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Identifying accounting conservatism in the presence of skewness

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ABSTRACT

Previous studies have cast doubt on the construct validity of the asymmetric timeliness (AT) coefficient from the Basu (1997) model as a measure of conditional conservatism. The purpose of this paper is to clarify the exact conditions under which the AT coefficient fails to identify accounting conservatism. We show both analytically and by extensive simulations that the AT coefficient is not a reliable measure of accounting conservatism in the presence of skewness in returns and/or earnings unless returns are strictly exogenous. While earnings skewness is a predicted consequence of conditional conservatism, return skewness is arguably unrelated to conservative reporting. Return skewness therefore distorts the AT coefficient as a measure of conservatism. Simple skew reducing transformations or outlier-robust estimators do not overcome the distortion. Empirically, we provide evidence that cross-sectional variation in the AT coefficient, especially across groups sorted on firm size, is highly correlated with cross-sectional variation in skewness.

Keywords: conditional conservatism; asymmetric timeliness; piecewise linear regression; skewness.

JEL classification: M41, C15

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

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1. Introduction

Since Ball and Brown (1968), the financial accounting literature has studied the association between annual earnings and stock returns. There is a general consensus that accounting earnings lack timeliness (i.e., prices lead earnings), because generally accepted accounting principles (GAAP) trade-off relevance and timeliness of financial statement information in favor of reliability and verifiability (e.g., Dechow 1994; Collins et al. 1994; Kothari et al. 2010). Basu (1997) predicts that conditionally conservative conventions that underlie the accounting measurement process are the source of a state-dependent positive correlation between earnings and returns. Using firms' stock returns to measure news, Basu (1997) shows that the contemporaneous sensitivity of earnings to negative returns is two to six times higher than the sensitivity of earnings to positive returns. The incremental coefficient on negative returns in a piecewise-linear regression of scaled earnings on contemporaneous stock returns is known as the asymmetric timeliness (AT) coefficient and is the most widely used measure for assessing the degree of conservatism.[1]

In this paper, we analyze the validity of Basu's (1997) AT coefficient as a measure of accounting conservatism in the presence of skewed returns and earnings. Our analysis is motivated by the well-known fact that the distribution of long-run abnormal stock returns is positively skewed (e.g., Barber and Lyon 1997; Lyon et al. 1999), while the distribution of scaled earnings is negatively skewed (e.g., Deakin 1976, Frecka and Hopwood 1983; Givoly and Hayn 2000; Dietrich et al 2007).[2] Several recent studies cast doubt on the construct validity of the AT coefficient as a measure of conditional conservatism. Most notably, Dietrich et al. (2007) addresses

[1] Since Basu (1997), the terms Basu coefficient, asymmetric timeliness coefficient, and differential timeliness measures have been used in the literature interchangeably. As of 24 September 2020, 1,205 citations to Basu (1997) are recorded on Web of Science Core Collection and 5,262 are in Google Scholar.

[2] We treat the positive and negative skewness of returns and earnings as 'stylized facts.' Various studies have provided theoretical explanations for asymmetry in the (joint) distributions of earnings and returns (e.g., Black, 1976; Zhang, 2000; Albuquerque, 2012; Hemmer and Labro, 2019; and Breuer and Windisch, 2019).

the *sample truncation bias* resulting from dividing the sample based on a endogenous variable (returns), while Patatoukas and Thomas (2011, 2016) and Dutta and Patatoukas (2017) uncover biases in the AT coefficient induced by higher-order moments in the distribution of returns.[3]

The purpose of this paper is to clarify the exact conditions under which the AT coefficient fails to identify accounting conservatism. We gauge the joint impact of return skewness, earnings skewness, and return endogeneity on the validity of the AT coefficient and make three distinct contributions to the literature. First, we find that not only the positive skewness of returns but also the negative skewness of earnings can generate a spurious positive AT coefficient that is unrelated to conditional accounting conservatism. While negative earnings skewness is itself a predicted consequence of conservatism, it is certainly possible that cross-sectional differences in earnings skewness exist for reasons other than conditional conservatism (e.g. due to “big bath” reporting behavior), resulting in misleading inferences based on the AT coefficient. Second, we emphasize that the adverse impact of skewness on the AT coefficient only materializes when returns are endogenous, implying that skewness *per se* is not a sufficient condition for a spurious AT coefficient. In practice however, skewness generally distorts the AT coefficient, since strict exogeneity of returns with respect to earnings is not a realistic assumption to make. Third, we show that simple skew-reducing transformations of the data and outlier-robust estimators do not solve the issue. Asymmetry in the distributions of returns and earnings is generally a sign of nonlinearity in the underlying latent factors of returns and skewness (e.g. Ball et al. 2013a; Hemmer and Labro, 2019; and Breuer and Windisch, 2019). Adjusting for skewness ex-post using logarithmic and rank transformations, or by using outlier-robust estimators, does not remove this

[3] Other studies, including Gigler and Hemmer (2001), Givoly et al. (2007), Banker et al. (2016, 2017), Banker et al. (2017), Lawrence et al. (2018) point out the impact of various confounding factors, unrelated to conservative reporting, on the AT coefficient.

underlying nonlinearity and we find that spurious AT coefficients appear even after applying these transformations.

Overall, our results demonstrate that asymmetry in the distribution of both returns and earnings contaminates the AT coefficient as measure of conservatism. We first show analytically that the skewness of returns and earnings have predictable effects on the AT coefficient. We then conduct an extensive simulation study to document that a significant nonzero AT coefficient may emerge spuriously even if there is no conditional conservatism.[4] Building on the findings by Dietrich et al (2007), we document by simulation that a skewness-induced spurious component of the AT coefficient does not exist when returns are a strictly exogenous variable: when we simulate earnings as a linear function of exogenously realized returns, we do not find a spurious AT coefficient, even in the presence of skewness. This result follows from the well-known fact that unbiasedness of the OLS estimator does not require the variables to be Normally distributed, but it does require the independent variables to be exogenous (see, e.g. Greene, 2000). Next, our simulations demonstrate that the adverse effect of skewness on the AT coefficient occurs when the stock returns are an endogenous variable such that partition into positive and negative return samples is non-random. In other words, when we endogenize returns by specifying returns as a function of exogenous earnings, or when we generate earnings and returns simultaneously (i.e., both are endogenous), we do find a spurious AT coefficient when the variables are skewed. Since a strict exogeneity assumption of annual returns with respect to annual earnings is empirically unrealistic, the presence of skewness is of major concern for the measurement of conservatism.

[4] The accounting literature typically distinguishes the concept of unconditional conservatism from conditional conservatism (the traditional distinction is between balance sheet conservatism and income statement conservatism). Unconditional conservatism stems from predetermined aspects of the accounting process: the accountant should select from a range of possible values of net assets a relatively low value instead of the expected value (Ball and Shivakumar, 2005). Conditional conservatism is the accountants' tendency to require a higher degree of verification for recognizing good news than for recognizing bad news in financial statements (Basu, 1997).

We next study the latent variable model by Ball et al. (2013a), where earnings and returns are jointly realized as functions of unobservable components. We show analytically and by simulation that while the AT coefficient increases as a result of accounting conservatism, the AT coefficient is not necessarily zero in the absence of conservatism. Specifically, when the latent components are skewed, the AT coefficient is typically nonzero and significant, even in the absence of conservatism. A positive AT coefficient therefore does not necessarily identify conservatism. Within this latent-variable framework, we also illustrate that it is not possible to "fix" the AT measure by a logarithmic/rank transformation of the data or by using outlier-robust estimators. Skewness of the underlying components causes the relation between earnings and returns to be inherently nonlinear, which does not disappear when the observed returns and earnings are ex-post transformed to remove the skewness. This nonlinear relation between earnings and returns induces a nonzero AT coefficient while the underlying model is free of accounting conservatism, even after skew-reducing transformations have been applied to the data.

Empirically, we investigate cross-sectional variation in return skewness, earnings skewness, and asymmetric timeliness. Consistent with our analytical predictions, the empirical AT coefficients are strongly correlated to the skewness coefficients of unexpected earnings and unexpected returns.[5] Following Khan and Watts (2009), Ball et al. (2013b), and Patatoukas and Thomas (2016), the firm-specific characteristics that we consider are beginning-of-period size and the market-to-book ratio (MTB), because conservatism is expected to vary with these characteristics. Specifically, we construct deciles by independently sorting US firms on size and MTB, and estimate Basu's (1997) AT coefficient for each decile. In particular when sorting firms on size, it appears that cross-sectional variation in asymmetric timeliness coefficients merely

[5] Ball et al. (2013b) suggest measuring AT using the unexpected components of earnings and returns, as a remedy for the bias identified in Patatoukas and Thomas (2011).

reflects variation in return skewness. These empirical findings support our hypothesis that skewness constitutes a real concern in the context of the Basu model. In addition, Basu's (1997) AT coefficient indicates asymmetry in the timeliness of (unexpected) earnings and accruals, but also of cash flows. We take this as further evidence of spurious asymmetric timeliness, since cash flows are not subject to conservative reporting (e.g., Dietrich et al., 2007: Collins et al., 2014; Dutta and Patatoukas, 2017).

Taken together, our analytical, numerical, and empirical results indicate that AT coefficients are significantly distorted in the presence of skewness, such that inference based on estimated AT coefficients may be misleading. Concerning the distribution of earnings and accruals, we cannot rule out a "reverse causality" explanation, in which the skewness of observed earnings or accruals is by itself the result of accounting conservatism (Basu 1995; Ball et al. 2000; Givoly and Hayn 2000; Ball and Shivakumar 2005; Peek et al. 2010; Dutta and Patatoukas, 2017).[6] We can, however, safely assume that return skewness is unrelated to conservatism, and therefore contaminates the AT coefficient as a measure of conservatism. We stress that the OLS estimator of the AT coefficient is not statistically *biased*. The estimator correctly indicates asymmetry (or nonlinearity) in the earnings-returns relation, but this asymmetry is potentially driven by factors unrelated to conservatism. We conclude, therefore, that the AT coefficient does not reliably *identify* conditional conservatism in the presence of return skewness.

The following section outlines the Basu (1997) model and demonstrates the potentially adverse effects of the skewness of earnings and returns on the AT measure. In Section 3, we conduct a simulation exercise to demonstrate the properties of the AT measure under different

[6] For example, ASC 360 requires estimation of future undiscounted net cash flow to define the threshold loss level that triggers the asset write-down. If an impairment loss is recognized, then the amount is based on discounted net cash flows, potentially causing a large loss.

assumptions regarding the distribution and endogeneity of both returns and earnings. In Section 4, we examine the effect of skewness within the Ball et al. (2013a) latent variable framework and test the effect of skew reducing transformations. Section 5 present empirical results. Concluding remarks are provided in the final section of the paper.

2. Analytical background

In this section, we describe the Basu (1997) model and demonstrate analytically that skewness of earnings and returns can lead to nonzero values of the asymmetric timeliness (AT) coefficient, even in the absence of conditional conservatism. The Basu (1997) model, as modified by Ball et al. (2013a,b), can be described as follows:

$$I_{it} = \alpha_0 + \alpha_1 D_{it} + \beta_0 R_{it} + \beta_1 R_{it} \times D_{it} + \varepsilon_{it}, \tag{1}$$

where i and t are firm and year subscripts, respectively; I denotes price deflated unexpected earnings per share; R denotes unexpected stock returns; D is an indicator variable taking a value of 1 when $R < E[R]$, and zero otherwise; and β_1 is the AT coefficient. Because R and I represent *unexpected* returns and *unexpected* earnings, respectively, we assume that $E[R] = E[I] = 0$, where E is the standard expectation operator.[7] The AT coefficient can be equivalently obtained by estimating the simple regression

$$I_{it} = \alpha + \beta R_{it} + \varepsilon_{it} \tag{2}$$

separately for subsamples of observations with $R < 0$ and $R \geq 0$, and taking the difference between the slope estimates:

$$E\left[\hat{\beta}_1\right] = E\left[\hat{\beta}|R < 0\right] - E\left[\hat{\beta}|R \geq 0\right]. \tag{3}$$

[7] Henceforth for brevity, we use the terms earnings and returns to refer to their *unexpected* counterparts if not explicitly stated otherwise.

The OLS estimator of β in Eq. (2) is equal to:

$$\hat{\beta} = \frac{Cov(R, I)}{Var(R)} = \frac{\sigma_R \sigma_I \rho_{R,I}}{\sigma_R^2} = \frac{\sigma_I \rho_{R,I}}{\sigma_R}, \tag{4}$$

where σ_R is the standard deviation of returns; σ_I is the standard deviation of earnings; and $\rho_{R,I}$ is the correlation coefficient between returns and earnings. Using the previous notation, the AT coefficient and Eq. (3) can be expressed as follows:

$$E[\hat{\beta}_1] = E\left[\frac{(\sigma_{I|R<0})(\rho_{I,R|R<0})}{(\sigma_{R|R<0})}\right] - E\left[\frac{(\sigma_{I|R\geq 0})(\rho_{I,R|R\geq 0})}{(\sigma_{R|R\geq 0})}\right]. \tag{5}$$

This equation appears in a slightly different form in Pope and Walker (1999), Ball et al. (2013a,b), Patatoukas and Thomas (2016), and Dutta and Patatoukas (2017). We use Eq. (5) to illustrate our two main points: both positive skewness of returns *and* negative skewness of earnings can lead to a positive AT coefficient.

When returns are positively skewed, it follows from the definition of skewness that:

$$\sigma_{R|R\geq 0} \geq \sigma_{R|R<0}. \tag{6}$$

I.e., when returns are positively skewed, the standard deviation of returns is expected to be higher for a subsample of observations above the mean than for a subsample of observations below the mean. Assuming fixed values of σ_I and $\rho_{R,I}$, the first term of Eq. (5) is then larger than the second term because the denominators differ. The OLS estimator $\hat{\beta}_1$ in Eq. (1) will be positive even in the absence of conditional conservatism, simply due to return skewness. Dutta and Patatoukas (2017) show empirically that the conditional variance of positive unexpected returns is almost six times the conditional variance of negative unexpected returns. They conclude that "…asymmetry in the returns distribution has the potential to yield spurious evidence of conditional conservatism *even* if accounting is entirely symmetric".[8] However, it is important to note that unbiasedness of the OLS estimator does not require variables to be Normally distributed. As we show in the following section, skewness of returns does not always lead to a nonzero AT coefficient, because the assumption of fixed values of σ_I and $\rho_{R,I}$ does not necessarily hold. Specifically, as our simulations in the next section illustrate, if returns are specified as a strictly exogenous variable, the difference in σ_R (Eq. 6) is offset by simultaneous differences in σ_I and $\rho_{R,I}$, such that the AT coefficient (Eq. 5) will be zero.

Next, we show that, under empirically plausible conditions, negative skewness of earnings can generate a similar spurious positive estimate of the AT coefficient. Specifically, under the maintained assumption that earnings and returns are positively correlated (even in the absence of conditional conservatism), dividing the sample into subsamples of relatively high (low) returns will coincide with subsamples of relatively high (low) earnings. Thus, when earnings are negatively skewed, it follows that:

$$\sigma_{I|R\geq 0} \approx \sigma_{I|I\geq 0} < \sigma_{I|I<0} \approx \sigma_{I|R<0}. \tag{7}$$

I.e., when earnings are negatively skewed and positively correlated to returns, the standard deviation of earnings is anticipated to be higher for a subsample of earnings observations paired with relatively low returns than for a subsample of earnings observations paired with relatively high returns. Assuming fixed values of σ_R and $\rho_{R,I}$, the first term of Eq. (5) is in that case larger than the second term, because the numerator is larger in the first term. This implies that the OLS

[8] As predicted by this insight, Khan and Watts (2009) find that return volatility increases monotonically with the conservatism score (C_Score) decile. It is difficult to elucidate how much of this variation is caused by conservatism and how much should be attributed to return skewness. As another example, Ramalingegowda and Yu (2012) find that higher ownership by monitoring institutions leads to more conservative reporting. This positive association is more pronounced among firms with more growth options and higher information asymmetry. It is also expected that firms with more growth options and higher information asymmetry have higher return skewness. However, their lead-lag tests yield evidence consistent with their hypothesis and add credibility to the findings.

estimator $\hat{\beta}_1$ in the Basu model (1) can be positive in the presence of negative earnings skewness, even in the absence of conditional conservatism.

3. Simulation results

In this section, we conduct a simple simulation exercise to illustrate the points made in the previous section: we generate observations of returns and earnings in the absence of accounting conservatism and examine the circumstances under which a spurious nonzero AT coefficient appears. We start from the assumption that earnings are a linear function of returns: we treat returns as an exogenous variable, while earnings realize endogenously as a function of returns and an *i.i.d.* innovation term:

Data generating process 1: Earnings are a linear function of returns

$$R_i \sim i.i.d.(0,1)$$

$$\epsilon_i \sim i.i.d.(0,1)$$

$$I_i = \gamma_1 + \gamma_2 R_i + \epsilon_i$$

For simplicity, and without loss of generalization, we assume that both R and the innovation term ϵ have mean zero and standard deviation one, and we calibrate $\gamma_1 = 0$ and $\gamma_2 = 0.6$, implying a positive linear relation between returns and earnings. We simulate N=1,000 observations of R and ϵ from a Normal distribution, such that neither R nor ϵ are skewed. Next, we estimate the Basu model, Eq. (1), on the sample of simulated data. This process is repeated r=10,000 times. The first column of Table 1 reports the regression results: sample averages and standard deviations of the r=10,000 estimated coefficients. The table also reports additional statistics on the simulated distribution of returns and earnings. As expected, since the relation between R and I is modeled as linear, the coefficient on the dummy term and the AT coefficient on the interaction term are not significantly different from zero.

[Table 1]

We generate three additional simulated samples by: (*i*) transforming R into a right (positively) skewed variable; (*ii*) transforming ϵ into a left (negatively) skewed variable; and (*iii*) transforming both R and ϵ into right and left skewed variables, respectively.[9] Columns 2-4 of Table 1 report the estimated coefficients of the Basu models with skew-transformed simulated data. As the results in Table 1 indicate, the AT coefficient β_1 remains insignificant even if R is right-skewed and/or ϵ is left-skewed. This result clearly shows that, when the data generating process specifies earnings as a linear function of returns, skewness of the underlying variables by itself does not cause a bias in the AT coefficient. This result is expected, as unbiasedness and consistency of the OLS estimator relies on exogeneity of the independent variable (i.e. R and ϵ are uncorrelated), but does not require the assumption of Normally distributed data (e.g. Greene, 2000). To reconcile his finding with the analytical result in the prior section, recall that below Eq. (6), we made the assumption that σ_I and $\rho_{R,I}$ are fixed values (i.e. σ_I and $\rho_{R,I}$ do not differ between positive and negative return samples). As shown in the second column of Table 1, this assumption does not hold in our simulation exercise. The higher variance of returns in positive sample (indicative of

[9] We skew-transform I and R by transforming the realizations of the Standard Normal distribution into realizations of a skew-normal distribution. Specifically, right-skewed observations of returns are obtained by the following transformation: $R_i^{skew} = F_+^{-1}\big(\Phi(R_i)\big)$, in which R_i is an observation from a Standard Normal distribution, $\Phi(.)$ is the cumulative density function (CDF) of the Standard Normal distribution, and F_+ is the CDF of a Skew-Normal distribution, with mean 0, standard deviation 1, and skewness (shape) parameter +10, indicating positive (right) skewness. Similarly, left-skewed observations of earnings are obtained by the following transformation: $I_i^{skew} = F_-^{-1}\big(\Phi(I_i)\big)$, in which I_i is an observation from the Standard Normal distribution and F_- is the CDF of a Skew-Normal distribution, with mean 0, standard deviation 1, and skewness (shape) parameter -10, indicating negative (left) skewness. See Azzalini (2013) for details on the Skew-Normal distribution.

positive skewness) is offset by a higher variance of earnings and a higher correlation between earnings and returns in positive return samples. Therefore, the relation between earnings and returns remains linear and the expected value of the AT coefficient (Eq. 5) remains zero, despite the underlying skewness.

Next, we specify returns as a linear function of earnings. This corresponds to the situation described by Dietrich et al. (2007), where the Basu regression models reverses a structural equation (i.e. returns, the independent variable in the Basu regression, are specified as an endogenous variable that depends on earnings):

Data generating process 2: Returns are a linear function of earnings

$$I_i \sim i.i.d.(0,1)$$

$$\omega_i \sim i.i.d.(0,1)$$

$$R_i = \theta_1 + \theta_2 I_i + \omega_i$$

Similar to the first data generating process, we calibrate $\theta_1 = 0$ and $\theta_2 = 0.6$. We repeat the same simulation exercise: we generate simulated samples of N=1,000 observations of R, ω, and I, under Normal and skewed distributions, and estimate the Basu model (Eq. 1) using the simulated data. Table 2 reports sample averages and standard deviations of the r=10,000 estimated coefficients. In the absence of skewness (first column), the AT coefficient remains insignificant. However, when I and/or ω are skewed a spurious significant AT coefficient arises. This simulation result confirms the prediction by Dietrich et al (2007): the AT coefficient is a biased measure of conditional conservatism when the sample is truncated based on the sign of returns, which is endogenous. However, as our simulations point out, this sample truncation bias appears only in the presence of skewness.

[Table 2]

Finally, we consider the case where R is not specified as a linear function of I or vice versa. Instead, we simulate values of R and I simultaneously from a joint distribution, such that both R and I are endogenous.

Data generating process 3: Earnings and returns are jointly distributed

$$\begin{bmatrix} R_i \\ I_i \end{bmatrix} \sim i.i.d. \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

As before, we simulate a sample of N=1,000 observations of R and I, and estimate the Basu model (Eq. 1), on the sample of simulated data. The first column of Table 3 reports the regression results when the data is simulated from a Multivariate Normal distribution. As expected, since the relation between R and I is linear, the coefficient on the dummy term and the AT coefficient on the interaction term are not significantly different from zero.

[Table 3]

We proceed by transforming R and/or I into positively and negatively skewed variables, respectively. As the results in Table 3 indicate, the AT coefficient β_1 is positive and significant once R is right-skewed and/or I is left-skewed, even if we have not imposed any structure related to accounting conservatism on the data-generating process. The significant AT coefficient reflects asymmetry due to skewness, rather than conservatism.

Figure 1 plots N=1,000 simulated observations of R and I, following data generating process 3, and reports the fitted Basu model (solid line) and a simple regression of I on R over the full sample (dashed line). In Panel A, where both R and I are Normally distributed, there is no evidence of conservatism, as anticipated. However, when adding positive skew to R, the asymmetric timeliness coefficient is positive, causing a "kink" in the Basu regression line (Panel B). The kink is also observable, albeit weaker, when earnings are negatively skewed (Panel C). This kink, which may be erroneously interpreted as evidence of accounting conservatism, is most profound when both returns are positively skewed and earnings are negatively skewed (Panel D).

[Figure 1]

The simulation results in this section are summarized in Figure 2, showing that skewness induces the AT coefficient to be spuriously nonzero in the absence of conservatism, except when returns are strictly exogenous. When returns are strictly exogenous, the AT coefficient is zero in the absence of conservatism, regardless of the skewness of the underlying variables (Table 1). When returns are endogenous (Tables 2 and 3), the AT coefficient is biased, but only when the underling variables are skewed. The scenario of skewness and return endogeneity (bottom-right quadrant of Figure 2), in which the AT coefficient is biased, is the most relevant scenario empirically: it is well documented that both returns and earnings exhibit skewness, while strict exogeneity of returns (i.e. returns realizing independently from earnings) is clearly an unrealistic assumption to make. Several recent papers, including Ball et al. (2013a), and Dutta and Patatoukas (2017) specify both earnings and returns as simultaneously determined (i.e. endogenous) variables of latent underlying factors. In the next section, we assess the effect of skewness of these latent factors on the AT coefficient.

[Figure 2]

4. Skewness and asymmetric timeliness in a latent factor model

4.1 Ball, Kothari, and Nikolaev (2013a) model of accounting income recognition

Ball et al. (2013a) formulate the relation between accounting income and economic income by distinguishing four unobserved (latent) components of information that are designed to capture the salient properties of income recognition as it is practiced. Specifically, Ball et al. (2013a) describe the relation between unexpected returns (R_{it}) and unexpected earnings (I_{it}) as follows:

$$R_{it} = x_{it} + y_{it} + g_{it} \tag{8}$$

$$I_{it} = x_{it} + w_{it}y_{it} + (1 - w_{it-1})y_{it-1} + g_{it-1} + \varepsilon_{it} - \varepsilon_{it-1}, \tag{9}$$

where the subscripts *i* and *t* denote firm and year, respectively. Returns consist of three unobserved information components x_{it}, y_{it}, and g_{it}. The information component x_{it} is incorporated into accounting income contemporaneously. The second information component y_{it} is subject to conditional conservatism. It is incorporated into accounting income contemporaneously or with a lag, depending on its state. When y_{it} is negative, it is reported immediately in accounting income ($w_{it} = 1$ if $y_{it} < 0$), while reporting y_{it} is delayed to the next period during positive states ($w_{it} = 0$ if $y_{it} \geq 0$).[10] The third information component g_{it} is always incorporated into accounting income with delay. The fourth component ε_{it} is an accounting error that is reversed in the next period.

We assume that the unobserved components $x_{i,t}$, $y_{i,t}$, $g_{i,t}$, and $\varepsilon_{i,t}$ have mean zero and are serially uncorrelated. However, we do allow, following Ball et al. (2013a), for a positive contemporaneous correlation ρ between x_{it} , y_{it}, and g_{it}. Given these properties, the covariance between *I* and *R*, conditional on a negative state ($w_{it} = 1$), is:

[10] In the Ball et al. (2013a) setting, timely recognition is triggered when y_{it} is below an exogenous threshold *c*. Without loss of generality, we set this threshold *c* equal to zero, which is the unconditional mean of y. Pope and Walker (1999) and Dutta and Patatoukas (2017) treat conditional conservatism as a continuous variable in their model.

$$\sigma_{RI|w=1} = Cov\big((x_{it} + y_{it} + g_{it}), (x_{it} + y_{it} + (1 - w_{it-1})y_{it-1} + g_{it-1} + \varepsilon_{it} - \varepsilon_{it-1})\big|w_{it} = 1\big)$$

$$= Cov\big((x_{it} + y_{it} + g_{it}), (x_{it} + y_{it})\big|w_{it} = 1\big) \tag{10}$$

$$= \sigma^2_{x|w=1} + \sigma^2_{y|w=1} + 2\sigma_{xy|w=1} + \sigma_{xg|w=1} + \sigma_{yg|w=1},$$

while the covariance between *I* and *R*, conditional on a positive state ($w_{it} = 0$), is:

$$\sigma_{RI|w=0} = Cov\big((x_{it} + y_{it} + g_{it}), (x_{it} + (1 - w_{it-1})y_{it-1} + g_{it-1} + \varepsilon_{it} - \varepsilon_{it-1})\big|w_{it} = 1\big)$$

$$= Cov\big((x_{it} + y_{it} + g_{it}), x_{it}\big|w_{it} = 1\big) \tag{11}$$

$$= \sigma^2_{x|w=0} + \sigma_{xy|w=0} + \sigma_{xg|w=0}.$$

Ball et al (2013a) assume that the unobserved components *x*, *y*, and *g* follow a symmetric (non-skewed) distribution. In this case, since $\sigma_{A|w=1} = \sigma_{A|w=0}$ for $A \in \{x, y, g, xy, xg, yg\}$, it follows that $\sigma_{RI|w=1} - \sigma_{RI|w=0} = \sigma^2_y + \sigma_{yg}$, which is a strictly positive number implying that $\sigma_{RI|w=1} \geq \sigma_{RI|w=0}$. In the absence of conservative reporting, (i.e. when the component *y* is not included in the model), the difference between $\sigma_{RI|w=1}$ and $\sigma_{RI|w=0}$ reduces to zero. In summary, conservative accounting practice causes the covariance between returns and earnings to be higher in negative states than in positive states. Given this result, the asymmetric timeliness coefficient β_1 in Eq. (1) is expected to be positive in the presence of conservatism and zero in the absence of conservatism.[11] However, this result depends crucially on the assumption that *x*, *y*, and *g* follow a symmetric distribution. When these components are skewed, such that $\sigma_{A|w=1} \neq \sigma_{A|w=0}$, the inequality $\sigma_{RI|w=1} \geq \sigma_{RI|w=0}$ is not necessarily valid, and hence the sign of β_1 is unclear.

We illustrate this insight by a simulation exercise. We simulate the components x, y, g, and ε for a cross-section of *N*=1,000 firms with *t*=2 time-series observations per firm. For each firm *i,*

[11] Note that the condition $w_{i,t} = 1$ (or $y_{it} < 0$) is not empirically feasible, since *w* and *y* are not observable. As Ball et al. (2013a) demonstrate, the empirical condition $R_{it} < 0$ used in the Basu regression (Eq. 1) closely approximates the condition $y_{it} < 0$, given the definition of returns (Eq. 8) and the positive correlation between x*, y*, and *g*.

we thus draw eight random numbers $(x_{i0}, x_{i1}, y_{i0}, y_{i1}, g_{i0}, g_{i1}, \varepsilon_{i0}, \varepsilon_{i1})$ from a Multivariate Normal (i.e. non-skewed) distribution. From these simulated random numbers, we compute R_{i1} and I_{i1}, implied by Eq. (8)-(9), respectively, for each firm *i*. We also use the simulated variables $(x_{i0}, x_{i1}, g_{i0}, g_{i1}, \varepsilon_{i0}, \varepsilon_{i1})$ to generate returns and earnings from a restricted specification of the model that does not feature accounting conservatism. This model is equal to the model by Ball et al. (Eq. 8-9), with the difference that the term *y* is excluded from the model:

$$R_{it} = x_{it} + g_{it} \tag{12}$$

$$I_{it} = x_{it} + g_{it-1} + \varepsilon_{it} - \varepsilon_{it-1}. \tag{13}$$

We then use the simulated samples of *N* observations of earnings and returns to estimate the coefficients of the Basu (1997) regression Eq. (1), both in the presence and absence of conservatism.

This process is repeated *r*=10,000 times, and we report the means of the 10,000 estimates in Table 4. We consider four different values of the correlation ρ between *x, y,* and *g* ($\rho \in \{0, 0.2, 0.5, 0.8\}$). The top panel of Table 4 shows that in the presence of conservatism, the mean of the estimated AT coefficients (β_1) is indeed positive and significant. In the absence of conservatism (right panel), the mean of the estimated AT coefficients (β_1) is, as expected, insignificant and close to zero. With Normally-distributed data, the AT coefficient thus correctly identifies conservatism.

[Table 4]

We repeat this experiment after transforming the Standard Normally distributed variables *x, y,* and *g* into Skew-Normally distributed variables, with positive (right) skewness, which results in skewness of the realized earnings and returns. The results are reported in the lower three panels of Table 4. After allowing the unobserved components of returns and earnings to be skewed, the mean AT coefficients β_1 remain significant, but they are no longer uniformly positive. Hence, even if the data are generated by a model that features accounting conservatism, the Basu regression could indicate negative rather than positive asymmetric timeliness, due to the non-symmetric distribution of the underlying components.

Using the restricted model that is free of conservatism Eq. (12)-(13), a statistically significant AT coefficients (β_1) appears once we allow for skewness of the variables *x* and *g*. This constitutes a clear example of "spurious conservatism", in which the statistical distribution of the underlying components leads to an asymmetric relation between returns and earnings, which may be interpreted incorrectly as accounting conservatism. The results in Table 4 further indicate that skewness does not only affect the AT coefficient (β_1), but also the estimated individual effect of the positive-return dummy variable (α_1) is spuriously different from zero in the presence of skewness.

The final column of Table 4 reports the difference between the estimated AT coefficient in the presence and absence of conservatism. It is worth emphasizing that the difference is in all cases positive. This implies that the Basu regression is able to separate two groups of firms with and without conservative accounting practice, if and only if the returns and earnings in both groups have similar distributional properties. However, this may be difficult to achieve in practice, given the strong time-series and cross-sectional differences in the skewness of earnings and returns. For example, Zhang (2013) provides evidence that firms with low book-to-market ratios (i.e., glamour stocks) have significantly more positive skewness in their return distributions compared to the return distributions of firms with high book-to-market ratios (i.e., value stocks). As a result, it is difficult to disentangle the effects of skewness from conditional conservatism.

It is also noteworthy that the skewness of the simulated earnings does not seem to depend on the presence of conservatism. The skewness coefficients of earnings reported in Table 4 do vary with the skewness and correlations of the underlying components, but do not differ systematically between the full model (left panel) and the restricted model that is free of conservatism (right panel). While Ball and Shivakumar (2005) and Givoly and Hayn (2000) argue that negative earnings skewness may be in itself caused by accounting conservatism, within the model by Ball et al. (2013a) there is apparently no such direct effect of conservatism on earnings skewness.[12]

4.2 Skew-reducing transformations

A tempting solution to the skewness-induced component of the AT coefficient is to transform the variables. For example, a logarithmic transformation reduces right skewness, while a rank-transformation removes both positive and negative skewness from a variable. We apply both these transformations to our simulated observations of R and I before estimating the Basu model (Eq. 1). The resulting AT coefficients, reported in Table 5, show that these data transformations do not solve the problem at hand. Using log and rank transformed data, we continue to find that the AT coefficient varies with the distributional properties of the latent factors. As a result, the AT coefficient is not uniformly positive in the presence of conservatism, while it is often significantly different from zero in the absence of conservatism.

[Table 5]

[12] We also note that our simulations do not generate the stylized fact of positively skewed returns and negatively skewed earnings. Since earnings and returns contain the same latent components, both earnings and returns are skewed in the same direction. To establish return- and earnings-skewness in opposite direction, the Ball et al. (2013b) model needs to be extended with skewed returns-specific and earnings-specific shocks. The unadjusted model by Ball et al. (2013b) nevertheless suffices to demonstrate the adverse impact of skewness (of either direction) on the AT coefficient.

The reason that these data transformations do not help to identify conservatism, is that the skewness originates in the latent factors x, y, and g. The skewness of these latent factors causes the observable variables R and I themselves to be skewed, but also causes the relation between the two variables to be inherently nonlinear. Ex-post removing the univariate skewness from R and I does not remove the nonlinearity from the relation between R and I. This nonlinearity, which is in our simulation unrelated to accounting conservatism, is reflected by a statistically significant AT coefficient, even if the variables in the regression are transformed to remove skewness.

Table 5 also points out that the AT coefficient does not identify conservatism when the model is estimated using the Theil (1950) – Sen (1968) (TS) estimator, which mitigates the impact of outlier observations (Kim and Ohlson, 2018). The TS estimator does not provide a solution to the skewness-induced spurious AT coefficient, since the asymmetry in the relation between earnings and returns is not only confined to the tails of the distribution.

Finally, Table 5 reports $\Delta R^2 = R^2_{(-)} - R^2_{(+)}$: the difference between the R-squared from regressing earnings on returns in the negative and positive news subsamples. This measure was in connection to the AT coefficient proposed by Basu (1997), who hypothesizes that conservative reporting induces a stronger relation between earnings and returns, and thus a higher R-squared, under bad news. The results in Table 5 reveal that the differential R-squared is also contaminated by skewness. While ΔR^2 is generally higher in the presence of conservatism (Panel A), it is not necessarily zero in the absence of conservatism (Panel B). This result is also implied by the simulation results in Tables 1, 2, and 3, showing that the correlation between earnings and return (ρ) is not stable across positive and negative news samples. The squared correlation, or R-squared, can thus vary between positive and negative news states for reasons unrelated to conservative reporting.

5. Empirical results

5.1 Sample construction and variable definitions

The empirical data for this study are obtained from the intersection of annual Compustat and monthly Center for Research in Security Prices (CRSP) files.[13] Annual returns are computed by cumulating monthly returns starting from the fourth month after the firm's fiscal year end. We follow the prior literature in eliminating utilities (SIC 4900–4999) and all financial services companies (SIC 6000–6999). Following Patatoukas and Thomas (2016) and Collins et al. (2014), we also delete firm years with missing data to compute returns, earnings, market-to-book ratio, firm size (market capitalization), and exclude firm years with lagged share price less than $1. We calculate cash flows and accruals using the cash flow statement approach, which restricts the sample period to 1988–2017 (T=30). These filters result in a sample of 12,801 distinct firms and a total of 109,344 firm-year observations.

Patatoukas and Thomas (2011) observe a significant AT coefficient for price-deflated *lagged* earnings per share and point out that lagged earnings cannot be related to current news. Ball et al. (2013b) argue that this bias arises from a nonlinear correlation between the expected components of earnings and returns. Following the suggestion by Ball et al. (2013b), we run fixed-effect panel regressions for observed returns ($\tilde{R}$) and market capitalization-deflated earnings ($\tilde{I}$), to obtain unexpected returns and earnings: [14]

[13] To construct these variables, we use to the following Compustat items: *IBC, PRCC_F, CSHO, CEQ, DLTT, DLC, OANCF,* and *XIDOC.*
[14] We scale total earnings by lagged market capitalization, as opposed to scaling earnings-per-share by the lagged share price. The use of per share numbers (e.g., Compustat items *EPSPI, EPSFX, EPSPX, EPSFI*) is potentially problematic, because the number of shares used to calculate per-share numbers are weighted-averages of common shares outstanding during the period, which are affected by factors unrelated to accounting and economic income (e.g. by stock splits, new stock issues, treasury stock acquisitions, and similar transactions that occur through the period).

$$\tilde{R}_{it} = \alpha_i^R + \gamma_t^R + \varepsilon_{it}^R \tag{17}$$

$$\tilde{I}_{it} = \alpha_i^I + \gamma_t^I + \varepsilon_{it}^I, \tag{18}$$

in which α_i and γ_t are firm- and year-fixed effects, respectively. In our empirical analysis below, we proxy unexpected returns and earnings by the residuals from the above regressions, i.e., $R_{it} = \varepsilon_{it}^R$ and $I_{it} = \varepsilon_{it}^I$.[15]

In addition to earnings, we also consider accruals and cash flows separately. Basu (1997) notes that accruals enable accountants to recognize bad news about future cash flow on an asymmetrically timely basis. Collins et al. (2014) further argue that because recognition of operating cash flows does not reflect differential verification thresholds for recognizing unrealized gains versus losses, asymmetric timeliness in cash flows adds noise or bias to tests of conditional conservatism and therefore recommend the use of accruals-based estimates of the AT coefficient. Dutta and Patatoukas (2017) show that AT coefficient estimated with accruals instead of earnings increase in expected returns and asymmetry in the distribution of returns, and decrease in cash flow persistence (which are non-accounting factors). We follow Patatoukas and Thomas (2016) and use unexpected accruals. In a similar vein as above, we compute unexpected components of observed variables as follows:

$$\tilde{Y}_{it} = \alpha_i^Y + \gamma_t^Y + \varepsilon_{it}^Y, \tag{19}$$

where $\tilde{Y}_{it}$ is replaced by market capitalization-deflated accruals and cash flows in two separate regressions. We denote the resulting residuals as unexpected accruals (ACC_{it}) and unexpected cash flows (CFO_{it}).

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[15] Instead of adjusting variables prior to the main regression, it is typically recommended to control for fixed effects within the main regression (e.g. Chen et al. 2018). However, since the bad-news dummy (*D*) in the Basu model (1) cannot be constructed before adjusting returns, we need to employ this two-step estimation approach. We further note that our results are qualitatively similar if we compute unexpected returns based on size and market-to-book portfolios, as in Ball et al. (2013b).

Table 6 reports descriptive statistics. Due to the removal of fixed effects (Eq. 17-19), the mean values of our *unexpected* variables are zero by construction. The mean value of the indicator variable for negative unexpected returns (*D*) is 0.556, which is comparable to Dutta and Patatoukas (0.577). As expected, unexpected returns (*R*) and unexpected cash flows (*CFO*) exhibit positive skewness (1.336 and 0.612, respectively), while unexpected earnings (*I*) and unexpected accruals (*ACC*) exhibit negative skewness (-2.089 and -1.854, respectively).

[Table 6]

5.2 Empirical results

Previous studies show that AT estimates behave as a predictable function of book-to-market and size (e.g., Khan and Watts 2009, Ball et al. 2013b). In this section, we investigate whether within-sample cross-sectional skewness coefficients are associated with cross-sectional AT coefficient estimates. In order to examine this, we split the sample within each year into deciles by independently sorting firms on two firm characteristics: market capitalization (*Size*), and the market-to-book ratio (*MTB*), both measured at the beginning of period. Table 6 also reports summary statistics on *Size* and *MTB*.

Table 7 reports estimated AT coefficients for each *Size* and *MTB* decile. Estimates are obtained following the Fama-MacBeth (1973) approach: in each year, we use the observations of unexpected returns and earnings for all firms in a decile to estimate the cross-sectional regression Eq. (1). The reported coefficients are the time-series means of the annual cross-sectional AT coefficients ($\widehat{\beta_1}$). Table 7 also reports the time-series averages of the cross-sectional skewness coefficients of unexpected earnings and returns, within each decile.

[Table 7]

The estimated AT coefficients are positive and significant for all *Size* deciles. Moreover, there is a clear decreasing pattern in the AT coefficients when moving up in the size distribution, with the difference between the Small and Large decile being highly significant. However, the return skewness coefficients also show a strong negative correlation with firm size. This is clearly visualized in Figure 3A, which shows the average AT coefficient and returns skewness coefficient by decile. Given the results in earlier sections, it is thus possible that cross-sectional variation in the AT coefficient across size deciles merely reflects cross-sectional variation in return skewness, which is unrelated to conditional conservatism. From the *MTB* deciles we can see that the AT coefficient is higher for value stocks than for growth stocks, while the correlation to return skewness is clearly weaker than for the size deciles (Figure 3B). Table 7 also reports variation in earnings skewness, which is across MTB deciles negatively correlated to variation in the AT coefficients, consistent with our analytical and simulation analysis.

[Figure 3]

To further evaluate cross-sectional variation in the AT coefficient, we also look at the accruals and cash flows components of earnings separately. Conservative reporting is expected to lead to asymmetry in the relation between accruals and returns, but not in the relation between cash flows and returns.

The last two columns of Table 7 report the AT coefficients for size and MTB deciles, estimated using unexpected accruals and unexpected cash flows, respectively, instead of unexpected earnings. We find across both size and MTB deciles that the AT coefficients are mostly higher for accruals than for cash flows. While this pattern is consistent with conservative reporting of accruals but not of cash flows, it is also possible that the difference merely reflects differences in the skewness of cash flows and accruals: Table 6 shows that accruals are strongly negatively skewed, like earnings, while cash flows are slightly positively skewed. Moreover, we find significantly positive AT coefficients for cash flows within several *Size* and *MTB* deciles. Since cash flow reporting is not subject to conservative accounting, these positive AT coefficients must reflect something else than conservatism. In fact, a positive AT coefficient for cash flows is a predicted consequence of return skewness in the model by Dutta and Patatoukas (2017).

In summary, our empirical analysis confirms that it is not possible to make conclusive arguments about the degree of accounting conservatism based on estimated AT coefficients: cross-sectional variation in AT coefficients is strongly correlated to return skewness, which is unrelated to conservatism.

6. Conclusions

This paper analyzes the accuracy of the AT coefficient as a measure of conditional conservatism in the presence of skewed returns and earnings. Specifically, we use simulations to clarify the effect of skewness within three situations: (*i*) exogenous returns and endogenous earnings; (*ii*) exogenous earnings and endogenous returns; and (*iii*) jointly distributed (both endogenous) returns and earnings. Only when returns are exogenous, the AT coefficient is insensitive to skewness. We extend our simulation exercise to the Ball et al. (2013a) latent factor model of accounting income. This is important because skewness reduces the analytical tractability of the relation between earnings and returns within the model. Our results indicate that skewness of the underlying factors has a significant adverse impact on the AT coefficient.

Empirically, we examine cross-sectional variation in asymmetric timeliness across size and MTB deciles. Especially size-based variation in the AT coefficient is strongly related to variation in return skewness, suggesting that the variation in asymmetric timeliness does not necessarily reflect accounting conservatism. Consistent with prior studies, we do not only find positive AT coefficients for earnings and accruals, but also for cash flows, which are not subject to conservative reporting.

We also test different mechanical econometric adjustments to the estimation of the AT coefficient, including logarithmic and rank transformations of the data, outlier-robust estimation procedures, and differences in R-squared. These adjustments are not successful in eliminating the adverse impact of skewness. Overall, our results demonstrate that Basu's (1997) piecewise linear regression framework correctly identifies asymmetry, or nonlinearity, in the relation between earnings and returns. While conservatism is plausibly one of the economic explanations of this asymmetry, there is no reason to assume it is the only explanation, as exemplified by the observed positive skewness of returns. It is therefore important to recognize that the AT coefficient is not able to provide conclusive evidence on the degree of asymmetric timeliness in financial reporting, without disentangling actual asymmetric timeliness from nonlinearities caused by other confounding economic explanations. We recommend that research continues to triangulate inferences using multiple measures of conditional conservatism (see, Basu 1997; Ryan 2006). The development of empirical methods targeted to isolate the effect of conditional conservatism from distributional patterns unrelated to conservative reporting is an important avenue for future research.

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Table 1: Simulation results - Earnings as a linear function of Returns

This table reports the regression results from a Basu (1997) model estimated using simulated data:

$$I_i = \alpha_0 + \alpha_1 D_i + \beta_0 R_i + \beta_1 R_i \times D_i + \varepsilon_i,$$

where D is an indicator variable taking a value of 1 when R<0, and zero otherwise. The simulated data are generated from our data generating process 1, where earnings are endogenous and specified as a linear function of exogenous returns: $I_i = \gamma_1 + \gamma_2 R_i + \epsilon_i$, with $\gamma_1 = 0$ and $\gamma_2 = 0.6$. In Column (1), both R and ϵ are Normally distributed (with zero mean and unit variance). In Column (2), R is trasformed into a right (positively) skewed variable. In Column (3), ϵ is transformed into a left (negatively) skewed variable. In Column (4), both R and ϵ are right and left skewed, respecively. Entries in the table report the mean regression coefficients from r=10,000 simulated samples of N=1,000 observations each. Standard deviations are reported in parenthesis. In addition to the mean regression coefficients, the table reports the average skewness coefficients of earnings and returns, as well as the variances and correlation (ρ) of returns and earnings for subsamples of positive and negative returns, indicated by [+] and [-], respectively. *, **, and *** denote statistical significance levels of 10%, 5%, and 1%, respectively (two-tailed).

	(1)	(2)	(3)	(4)
	R and ϵ Normal	R Skewed	ϵ Skewed	R and ϵ Skewed
Intercept	0.001	0.001	0.001	0.001
	(0.08)	(0.08)	(0.07)	(0.07)
R	0.599***	0.599***	0.600***	0.599***
	(0.08)	(0.06)	(0.08)	(0.06)
D	0.000	0.000	0.000	0.000
	(0.11)	(0.11)	(0.11)	(0.11)
$R \times D$	0.002	0.002	0.002	0.002
	(0.11)	(0.12)	(0.11)	(0.12)
Adj. R^2	0.264	0.264	0.265	0.264
Skew (R)	-0.001	0.933	-0.001	0.933
Skew (I)	-0.001	0.126	-0.589	-0.463
Var(R)[-]	0.363	0.152	0.363	0.152
Var(R)[+]	0.363	0.601	0.363	0.601
Var(I)[-]	1.132	1.055	1.127	1.051
Var(I)[+]	1.129	1.214	1.126	1.211
ρ[-]	0.340	0.228	0.341	0.229
ρ[+]	0.339	0.421	0.340	0.422

Table 2: Simulation results - Returns as a linear function of Earnings

This table reports the regression results from a Basu (1997) model estimated using simulated data:

$$I_i = \alpha_0 + \alpha_1 D_i + \beta_0 R_i + \beta_1 R_i \times D_i + \varepsilon_i,$$

where D is an indicator variable taking a value of 1 when R<0, and zero otherwise. The simulated data are generated from our data generating process 2, where returns are endogenous and specified as a linear function of exogenous earnings: $R_i = \theta_1 + \theta_2 I_i + \omega_i$, with $\theta_1 = 0$ and $\theta_2 = 0.6$. In Column (1), both I and ω are Normally distributed (with zero mean and unit variance). In Column (2), I is trasformed into a left (negatively) skewed variable. In Column (3), ω is transformed into a right (positively) skewed variable. In Column (4), both I and ω are left and right skewed, respecively. Entries in the table report the average regression coefficients from r=10,000 simulated samples of N=1,000 observations each. Standard deviations are reported in parenthesis. In addition to the average regression coefficients, the table reports the average skewness coefficients of earnings and returns, as well as the variances and correlation (ρ) of returns and earnings for subsamples of positive and negative returns, indicated by [+] and [-], respectively. *, **, and *** denote statistical significance levels of 10%, 5%, and 1%, respectively (two-tailed).

	(1)	(2)	(3)	(4)
	I and ω Normal	I Skewed	ω Skewed	I and ω Skewed
Intercept	-0.001	0.150***	0.231	0.281***
	(0.06)	(0.05)	(0.07)	(0.05)
R	0.442***	0.269***	0.209***	0.118***
	(0.06)	(0.04)	(0.05)	(0.04)
D	0.001	0.024	0.153*	0.318***
	(0.09)	(0.09)	(0.09)	(0.08)
$R \times D$	0.000	0.347***	0.681***	0.992***
	(0.08)	(0.08)	(0.07)	(0.06)
Adj. R^2	0.264	0.264	0.265	0.264
Skew (R)	0.000	-0.127	0.586	0.461
Skew (I)	-0.001	-0.934	-0.001	-0.934
Var(R)[-]	0.494	0.537	0.323	0.375
Var(R)[+]	0.494	0.601	0.363	0.601
Var(I)[-]	0.832	1.142	0.789	1.102
Var(I)[+]	0.831	0.539	0.892	0.578
ρ[-]	0.340	0.422	0.569	0.647
ρ[+]	0.340	0.247	0.186	0.127

Table 3: Simulation results - Earnings and Returns jointly distributed

This table reports the regression results from a Basu (1997) model estimated using simulated data:

$$I_i = \alpha_0 + \alpha_1 D_i + \beta_0 R_i + \beta_1 R_i \times D_i + \varepsilon_i,$$

where D is an indicator variable taking a value of 1 when R<0, and zero otherwise. The simulated data are generated from our data generating process 3, where earnings and returns are both endogenous and jointly (simultaneously) distributed: $\begin{bmatrix} R_i \\ I_i \end{bmatrix} \sim i.i.d.\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$. We calibrate $\rho = 0.6$. In Column (1), R and I are multivariate Normally distributed. In Column (2), R is transformed into a right (positively) skewed variable In Column (3), I is trasformed into a left (negatively) skewed variable. In Column (4), both R and I are right and left skewed, respecively. Entries in the table report the average regression coefficients from r=10,000 simulated samples of N=1,000 observations each. Standard deviations are reported in parenthesis. In addition to the average regression coefficients, the table reports the average skewness coefficients of earnings and returns, as well as the variances and correlation (ρ) of returns and earnings for subsamples of positive and negative returns, indicated by [+] and [-], respectively. *, **, and *** denote statistical significance levels of 10%, 5%, and 1%, respectively (two-tailed).

	(1)	(2)	(3)	(4)
	R and *I* Normal	*R* Skewed	*I* Skewed	*R* and *I* Skewed
Intercept	-0.001	0.139**	0.116**	0.237***
	(0.06)	(0.06)	(0.05)	(0.05)
R	0.600***	0.441***	0.438***	0.308***
	(0.06)	(0.05)	(0.04)	(0.03)
D	0.000	0.110	-0.013	0.131
	(0.08)	(0.09)	(0.09)	(0.09)
$R \times D$	-0.001	0.505***	0.274***	0.799***
	(0.08)	(0.10)	(0.08)	(0.10)
Adj. R^2	0.359	0.354	0.344	0.333
Skew (R)	-0.001	0.933	-0.001	0.933
Skew (I)	0.001	0.001	-0.933	-0.933
Var(R)[-]	0.364	0.152	0.364	0.152
Var(R)[+]	0.363	0.601	0.363	0.601
Var(I)[-]	0.770	0.785	1.040	1.024
Var(I)[+]	0.771	0.758	0.520	0.479
ρ[-]	0.411	0.416	0.420	0.419
ρ[+]	0.411	0.392	0.366	0.345

Table 4: Simulation of the Ball et al. (2013a) model

This table reports the regression results from a Basu (1997) model estimated using simulated data:

$$I_i = \alpha_0 + \alpha_1 D_i + \beta_0 R_i + \beta_1 R_i \times D_i + \varepsilon_i,$$

where D is an indicator variable taking a value of 1 when R<0, and zero otherwise. The simulated data are generated using the model by Ball et al. (2013a). We simulate N=1,000 observations of the components x, y, g, and ε, which imply realizations of returns (R) and earnings (I), for different values of ρ. We then estimate Eq. (1) on the simulated data and calculate the skewness of R and I. We repeat this process r=10,000 times. Entries in the table report the mean regression coefficients from r=10,000 simulated samples. For Panel A, we simulate from the full model (Eq. 8-9), while for Panel B we simulate from a reduced model that excludes y and is therefore free of accounting conservatism (Eq. 12-13). The final column reports the difference between the mean AT coefficient reported in Panels A and B. In the top panel, x, y, g, and ε are sampled from a Standard Normal distribution, while in the other panels x, y, and g are sampled from a Skew-Normal distribution with mean zero, standard deviation one, and shape parameter +10, indicating positive (right) skewness. Mean coefficients that are significantly different from zero at the 5% (10%) level are reported in bold (italics).

		A: Conservatism						B: No conservatism (y=0)						Difference
	ρ	α_0	α_1	β_0	β_1	Skew(R)	Skew(I)	α_0	α_1	β_0	β_1	Skew(R)	Skew(I)	β_1
No skewness	0	**0.12**	0.00	**0.41**	**0.18**	0.00	0.00	0.00	0.00	**0.50**	0.00	0.00	0.00	**0.17**
	0.2	**0.17**	0.00	**0.40**	**0.21**	0.00	0.00	0.00	0.00	**0.50**	0.00	0.00	0.00	**0.21**
	0.5	**0.26**	-0.01	**0.37**	**0.26**	0.00	0.00	0.00	0.01	**0.50**	0.00	0.00	0.00	**0.26**
	0.8	**0.34**	0.00	**0.35**	**0.30**	0.00	0.00	0.00	0.00	**0.50**	0.00	0.00	0.00	**0.30**
x skewed	0	**-0.05**	**0.07**	**0.53**	**-0.02**	**0.18**	**0.09**	**-0.21**	-0.01	**0.67**	**-0.38**	**0.33**	**0.12**	**0.36**
	0.2	0.01	**0.05**	**0.49**	**0.04**	**0.22**	**0.10**	**-0.20**	**-0.03**	**0.65**	**-0.35**	**0.37**	**0.12**	**0.38**
	0.5	**0.08**	**0.04**	**0.45**	**0.11**	**0.27**	**0.11**	**-0.17**	**-0.05**	**0.61**	**-0.29**	**0.42**	**0.12**	**0.39**
	0.8	**0.17**	**0.02**	**0.42**	**0.17**	**0.31**	**0.13**	**-0.15**	**-0.06**	**0.59**	**-0.24**	**0.47**	**0.12**	**0.40**
y skewed	0	**0.15**	**-0.07**	**0.36**	**0.17**	**0.18**	**0.06**							
	0.2	**0.19**	**-0.08**	**0.36**	**0.19**	**0.22**	**0.09**							
	0.5	**0.28**	**-0.10**	**0.34**	**0.24**	**0.27**	**0.13**							
	0.8	**0.40**	**-0.16**	**0.32**	**0.28**	**0.31**	**0.16**							
g skewed	0	**0.25**	**0.03**	**0.33**	**0.39**	**0.18**	**0.09**	**0.21**	**0.02**	**0.33**	**0.38**	**0.33**	**0.11**	0.01
	0.2	**0.28**	**0.07**	**0.33**	**0.39**	**0.22**	**0.10**	**0.19**	**0.04**	**0.36**	**0.34**	**0.37**	**0.12**	**0.05**
	0.5	**0.36**	**0.09**	**0.32**	**0.42**	**0.27**	**0.10**	**0.16**	**0.06**	**0.39**	**0.28**	**0.42**	**0.12**	**0.14**
	0.8	**0.44**	**0.12**	**0.31**	**0.45**	**0.31**	**0.11**	**0.13**	**0.07**	**0.41**	**0.23**	**0.47**	**0.12**	*0.21*

Table 5: Skew-reducing transformations

This table reports the mean estimate of the AT coefficient β_1 from a Basu (1997) model (Eq. 1), using r=10,000 samples of simulated data generated using the model by Ball et al. (2013a). See Table 4 for details on the simulation exercise. The simulated variables R and I are transformed to reduce skewness. The first column reports AT coefficients estimated after logarithmic transformation of the data: log*(1+R/100)* and log*(1+I/100)*. The second column reports the AT coefficients for rank-transformed data: *Rank(R)* and *Rank(I)*. The third column reports the difference between the Theil (1950) – Sen (1968) (TS) estimator of the slope between (untransformed) earnings on returns for subsamples of positive and negative returns. The fourth column reports $\Delta R^2 = R^2_{(-)} - R^2_{(+)}$: the difference between R-squared from OLS regressions of (untransformed) earnings on returns (Eq. 2) for subsamples of positive and negative returns.

		A: Conservatism				B: No conservatism			
	ρ	*Log*	*Rank*	*TS*	ΔR^2	*Log*	*Rank*	*TS*	ΔR^2
No skewness	0	**0.17**	**0.13**	**0.16**	**0.04**	-0.01	0.00	0.00	0.00
	0.2	**0.20**	**0.18**	**0.18**	**0.06**	-0.01	0.00	0.00	0.00
	0.5	**0.25**	**0.24**	**0.24**	**0.10**	**-0.01**	0.00	0.00	0.00
	0.8	**0.29**	**0.32**	**0.29**	**0.14**	**-0.01**	0.00	0.00	0.00
x skewed	0	**-0.03**	**-0.07**	**-0.03**	**-0.01**	**-0.39**	**-0.35**	**-0.35**	**-0.08**
	0.2	**0.03**	**-0.05**	**0.03**	-0.01	**-0.36**	**-0.38**	**-0.32**	**-0.09**
	0.5	**0.09**	0.00	**0.10**	**0.02**	**-0.30**	**-0.39**	**-0.27**	**-0.11**
	0.8	**0.15**	**0.04**	**0.17**	**0.03**	**-0.25**	**-0.39**	**-0.21**	**-0.12**
y skewed	0	**0.16**	**0.08**	**0.15**	**0.03**				
	0.2	**0.17**	**0.08**	**0.16**	**0.03**				
	0.5	**0.22**	**0.13**	**0.22**	**0.07**				
	0.8	**0.27**	**0.17**	**0.27**	**0.09**				
g skewed	0	**0.37**	**0.24**	**0.34**	**0.07**	**0.38**	**0.18**	**0.36**	**0.05**
	0.2	**0.38**	**0.25**	**0.35**	**0.10**	**0.33**	**0.14**	**0.32**	**0.05**
	0.5	**0.41**	**0.28**	**0.38**	**0.12**	**0.27**	**0.07**	**0.26**	**0.04**
	0.8	**0.43**	**0.31**	**0.42**	**0.16**	**0.22**	0.00	**0.21**	**0.02**

Table 6: Descriptive statistics

This table reports pooled descriptive statistics for the following variables: unexpected returns (*R*), unexpected earnings (*I*), unexpected accruals (*ACC*), unexpected cash flows (*CFO*), an economic loss dummy (*D*) indicating negative unexpected returns, market capitalization (*Size*) and the market-to-book ratio (*MTB*). Unexpected variables are obtained by fixed effects regressions (Eq. 17-19). The sample includes 109,344 firm-year observations from 1988 to 2017.

	Mean	Std. Dev.	Skewness	Q1	Median	Q3
R	0.000	0.485	1.336	-0.296	-0.052	0.201
I	0.000	0.131	-2.089	-0.028	0.008	0.054
ACC	0.000	0.159	-1.854	-0.036	0.009	0.063
CFO	0.000	0.128	0.612	-0.051	-0.003	0.044
D	0.556	0.497	-0.224	0.000	1.000	1.000
Size	5.612	2.182	0.336	3.996	5.477	7.059
MTB	3.165	4.780	2.715	1.232	2.081	3.670

Table 7: Empirical AT coefficients and skewness

Each year, we sort firms into *Size* (Panel A) and *MTB* (Panel B) deciles. The first and second column reports the average Pearson skewness coefficient of unexpected returns (R) and unexpected earnings (I). From the third to fifth column, we report the time-series averages of the AT coefficients from the Basu (1997) model (Eq.1) within each decile using I, unexpected accruals (ACC), and unexpected cash flows (CFO) as dependent variables. t-statistics based on HAC standard errors in parenthesis. The sample includes 109,344 firm-year observations from 1988 to 2017. *, **, and *** denote statistical significance levels of 10%, 5%, and 1%, respectively (two-tailed).

Panel A: *Size* deciles	Skewness R	Skewness I	AT coef. on I	AT coef. on ACC	AT coef. on CFO
Decile 1 (Small)	1.351	-1.289	0.129***	0.095***	0.028*
			(7.59)	(5.59)	(1.75)
Decile 2	1.355	-1.513	0.127***	0.073***	0.055***
			(7.06)	(4.56)	(3.67)
Decile 3	1.257	-1.631	0.093***	0.054***	0.040***
			(7.15)	(4.50)	(4.00)
Decile 4	1.171	-1.782	0.087***	0.060***	0.029***
			(5.80)	(3.53)	(2.64)
Decile 5	1.127	-1.682	0.075***	0.066***	0.009
			(7.50)	(5.50)	(0.90)
Decile 6	0.975	-1.663	0.054***	0.049***	0.007
			(4.91)	(3.77)	(0.50)
Decile 7	0.930	-2.063	0.054***	0.049***	0.006
			(4.91)	(4.08)	(0.50)
Decile 8	0.776	-2.085	0.053***	0.048**	0.006
			(5.30)	(2.53)	(0.60)
Decile 9	0.730	-2.128	0.031***	0.024**	0.006
			(2.82)	(2.00)	(0.75)
Decile 10 (Large)	0.534	-1.804	0.017	0.010	0.007
			(1.70)	(0.56)	(0.39)
Small-Large	0.818***	0.515	0.112***	0.085***	0.020
	(5.64)	(1.38)	(6.22)	(4.05)	(0.83)

Table 7 (continued)

Panel B: *MTB* deciles	Skewness *R*	Skewness *I*	AT coef. on *I*	AT coef. on *ACC*	AT coef. on *CFO*
Decile 1 (Value)	1.239	-1.320	0.205***	0.148***	0.051***
			(10.59)	(5.10)	(2.68)
Decile 2	1.280	-1.553	0.219***	0.186***	0.032***
			(14.60)	(16.91)	(2.91)
Decile 3	1.225	-1.498	0.159***	0.118***	0.040**
			(14.45)	(5.62)	(2.35)
Decile 4	1.383	-1.378	0.119***	0.072***	0.047***
			(9.92)	(4.00)	(2.94)
Decile 5	1.248	-1.468	0.064***	0.022	0.041***
			(4.92)	(1.47)	(3.42)
Decile 6	1.337	-1.461	0.061***	0.038***	0.021**
			(5.08)	(2.92)	(2.10)
Decile 7	1.197	-1.141	0.057***	0.031***	0.025***
			(4.38)	(3.10)	(3.13)
Decile 8	1.209	-1.010	0.018**	0.001	0.016*
			(2.00)	(0.17)	(1.78)
Decile 9	1.171	-0.506	0.010	0.003	0.009
			(1.43)	(0.60)	(1.13)
Decile 10 (Growth)	1.081	-0.873	0.013	0.003	0.011
			(1.44)	(0.43)	(1.00)
Value-Growth	0.158***	-0.447**	0.112***	0.145***	0.040*
	(1.70)	(-2.03)	(6.22)	(5.18)	(1.90)

Figure 1: Basu (1997) regressions on simulated data

This figure plots N=1,000 simulated observations of unexpected earnings (I) and unexpected returns (R) with the corresponding simple regression (dashed line) and a piecewise-linear Basu (1997) regression (solid line). In Panel A, I and R are Multivariate Normally distributed, with a correlation of 0.6 (data generating process 3). In Panel B, I is Normally distributed and R is right-skewed. In Panel C, I is left-skewed and R is Normally distributed. In Panel D, both I and R are left- and right-skewed, respectively.

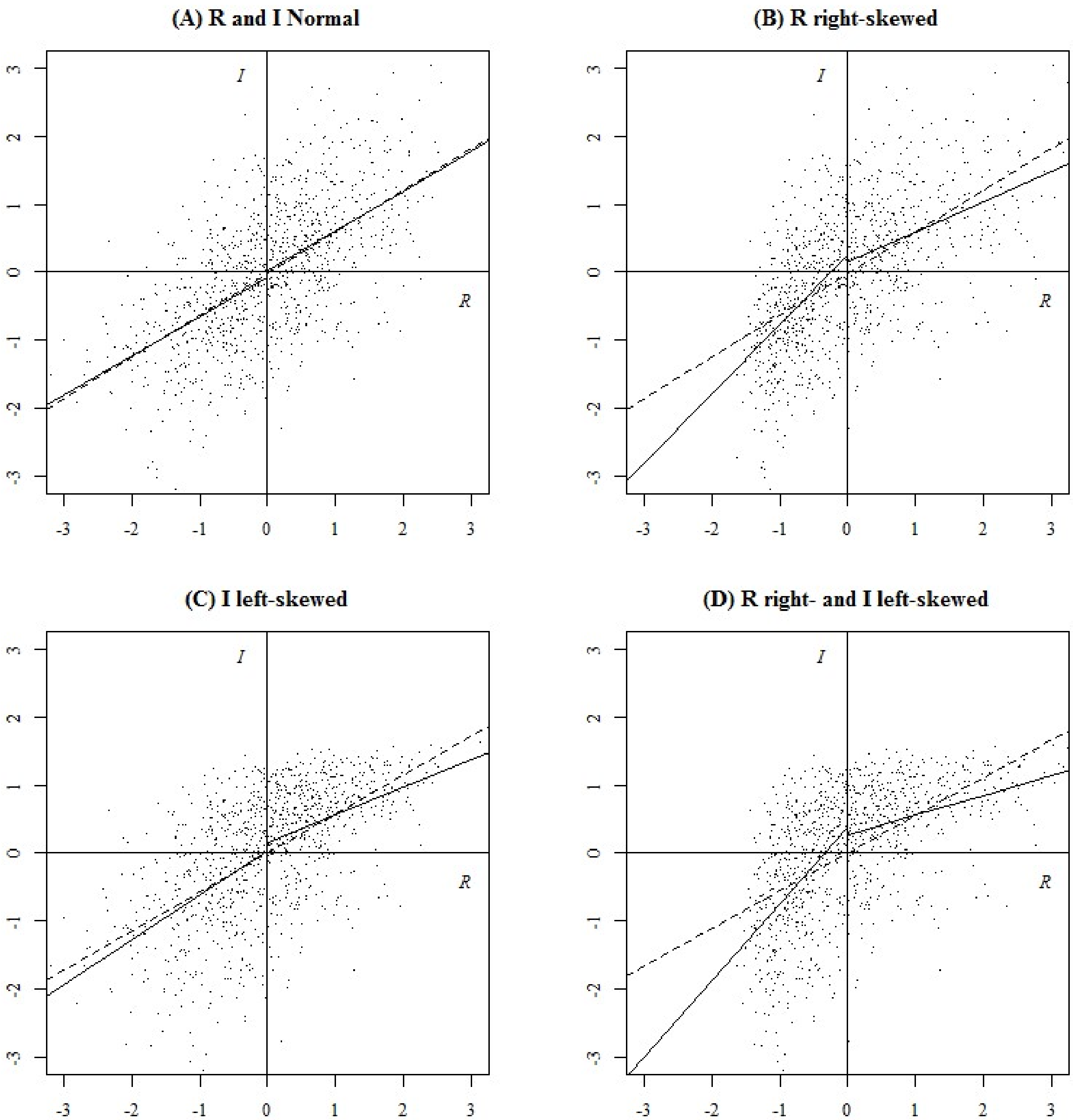

Figure 2: The AT coefficient in four scenarios

This figure summarizes the simulation results in Section 3. Skewness of the underlying variables induces a spurious AT coefficient when returns are endogenous. In the presence of non-skewed data and/or exogenous returns, the AT coefficient correctly identifies conservatism.

	Exogenous Returns	Endogenous Returns
Earnings and Returns not skewed	✓ AT coefficient identifies conservatism	✓ AT coefficient identifies conservatism
Earnings and/or Returns skewed	✓ AT coefficient identifies conservatism	✗ AT coefficient **does not** identify conservatism

Figure 3: AT coefficients and return skewness

This figure reports the average AT coefficient (left axis) and Pearson skewness coefficient of returns (right axis) by size deciles and Market-to-Book deciles. See Table 7 for estimation details.