t-1} + \]

\[ \beta_6 D_{i,t} MTB_{i,t-1} + \beta_7 D_{i,t} Lev_{i,t-1} + \beta_8 UR_{i,t} + \beta_9 UR_{i,t} Size_{i,t-1} + \]

\[ \beta_{10} UR_{i,t} MTB_{i,t-1} + \beta_{11} UR_{i,t} Lev_{i,t-1} + \beta_{12} D_{i,t} UR_{i,t} + \beta_{13} D_{i,t} UR_{i,t} Size_{i,t-1} + \]

\[ \beta_{14} D_{i,t} UR_{i,t} MTB_{i,t-1} + \beta_{15} D_{i,t} UR_{i,t} Lev_{i,t-1} + \beta_{16} VarR_{i,t} + \beta_{17} D_{i,t} VarR_{i,t} + \]

\[ \beta_{18} UR_{i,t} VarR_{i,t} + \beta_{19} D_{i,t} UR_{i,t} VarR_{i,t} + \varepsilon_{i,t}. \]  

(OA3)

Like Khan and Watts [2009], we estimate equation (OA3) annually. For this reason, we cannot use firm fixed effects and replace observed returns, R_{i,t}, with unexpected returns, UR_{i,t}. Using the annual coefficient estimates, we calculate our modified C_Score as \( \beta_{12} + \beta_{13} Size_{i,t-1} + \beta_{14} MTB_{i,t-1} + \beta_{15} Lev_{i,t-1} \) for each firm year.

To validate our modified C_Score, we partition the sample annually into deciles based on this measure and estimate our modified Basu model, equation (2), for each decile. Table OA2, Panel A, column (2) reports the AT estimate \( \beta_3 \) from the estimation of our modified Basu model, equation (2) for each decile of modified C_Score. As expected, the AT estimate increases strongly and monotonically with the modified C_Score deciles, with the two variables having a high rank correlation of 0.927.

To provide further validation, for each decile of modified C_Score we estimate an alternative measure of conditional conservatism developed by Dutta and Patatoukas [2017], the...
spread in the conditional variances of accruals, \( SCV_{i,t} = \text{Var}(ACC_{i,t} | UR_{i,t} < 0) - \text{Var}(ACC_{i,t} | UR_{i,t} \geq 0) \). Dutta and Patatoukas [2017] show that the variance of \( ACC_{i,t} \) is higher when news is bad \( (UR_{i,t} < 0) \) than when it is good \( (UR_{i,t} \geq 0) \), i.e., that \( SCV_{i,t} \) is positive. In contrast, they show that the variance of the placebo \( ACC_{i,t-1} \), i.e., lagged accruals, does not differ significantly when current news is bad \( (UR_{i,t} < 0) \) than when it is good \( (UR_{i,t} \geq 0) \). Columns (3), (4) and (5) of Table OA2 report \( SCV \) calculated with conditionally conservative accruals \( (CCACC_{i,t}) \), with unexpected conditionally conservative accruals \( (UCCACC_{i,t}) \), and with accruals before depreciation and amortization expense \( (ACCBFD_{i,t}) \) respectively, for each decile of modified C_Score. In the three columns, \( SCV_{i,t} \) increases strongly and almost monotonically with the modified C_Score deciles, with the three accruals variables having very high rank correlations with \( SCV_{i,t} \) of 0.988 in the three cases.

Finally, for comparison purposes, we conduct similar analysis forming deciles based on Khan and Watts’ [2009] original C_Score. Table OA2, Panel B, column (2) reports that the AT estimate \( \beta_3 \) of our modified Basu model, equation (8), increases with the original C_Score decile, with the two variables having a rank correlation of 0.903. Columns (3), (4) and (5) report that the rank correlations of original C_Score decile with the same three \( SCV_{i,t} \) measures are 0.867, 0.915 and 0.782, respectively. Hence, our modified C_Score appears to constitute a significant improvement in construct validity over Khan and Watt’s [2009] original C_Score, although the original C_Score still does a decent job in capturing conditional conservatism.
References


Appendix A: Additional variable definitions

**DOM**
Proxy of aggregation of equity returns based on Givoly, Hayn, and Natarajan [2007]: $(|CUM^+| - |CUM^-|) / \text{Larger of (}|CUM^+| \text{ or } |CUM^-|)$, where $CUM^+$ and $CUM^-$ are the accumulations over intervals of 5 days in the reporting period (the fiscal year) with positive and negative total returns, respectively. It captures the extent to which aggregate returns of a period are dominated by relatively few price-moving events.

**CCACC**
Conditionally conservative accruals scaled by market value of equity at the beginning of the fiscal year $(PRCC_F*CSHO)_{t-1}$. Conditionally conservative accruals are measured as in Larson et al. [2018] as $\min(\{-FOPO + TXBCO + STKCO, 0\}) + \min((XIDO - XIDOC), 0)$, where $\min(x,y)$ is the minimum of $x$ and $y$; Missing variables of any of the components of conditionally conservative accruals are treated as 0.

**UCCACC**
Unexpected conditionally conservative accruals measured as in Patatoukas and Thomas [2016] (footnote 15) as the estimated residuals from the regression model $CCACC_{i,t} = \alpha_0 + \alpha_1 CCACC_{i,t-1} + \varepsilon_{i,t}$ for the two-digit SIC industry and year.

**ACCBFD**
Accruals before depreciation and amortization expense from the cash flow statement, computed as income before extraordinary items minus cash flow from operations plus is extraordinary items and discontinued operations from the statement of cash flows plus depreciation and amortization expense, scaled by market value of equity at the beginning of the fiscal year, $(IB - OANCF + XIDOC + DPC)_t / (PRCC_F*CSHO)_{t-1}$. 
Figure OA.1: Bias attributable to the loss effect

This figure depicts, for each decile of lagged price, the means of negative lagged earnings $X_{t-1}$, and negative lagged CFO$_{t-1}$, with both variables scaled by lagged price, denoted Level of negative lagged earnings and Level of negative lagged earnings CFO, respectively. The figure also depicts the frequencies of negative lagged earnings and lagged CFO, denoted Frequency of negative earnings and Frequency of negative CFO, respectively.
Figure OA.2: *Other* scale-related bias

**Panel A**: Regression for large-firm sample

![Large scale](image)

**Panel B**: Regression for small-firm sample

![Small scale](image)
The figure depicts the joint impact of other scale-related differences in AT and the return effect on AT estimates. The figures depict a two-group sample, one group with large scale (and thus low return variance) and low AT and the other with small scale (and thus high return variance) and high AT. To portray this bias as distinct from the one attributable to the interaction of the loss effect with the return variance effect, we mean-adjust the dependent variable (and thus remove the average loss effect) for each group. To ensure mathematical consistency, the figure is drawn to scale for a simple numerical example in which returns take three possible values (-10%, 0%, 10%). The high scale group has 60% (20%) of its observations with 0% (both -10% and 10%) returns and the low scale group has 20% (40%) of its observations with 0% (both -10% and 10%) returns. To enhance visibility, observations with 0% returns have been plotted around zero in the returns axis. The large-firm and small-firm groups have equal total numbers of observations and (true) AT is six times larger for the small-firm group than for the large-firm group. The mean adjustment drives the value of the adjusted dependent variable for central values of returns for the small-firm group well above that for the large-firm group, whereas the value of the adjusted dependent variable for extreme values of returns are fairly similar for the two scale groups (in this example). Primarily because there are more observations with central values of returns in the high scale group, the estimate of AT in the pooled sample is well below the weighted average estimate of asymmetry in the two scale groups.
Table OA1
Effect of aggregation on the AT estimate (dominance effect of Givoly et al. [2007]).

<table>
<thead>
<tr>
<th>Size quintiles</th>
<th>Mean DOM</th>
<th>AT in modified Basu model without DOM controls</th>
<th>AT in modified Basu model with DOM controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (smallest)</td>
<td>0.766</td>
<td>0.204</td>
<td>0.242</td>
</tr>
<tr>
<td>2</td>
<td>0.722</td>
<td>0.113</td>
<td>0.113</td>
</tr>
<tr>
<td>3</td>
<td>0.694</td>
<td>0.117</td>
<td>0.114</td>
</tr>
<tr>
<td>4</td>
<td>0.660</td>
<td>0.079</td>
<td>0.048</td>
</tr>
<tr>
<td>5 (biggest)</td>
<td>0.612</td>
<td>0.017</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

Rank correlation with size quintile
-1.000 -0.900 -1.000

Size quintiles are determined annually based on the market value of equity at the beginning of the fiscal year. To avoid the influence of penny stocks, observations with stock price below one dollar are removed.

In column (1), DOM is the proxy of aggregation of equity returns over the fiscal year developed by Givoly et al. [2007] measured for intervals of five days over the fiscal year. It captures the extent to which aggregate returns of a period are driven by relatively few price-moving events.

In column (2), AT is the $\beta_3$ coefficient of estimating the following modified Basu regression, which includes firm fixed effects, for each size quintile:

$$UX_{it} = \alpha_i + \beta_1 D_{it} + \beta_2 UR_{it} + \beta_3 D_{it} UR_{it} + \beta_4 VarR_{it} + \beta_5 D_{it} VarR_{it} + \beta_6 UR_{it} VarR_{it} + \beta_7 D_{it} UR_{it} VarR_{it} + \beta_8 MTB_{it-1} + \beta_9 D_{it} MTB_{it-1} + \beta_{10} UR_{it} MTB_{it-1} + \beta_{11} D_{it} UR_{it} MTB_{it-1} + \beta_{12} D_{it} UR_{it} MTB_{it-1} + \beta_{13} D_{it} UR_{it} MTB_{it-1} + \beta_{14} URR_{it} MTB_{it-1} + \beta_{15} D_{it} UR_{it} DOM_{it} + \epsilon_{it}$$

where UX is current unexpected earnings, scaled by market value of equity at the beginning of the fiscal year. UR is the unexpected annual equity return for the fiscal year. D equals one if UR<0, and zero otherwise. VarR is the variance of equity returns. MTB is the market-to-book ratio of assets at the beginning of the fiscal year.

In column (3), AT is the $\beta_3$ coefficient of estimating the following regression, which includes firm fixed effects, augmented with DOM, defined as log(DOM) to control for the effect of aggregation:

$$UX_{it} = \alpha_i + \beta_1 D_{it} + \beta_2 UR_{it} + \beta_3 D_{it} UR_{it} + \beta_4 VarR_{it} + \beta_5 D_{it} VarR_{it} + \beta_6 UR_{it} VarR_{it} + \beta_7 D_{it} UR_{it} VarR_{it} + \beta_8 MTB_{it-1} + \beta_9 D_{it} MTB_{it-1} + \beta_{10} UR_{it} MTB_{it-1} + \beta_{11} D_{it} UR_{it} MTB_{it-1} + \beta_{12} DOM_{it-1} + \beta_{13} D_{it} DOM_{it} + \beta_{14} UR_{it} DOM_{it} + \beta_{15} D_{it} UR_{it} DOM_{it} + \epsilon_{it}$$
Table OA2
Firm-year measure of conditional conservatism (Khan and Watts [2009])

Panel A: modified C_Score

<table>
<thead>
<tr>
<th>Deciles of modified C_Score</th>
<th>(1) modified Basu AT</th>
<th>(2) modified C_Score SCV</th>
<th>(3) SCV CCACC</th>
<th>(4) SCV UCCACC</th>
<th>(5) SCV ACCBFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.028</td>
<td>0.09%</td>
<td>0.13%</td>
<td>0.09%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.094</td>
<td>0.30%</td>
<td>0.14%</td>
<td>0.14%</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.054</td>
<td>0.50%</td>
<td>0.31%</td>
<td>0.34%</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.075</td>
<td>0.60%</td>
<td>0.35%</td>
<td>0.58%</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.175</td>
<td>0.77%</td>
<td>0.47%</td>
<td>0.55%</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.150</td>
<td>0.63%</td>
<td>0.41%</td>
<td>0.71%</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.164</td>
<td>1.16%</td>
<td>0.89%</td>
<td>0.71%</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.219</td>
<td>1.32%</td>
<td>1.09%</td>
<td>1.31%</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.293</td>
<td>2.32%</td>
<td>1.79%</td>
<td>2.25%</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.380</td>
<td>3.96%</td>
<td>3.06%</td>
<td>6.15%</td>
<td></td>
</tr>
</tbody>
</table>

Rank correl. with mod. C_Score: 0.927, p-value: < 0.001

Panel B: original C_Score

<table>
<thead>
<tr>
<th>Deciles of original C_Score</th>
<th>(1) original C_Score AT</th>
<th>(2) modified Basu AT</th>
<th>(3) SCV CCACC</th>
<th>(4) SCV UCCACC</th>
<th>(5) SCV ACCBFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.123</td>
<td></td>
<td>0.69%</td>
<td>0.48%</td>
<td>0.61%</td>
</tr>
<tr>
<td>2</td>
<td>0.090</td>
<td></td>
<td>0.21%</td>
<td>0.16%</td>
<td>0.20%</td>
</tr>
<tr>
<td>3</td>
<td>0.080</td>
<td></td>
<td>0.27%</td>
<td>0.23%</td>
<td>0.23%</td>
</tr>
<tr>
<td>4</td>
<td>0.117</td>
<td></td>
<td>0.40%</td>
<td>0.30%</td>
<td>0.37%</td>
</tr>
<tr>
<td>5</td>
<td>0.134</td>
<td></td>
<td>0.67%</td>
<td>0.48%</td>
<td>0.57%</td>
</tr>
<tr>
<td>6</td>
<td>0.246</td>
<td></td>
<td>0.76%</td>
<td>0.59%</td>
<td>0.30%</td>
</tr>
<tr>
<td>7</td>
<td>0.257</td>
<td></td>
<td>1.14%</td>
<td>1.02%</td>
<td>0.90%</td>
</tr>
<tr>
<td>8</td>
<td>0.377</td>
<td></td>
<td>1.10%</td>
<td>0.90%</td>
<td>1.01%</td>
</tr>
<tr>
<td>9</td>
<td>0.322</td>
<td></td>
<td>1.66%</td>
<td>1.14%</td>
<td>1.76%</td>
</tr>
<tr>
<td>10</td>
<td>0.492</td>
<td></td>
<td>4.54%</td>
<td>3.18%</td>
<td>6.33%</td>
</tr>
</tbody>
</table>

Rank correl. with orig. C_Score: 0.903, p-value: < 0.001
Table OA2 (continued)

Panel A: the modified C_Score is based on the annual estimation of the following regression model:

\[ UX_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 Size_{it,1-1} + \beta_3 MTB_{it,1-1} + \beta_4 Lev_{it,1-1} + \beta_6 D_{it} MTB_{it,1-1} + \beta_7 D_{it} Lev_{it,1-1} + \beta_9 UR_{it} + \beta_{10} UR_{it} MTB_{it,1-1} + \beta_{11} UR_{it} Lev_{it,1-1} + \beta_{12} D_{it} UR_{it,1-1} + \beta_{13} D_{it} UR_{it} Size_{it,1-1} + \beta_{14} D_{it} UR_{it} MTB_{it,1-1} + \beta_{15} D_{it} UR_{it} Lev_{it,1-1} + \beta_{16} VarR_{it} + \beta_{17} D_{it} VarR_{it} + \beta_{18} UR_{it} VarR_{it} + \beta_{19} D_{it} UR_{it} VarR_{it} + \epsilon_{i,t} \]

The modified C_Score is \( \beta_{12} + \beta_{13} Size_{it,1-1} + \beta_{14} MTB_{it,1-1} + \beta_{15} Lev_{it,1-1} \) for each firm and year using the estimated coefficients from the annual regressions. UX is current unexpected earnings, scaled by market value of equity at the beginning of the fiscal year. UR is the unexpected annual equity return for the fiscal year. D equals one if UR<0, and zero otherwise. VarR is the variance of equity returns. Size is the natural logarithm of the market value of equity at the beginning of the fiscal year. MTB is the market-to-book ratio of assets at the beginning of the fiscal year. Lev is total interest-bearing debt scaled by market value of equity at the beginning of the fiscal year.

Column (2) contains the AT estimate \( \beta_3 \) from the estimation of our modified Basu model, equation (2), for each decile of the modified C_score:

\[ UX_{it} = \alpha_i + \beta_1 D_{it} + \beta_2 UR_{it} + \beta_3 D_{it} UR_{it} + \beta_4 VarR_{it} + \beta_5 D_{it} VarR_{it} + \beta_6 UR_{it} VarR_{it} + \beta_7 D_{it} UR_{it} VarR_{it} + \beta_8 VarR_{it} + \beta_9 D_{it} MTB_{it,1-1} + \beta_{10} UR_{it} MTB_{it,1-1} + \beta_{11} D_{it} UR_{it} MTB_{it,1-1} + \epsilon_{i,t} \]

Columns (3), (4) and (5) report the measure of conditional conservatism as the spread of conditional variances of accruals developed by Dutta and Patatoukas [2017], \( SCV = Var(Accruals | UR<0) - Var(Accruals | UR\geq0) \). SCV is estimated using three definitions of accruals: conditionally conservative accruals (CCACC), unexpected conditionally conservative accruals (UCCACC), and accruals before depreciation (ACCBFD). The detailed definition is on Appendix A of this Online Appendix.

Panel B: the original C_Score is based on the annual estimation of the following regression model:

\[ X_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 Size_{it,1-1} + \alpha_3 MTB_{it,1-1} + \alpha_4 Lev_{it,1-1} + \alpha_5 D_{it} Size_{it,1-1} + \alpha_6 D_{it} MTB_{it,1-1} + \alpha_7 D_{it} Lev_{it,1-1} + \alpha_8 R_{it} + \alpha_9 R_{it} Size_{it,1-1} + \alpha_{10} R_{it} MTB_{it,1-1} + \alpha_{11} R_{it} Lev_{it,1-1} + \alpha_{12} D_{it} R_{it} + \alpha_{13} D_{it} R_{it} Size_{it,1-1} + \alpha_{14} D_{it} R_{it} MTB_{it,1-1} + \alpha_{15} D_{it} R_{it} Lev_{it,1-1} + \epsilon_{i,t} \]

The original C_Score is \( \alpha_{12} + \alpha_{13} Size_{it,1-1} + \alpha_{14} MTB_{it,1-1} + \alpha_{15} Lev_{it,1-1} \) for each firm and year using the estimated coefficients from the annual regressions. X is current earnings, scaled by market value of equity at the beginning of the fiscal year. R is the observed annual equity return for the fiscal year. D equals one if R<0, and zero otherwise. The rest of variables have already been defined above.

Column (2) reports the AT estimate \( \beta_3 \) obtained from estimating the following modified Basu regression for each decile of the original C_Score:

\[ X_{it} = \alpha_i + \beta_1 D_{it} + \beta_2 R_{it} + \beta_3 D_{it} R_{it} + \beta_4 VarR_{it} + \beta_5 D_{it} VarR_{it} + \beta_6 R_{it} VarR_{it} + \beta_7 D_{it} R_{it} VarR_{it} + \beta_8 MTB_{it,1-1} + \beta_9 D_{it} MTB_{it,1-1} + \beta_{10} R_{it} MTB_{it,1-1} + \beta_{11} D_{it} R_{it} MTB_{it,1-1} + \epsilon_{i,t} \]

Columns (3), (4) and (5) report the same measures as in Panel A.