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## On Estimating Conditional Conservatism

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## *On Estimating Conditional Conservatism*

### **Abstract**

The concept of conditional conservatism has provided new insight into financial reporting and has stimulated considerable research since Basu (1997) developed it. While the concept encapsulated in the adage “anticipate no profits but anticipate all losses” is reasonably clear, estimating it is the subject of some discussion, notably by Dietrich et al. (2007), Givoly et al. (2007), and Ball, Kothari and Nikolaev (2011). Recently, Patatoukas and Thomas (2011) report important evidence of possible bias in firm-level cross-sectional estimates of conditional conservatism (asymmetric earnings timeliness) which they attribute to scale effects. They advise researchers to avoid using conditional conservatism estimates or making inferences from prior research using them, a view we regard as excessively alarmist. Our theoretical and empirical analyses suggest the explanation is a correlated omitted variables problem that can be addressed in a straightforward fashion, for example by fixed-effects regression. We show that cross-sectional correlation between the expected components of earnings and returns confounds the relation between the news components, and biases estimates of how earnings incorporates the news in returns (e.g., timeliness). We also show that the correlation between the expected components of earnings and returns depends on the sign of returns, biasing estimates of asymmetric timeliness. When firm-specific effects in earnings are taken into account, estimates of asymmetric timeliness do not exhibit the bias, are statistically and economically significant (though smaller in magnitude and perhaps more consistent with priors), and behave as a predictable function of market-to-book, size and leverage. It would be surprising if this was not the case. Conditional conservatism accords with the long-standing accounting principle of anticipating losses but not gains, with specific asymmetric accounting rules such as the lower-of-cost-or-market method for inventories and the rules for impairment of long term assets, and with loss recognition practices that occurred prior to the promulgation of formal rules.

## On Estimating Conditional Conservatism

### 1. Introduction

Since its introduction by Basu (1997), the concept of conditional conservatism has provided both new insight into financial reporting practice and an impetus to accounting research. The novel insight in the concept of *conditional* conservatism lies in defining conservatism as an asymmetric response to new information. Previously, conservatism had been viewed as an unconditional asymmetric response to uncertainty: when faced with a range of possible book values of stockholders' equity, select a low value. Basu's (1997) seminal contribution was the concept of financial reporting being more attuned to recognizing bad news about firm value than good news. This concept of conservatism requires financial reporting behavior to be correlated with real economic income, and in particular for the financial statements to better reflect contemporaneous real economic losses.<sup>1</sup> Because it is founded on new information, this concept of conservatism is capable of playing important economic roles, many of which have been explored in the literature.<sup>2</sup>

Basu (1997) also provides estimators of the conditional conservatism concept. We address the primary estimator, the incremental coefficient on negative returns in a piecewise linear regression of accounting income (scaled by beginning stock price) on contemporaneous stock return.<sup>3</sup> Because income recognition in accounting is largely a choice between timely and deferred incorporation of economic gains and losses, conditional conservatism also is known as asymmetrically timely loss recognition and the incremental coefficient on negative returns is known as the asymmetric timeliness coefficient. The focus on accounting income is due to it being a sensitive barometer of financial reporting in general, in that income statement variables

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<sup>1</sup> Accounting practices such as routinely expensing early, deferring revenue and under-reporting book value lead to unconditional but not conditional conservatism, because they are not correlated with contemporaneous real income.

<sup>2</sup> Watts (2003) and Ball, Kothari, and Nikolaev (2011) survey an extensive list of studies.

<sup>3</sup> The secondary estimator is a piecewise linear regression of change in accounting income on lagged change.

are structurally correlated with changes in balance sheet variables. Income statement timeliness thus is an indicator of financial reporting timeliness generally. The rationale for specifying accounting income as the dependent variable, in contrast to the earlier “earnings response coefficient” literature in which it is the independent variable, is that accounting income is the variable whose properties are being estimated. The independent variable, contemporaneous stock return, is a proxy for new information about firm value during the fiscal period, including accounting income.

Using a pooled cross-sectional and time-series regression, Basu (1997) reports that the sensitivity of accounting income to decreases in firm value (“bad news”) exceeds its sensitivity to increases in value (“good news”). This finding accords with the long-standing accounting principle of anticipating losses but not gains, with a host of asymmetric accounting rules such as the lower-of-cost-or-market method for inventories and the various asset impairment rules for long term tangible and intangible assets, and with loss recognition practices such as impairments and restructuring charges that occurred prior to the promulgation of formal rules.

While the concept of accounting income being more attuned to economic losses than economic profits is reasonably clear, estimating the actual effect of that asymmetry on accounting income is the subject of some discussion. Dietrich et al. (2007) and Givoly et al. (2007) offer criticisms of the Basu estimator. Ball, Kothari and Nikolaev (2011) conclude that these criticisms do not invalidate the Basu (1997) regression as an estimator of asymmetric incorporation of news in earnings. By formulating the earnings-returns relation entirely in terms of news, they implicitly assume that the expected components of earnings and returns are accounted for by the model’s intercept. Patatoukas and Thomas (2011), who we refer to as PT from this point onwards, provide important empirical evidence suggesting bias in the Basu estimator. They replace current-period price-deflated earnings per share as the dependent

variable in the Basu regression with its lagged counterpart and also with the inverse of lagged price, and observe a significantly negative incremental coefficient on negative returns (the proxy for “bad news”). They attribute this anomalous result to scale-related effects, arguing that price (which is used to scale earnings) is inversely related to stock return variance (causing a “variance effect”) and positively related to scaled earnings and hence negatively related to the incidence of losses (a “loss effect”).

We build on and provide a different interpretation of the anomalous evidence reported by PT. We begin by replicating their results. We then demonstrate that scale-related effects are not the explanation. To isolate the effects of scale, we eliminate approximately 99% of its variation by sorting observations into relatively narrow portfolios based on price, such that within each portfolio the cross-sectional variation in scale essentially is eliminated. If scale effects explain the anomalous evidence, it would disappear within these portfolios, but it persists: the estimated asymmetric timeliness remains considerable. We conclude that the data do not support the scale-related explanation.<sup>4</sup> It thus becomes necessary to look for a better explanation.

We show, both analytically and empirically, that the Basu regression’s incremental coefficient on negative returns is a biased estimator of the relation between the news components of returns and earnings when there is no control for cross-sectional variation in the expected components of returns and earnings. This is similar in nature to a correlated omitted variable problem, and confounds the Basu estimator unless controlled for. Bias due to correlated-omitted variables is a well-known econometric issue (Greene, 2003, chapter 8) that accounting researchers have encountered previously, for example in the context of discretionary accruals literature (e.g., McNichols, 2000; Kothari, Leone, and Wasley, 2005).

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<sup>4</sup> Furthermore, we obtain the same result when we isolate variance effects by sorting observations into 50 narrow portfolios based on the standard deviation of past returns, thus controlling for variance effects within each portfolio.

We offer several simple ways to improve on the standard Basu (1997) specification to address the bias. Both an uncomplicated control for a small number of well-known risk factors and a relatively crude way of removing the expected components of firms' earnings substantially reduce bias and increase confidence in estimates of asymmetric timeliness. Furthermore, a simple inclusion of firm fixed effects essentially eliminates the bias, which becomes insignificant. We also demonstrate that controlling for expected earnings eliminates the systematic variation of bias with several firm characteristics often used as proxies for conditional conservatism (Khan and Watts, 2010) as well as for risk (Fama and French, 1992, 1993).

PT advise researchers they “should heed the call in Dietrich et al. (2007) and Givoly et al. (2007) to avoid the [asymmetric timeliness coefficient] measure” (page 2), but they offer no solution to the problem. This advice is difficult to reconcile with accounting principles, rules and practices, which suggest that conditional conservatism is more than a statistical artifact. It also is difficult to reconcile with the large number of studies reporting Basu estimates of conditional conservatism that are consistent with credible hypotheses. The importance of this literature, together with advice that its results be discarded, makes this issue worthy of further study. Our objective in this paper therefore is to investigate further the cause and econometric nature of this intriguing bias, and to determine whether and how the bias can be reduced or eliminated empirically.

We conclude that PT's advice to completely avoid using the Basu estimator, and to avoid making inferences from research based on it, is unnecessarily alarmist. More work is needed to understand the economic nature of the relation between expected returns and the expected level of earnings, but in the meantime we recommend that researchers interested in measuring

conditional conservatism simply control for firm-specific effects, at least as a robustness check, to avoid potentially spurious inferences.<sup>5</sup>

Section 2 describes the econometric effects of failing to isolate the expected components of earnings and returns in estimating the Basu asymmetric timeliness coefficient. Data and descriptive statistics are summarized in section 3. Section 4 presents the result that scale effects do not bias the Basu asymmetric timeliness coefficient. Section 5 demonstrates that a non-linear correlation between the expected values of earnings and returns is present in the data, and that the problem can be addressed with simple and well-known methods including a fixed firm effects specification. Section 6 provides further analysis of time series and cross sectional variation in conditional conservatism estimates. In section 7 we discuss our results and their implications for empirical analyses of conditional conservatism, and provide concluding remarks.

## 2. Effect of failing to isolate the expected component in earnings

The widely-used Basu estimator is the regression function:

$$X_{it} / P_{it-1} = a_0 + a_1 D(R_{it} < 0) + b_0 R_{it} + b_1 D(R_{it} < 0) * R_{it} + \varepsilon_{it} \quad (1)$$

where  $X_{it}$  is earnings per share for firm  $i$  in year  $t$ ,  $P_{it-1}$  is beginning of period price,  $R_{it}$  is stock return,  $D(\cdot)$  is an indicator function taking the value of one when stock returns are negative and zero otherwise, and  $b_1$  is the asymmetric timeliness coefficient.

In this section, we show analytically that estimates of the relation between the news components of earnings and returns are biased by correlation between their expected components. We first show that the PT explanation also can be cast more formally as a correlated omitted variable problem.

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<sup>5</sup> This conclusion is similar to that of Beaver and Ryan (2009, p.8) when analyzing non-linearity caused by risky debt, rather than conditionally conservative financial reporting.



2.1. *Understanding the loss and variance effects hypothesis.* PT propose that estimates of conditional conservatism are affected by two empirical regularities related to scaling the variables in the Basu estimator by price. They report evidence that price is: (1) inversely related to return variance, which they refer to as the “variance effect”; and (2) positively related to the level and sign of *lagged* price-deflated earnings, which they refer to as the “loss effect.” They argue that these two scale-related effects, in combination, yield a pattern in the return-earnings relation that can be mistakenly attributed to conditional conservatism.

Interpretation of these results is difficult because the connection PT draw between scale-related effects and estimated Basu coefficients is strictly intuitive, without formal analysis. This makes it somewhat difficult to understand the exact nature of the econometric problem they propose. Moreover, their claim that the results are explained by the “sample truncation bias” thesis in Dietrich et al. (2007) is difficult to see, for two reasons. First, truncation and scaling are different econometric issues. Second, their interpretation is puzzling because it is inconsistent with the formal analysis of Ball, Kothari and Nikolaev (2011), who show that the Basu estimator does not suffer from truncation bias and provides a valid measure of conditional conservatism in the response of earnings to the news in stock returns. The latter observation provides an important clue in searching for the source of the bias: by definition, news is the difference between the actual outcome and its expected value, so perhaps the bias arises from the structure of the correlation between the expected values of earnings and returns.

It therefore is constructive to represent the arguments more formally. To do so, we use the following relations:

$$X_{it-1} / P_{it-1} = \alpha_{10} + \alpha_{11}p_{it-1} + v_{1it-1}, \quad (2a)$$

$$p_{it-1} = \alpha_{20} + \alpha_{21}D(R_{it} < 0) + \alpha_{22}R_{it} + \alpha_{23}D(R_{it} < 0) * R_{it} + v_{2it-1} \quad (2b)$$

where  $p_{it-1} = \log(P_{it-1})$ .<sup>6</sup> The loss effect implies  $\alpha_{11} > 0$ . The variance effect implies  $\alpha_{22} < 0$  and  $\alpha_{23} > 0$ . Because stock price is negatively correlated with its variance, the absolute magnitude of positive (negative) returns is negatively (positively) related to price.

Substituting equation (2b) into (2a) gives:

$$X_{it-1} / P_{it-1} = \alpha_{10} + \alpha_{11}\alpha_{21} + \alpha_{11}\alpha_{21}D(R_{it} < 0) + \alpha_{11}\alpha_{22}R_{it} + \alpha_{11}\alpha_{23}D(R_{it} < 0) * R_{it} + u_{it-1} \quad (3)$$

The loss and variance effects together predict a negative coefficient ( $\alpha_{11}\alpha_{22} < 0$ ) on  $R_{it}$  and a positive coefficient ( $\alpha_{11}\alpha_{23} > 0$ ) on the interaction term  $D(R_{it} < 0) * R_{it}$ , which is a central PT finding. This finding is anomalous, since it involves both earnings predicting future returns and the relation between earnings and future returns exhibiting an asymmetry that mimics (in sign but not in magnitude) that reported by Basu (1997) and myriad ensuing studies.

The scale-effects argument implies that scale is a correlated omitted variable and that it should be controlled for in Basu regressions (and perhaps more broadly). In Section 4 we show empirically that the scale explanation is unsatisfactory. An alternative explanation therefore is required, to which we now turn.

*2.2. Understanding the source of the bias.* To understand the nature of the bias, we initially examine it analytically. We show that an implicit assumption in using the Basu (1997) model to estimate the incorporation of news into earnings is that the expected components of earnings and returns do not vary in cross-section and thus are absorbed by the intercepts. The apparent bias in Basu estimates then arises from failure to control for cross-sectional differences in expected returns and earnings. To understand the implications of this implicit assumption we

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<sup>6</sup> While PT use  $1/P_{it-1}$  to demonstrate the variance effect, we specify scale as  $\log(P_{it-1})$  in equation (2b) to make the argument considerably more straightforward. The two variables are highly (negatively) correlated. Indeed, they are perfectly correlated in their ranks and thus produce identical sorting. The representation we use does not affect any of the conclusions.

decompose earnings and returns as  $X_{it} / P_{it-1} = \eta_{it-1} + x_{it}$  and  $R_{it} = \mu_{it-1} + r_{it}$ , where

$$x_{it} \equiv X_{it} / P_{it-1} - E_{it-1}[X_{it}] / P_{it-1}, \eta_{it-1} \equiv E_{it-1}[X_{it}] / P_{it-1}, r_{it} \equiv R_{it} - E_{it-1}[R_{it}] \text{ and } \mu_{it-1} \equiv E_{it-1}[R_{it}].$$

The following model addresses the asymmetric timeliness of earnings in incorporating news:

$$x_{it} = \alpha_0 + \alpha_1 D(r_{it} < 0) + \beta_0 r_{it} + \beta_1 D(r_{it} < 0) * r_{it} + \varepsilon_{it} \quad (4)$$

where all variables are defined above. The slope coefficients that minimize the sum of squared residuals are as follows:

$$\beta_0 = \frac{\text{cov}(r_{it}, x_{it} | r_{it} \geq 0)}{\text{var}(r_{it} | r_{it} \geq 0)}, \text{ and } \beta_1 = \frac{\text{cov}(r_{it}, x_{it} | r_{it} < 0)}{\text{var}(r_{it} | r_{it} < 0)} - \frac{\text{cov}(r_{it}, x_{it} | r_{it} \geq 0)}{\text{var}(r_{it} | r_{it} \geq 0)} \quad (4a, 4b)$$

In contrast, the slope coefficients that minimize the sum of squared errors in equation (1) are:

$$b_0 = \frac{\text{cov}(R_{it}, x_{it} | R_{it} \geq 0)}{\text{var}(R_{it} | R_{it} \geq 0)} + \frac{\text{cov}(R_{it}, \eta_{it-1} | R_{it} \geq 0)}{\text{var}(R_{it} | R_{it} \geq 0)} \equiv \tilde{\beta}_0 + \theta_0, \quad (5a)$$

$$b_1 = \frac{\text{cov}(R_{it}, x_{it} | R_{it} < 0)}{\text{var}(R_{it} | R_{it} < 0)} - \frac{\text{cov}(R_{it}, x_{it} | R_{it} \geq 0)}{\text{var}(R_{it} | R_{it} \geq 0)} + \frac{\text{cov}(R_{it}, \eta_{it-1} | R_{it} < 0)}{\text{var}(R_{it} | R_{it} < 0)} - \frac{\text{cov}(R_{it}, \eta_{it-1} | R_{it} \geq 0)}{\text{var}(R_{it} | R_{it} \geq 0)} \equiv \tilde{\beta}_1 + \theta_1. \quad (5b)$$

Comparing equations (4a) and (4b) with equations (5a) and (5b) shows that failure to control for the expected components of earnings and returns is likely to bias Basu model estimates of how earnings incorporates the unexpected component of returns. The bias can be decomposed into two factors. First, and most importantly for present purposes, the confounding parameters  $\theta_0$  and  $\theta_1$  will differ from zero due to any cross-sectional relation between expected earnings and expected returns. The focus of this paper is on demonstrating the existence of such a relation, its effect on Basu model estimates, and solutions to the problem. Second, holding expected earnings constant,  $\tilde{\beta}_0$  and  $\tilde{\beta}_1$  are biased estimates of  $\beta_0$  and  $\beta_1$  due to an errors-in-variables problem caused by using observed return  $R$  to measure the economic news variable  $r$ ,

which it does with error. To a large degree we would expect this problem to be mitigated by controls for expected earnings, or more crudely by a fixed effects specification, both of which we implement below.

A related issue is whether an errors-in-variables problem also is caused by failing to decompose returns into shocks to expected returns (discount rates) and shocks to cash flows (e.g., Campbell and Shiller, 1988a,b; Campbell and Vuolteenaho, 2004). Both shocks can be market-wide or idiosyncratic. We view the various ways in which accounting rules and practices respond to different types of shock as determining the natural properties of accounting income, and consequently as affecting the true values of the Basu regression slopes. Conversely, we do not view the existence of different types of shock as giving rise to a measurement error problem that requires correction. For example, mark-to-market accounting (as in the case of marketable securities) contemporaneously incorporates both types of shock in earnings, and implies relatively high Basu slopes. In contrast, historical cost accounting implies relatively low Basu slopes because it incorporates shocks to cash flows with a lag (when the cash flows are realized, as modified by accruals) and incorporates shocks to expected returns only when debt is refinanced or after new investments are made with a changed hurdle rate that implies a shock to the cost of equity capital. Lower-of-cost-or-market accounting implies asymmetric Basu slopes. We view these as the types of effects that the Basu model, in which accounting income is the dependent variable, is designed to capture, and do not view them as a measurement error issue.<sup>7</sup>

Based on the analysis above, we conclude the following:

1. The parameters  $b_0$  and  $b_0 + b_1$  are biased estimators of the sensitivity of earnings to good and bad economic news, i.e.,  $\beta_0$  and  $\beta_0 + \beta_1$ .
2. The incremental slope coefficient  $b_1$  is a biased estimator of the degree of asymmetry in how the bad and good news components of stock return are reflected in earnings, i.e.,  $\beta_1$ .

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<sup>7</sup> See also the analysis of information about growth options in Ball, Kothari and Nikolaev (2011).

The main source of bias arises when the confounding parameter  $\theta_1 \neq 0$  due to non-linearity in the cross-sectional relation between the expected earnings and returns.

The confounding parameters  $\theta_0$ , and  $\theta_1$  will generally not equal zero if expected earnings and returns exhibit any cross-sectional relation. As discussed below, in a cross-section of firms,  $\text{cov}(R_{it}, \eta_{it-1}) = \text{cov}(\mu_{it-1}, \eta_{it-1})$  is unlikely to equal zero for various reasons. Furthermore, the relation between  $\mu_{it-1}$  and  $\eta_{it-1}$  is likely to be non-linear, and the covariance between the expected components of earnings and returns is expected to vary across groups of companies with different characteristics. More specifically,  $\text{cov}(\mu_{it-1}, \eta_{it-1} | R_{it})$  is likely to vary with  $R_{it}$ , in which case  $\theta_1 \neq 0$  and the asymmetric timeliness coefficient will exhibit bias.

We conjecture that a non-linear relation between the expected values of earnings and returns occurs due to two offsetting effects. First, a positive effect on the relation between  $\mu_{it-1}$  and  $\eta_{it-1}$  arises because expected stock return and expected earnings per share scaled by price jointly reflect underlying economic factors (Ball 1978).<sup>8</sup> This effect is likely to be dominant in mature companies without substantial growth, where accounting income better reflects underlying economic factors. Second, the effect on reported earnings of accounting rules for revenue recognition and expensing are not independent of firm characteristics and, in turn, of expected returns. Other things equal firms making increased investments incur earnings-decreasing expenses under accounting rules (e.g., R&D), but have higher expected stock returns (Penman and Zhang, 2002; Eberhart, Maxwell and Siddique, 2004), generating a negative effect

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<sup>8</sup> Earnings scaled by book value of shareholders' equity reflects the average *ex post* rate of return on equity. Scaling earnings by the number of shares and then by price transforms the variable into a proxy for *ex ante* expected stock return (otherwise known as the cost of equity capital), because it controls for the capitalized value of earnings in excess (positive or negative) of the cost of equity capital. This proxy is likely to be more accurate for firms whose earnings are less affected by revenue recognition and expensing rules and practices.

of the relation between  $\mu_{it-1}$  and  $\eta_{it-1}$ . We conjecture that these opposing effects combine to produce a non-linear relation between expected earnings and expected returns.

In Section 4.4 below, we report that there in fact is a non-linear relation between average earnings and average returns, which we interpret as evidence of a non-linear relation between their expected values. In Section 4.5 we show that controlling for this confounding effect essentially eliminates the bias observed by PT. This also implies that the source of bias is a confounding non-linear relation between the expected components of earnings and returns (as distinct from their news components) as opposed to scale.

*2.3. Why does past earnings exhibit a non-linear relation with returns?* When PT substitute past earnings for current earnings in the Basu regression, they find that the incremental coefficient on negative returns is significant and positive, which they conclude to be inconsistent with conditional conservatism:

“Note that a strong correlation between lagged and current earnings does not alter this conclusion. That is, even though lagged earnings are related to current earnings, which are in turn related to current news, lagged earnings cannot be related to current news. This is because news can only reflect surprises.”

We propose that lagged earnings is a proxy for expected earnings and expected returns, not for news.

To explore this possibility, we start by defining  $X_{it} / P_{it-1} = \eta_i + v_{it}$ , where  $v_{it}$  is a noise component that is unrelated to next-period returns. The OLS regression coefficient  $b_1$  in the specification adopted by PT then is given by:

$$b_1 = \frac{\text{cov}(R_{it}, \eta_i | R_{it} < 0)}{\text{var}(R_{it} | R_{it} < 0)} - \frac{\text{cov}(R_{it}, \eta_i | R_{it} \geq 0)}{\text{var}(R_{it} | R_{it} \geq 0)} = \theta_1. \quad (6)$$

We show below that the correlation between current and past earnings is substantial. Thus, lagged earnings proxies for expected earnings and hence the incremental coefficient on negative returns in a lagged-earnings regression, like the coefficient in the standard unlagged

specification, also reflects the cross-section correlation between expected earnings and (expected) returns. Failure by researchers to control for the expectation components therefore introduces a cross-sectional bias in the Basu estimator of conditional conservatism. The sign and magnitude of the bias depend on the sign and magnitude of the relation between expected earnings and returns.

*2.4. How can the bias be ameliorated?* To eliminate the bias in conditional conservatism parameters, it is thus necessary to control for the expected components of earnings and returns. We first describe the method used to account for expected returns, which is a portfolio based approach similar to those used in studies that measure long-term abnormal stock performance. We then discuss the three different methods used to control for expected earnings.

*Computing unexpected return.* Fama and French (1992, 1993) find that size and book-to-market ratios are the most important determinants in the cross-section of firms' expected returns, and that other variables such as beta, leverage, and earnings-to-price ratios add limited explanatory power. Based on these findings, computations of unexpected returns in long-horizon event studies typically are based on size and market-to-book portfolios (e.g., Brock, Lakonishok, and LeBaron, 1992; Ikenberry, Lakonishok, and Vermaelen, 1995; Barber and Lyon, 1997, Lyon, Barber, and Tsai, 1999). However, we are not aware of an accepted way of compute unexpected annual returns and for the population of firms. We adopt a portfolio-based approach based on the Fama-French findings and similar to that of Lyon, Barber, and Tsai (1999). Each year we construct 5×5 reference portfolios by sorting observations on size and book-to-market. We compute the average return for each portfolio and use it as a measure of expected return for the firms in a given portfolio (see section 4 for additional details).

Estimating expected returns over a horizon as long as a year is a difficult task (e.g., Kothari and Warner, 1997). Because the errors in estimating expected returns are likely to be

correlated with expected earnings and hence cause the bias to not be completely eliminated, it also is important to isolate and control for the expected component of earnings. Fortunately, this is likely to be easier to achieve than isolating the expected component of returns, because returns have considerably higher levels of volatility).

*Computing unexpected earnings.* Our hypothesis is that cross-sectional correlation between the expected components of earnings and returns introduces an omitted variable when estimating the relation between their unexpected components. We therefore offer three comparatively simple and commonly-used methods of addressing this problem: control for firm characteristics that are related to the expected components of earnings (and returns); use an expectations model to remove the expected components; and isolate firm fixed-effects in earnings.

*Approach 1:* One approach is to simply add to the Basu regression those controls for firm characteristics that are likely to determine expected earnings and expected returns. These include size (measured by log of price per share and market capitalization), book-to-market ratio, stock price volatility, and leverage. These controls isolate the variation in earnings that is orthogonal to the specified firm characteristics and, to the extent the characteristics successfully proxy for expectations, this approach isolates unexpected earnings and unexpected returns.<sup>9</sup> However, because the specified firm characteristics do not fully explain expected returns, they are not expected to fully eliminate evidence of bias.

*Approach 2:* Within each year and 2 digit SIC code, we estimate a simple first order autoregressive expectation model for earnings and use it to compute unexpected earnings. Timely loss recognition practices imply, and prior research shows, that losses are less persistent than

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<sup>9</sup> Because these variables are measured *ex ante*, they do not control for the unexpected components of earnings or returns, consistent with the arguments in Ball, Kothari, and Nikolaev (2010).



profits (e.g., Basu 1997). Consequently, we allow for differential persistence between positive and negative earnings and estimate the following earnings expectation model:

$$X_{it} / P_{it-1} = \alpha_0 + \alpha_1 D(X_{it-1} < 0) + \alpha_2 X_{it-1} / P_{it-1} + \alpha_3 D(X_{it-1} < 0) X_{it-1} / P_{it-1} + x_{it} \quad (7)$$

where  $x_{it}$  is the unexpected earnings component. An advantage of this method is that it can be estimated in cross-section and does not require a long time series of earnings. A drawback is that the method assumes that the expectation model is the same for all firms in each industry.

*Approach 3:* We next consider a simple case where earnings expectations are time invariant but differ across companies. While this is a considerable simplification of reality, our analysis suggests that it is powerful enough to essentially eliminate the bias. In this case the expectation represents a fixed effect in earnings:

$$X_{it} = \eta_i + x_{it}, \quad (8)$$

Two common ways to deal with firm specific effects are (i) differencing and (ii) inclusion of fixed effects into the regression. Both methods yield econometrically consistent estimates of the parameters of interest (Greene 2003) and we report below that they yield similar results.

### 3. Data and descriptive statistics

We use the intersection of the Compustat (Merged Fundamental Annual File) and CRSP databases and limit the sample to the period 1963-2010.<sup>10</sup> To replicate the analysis in PT (Table 3), we impose the following data requirements each firm-year  $t$ : (i) beginning of period price not less than \$1; (ii) earnings before extraordinary items available for three consecutive years,  $t$ ,  $t - 1$ , and  $t - 2$ ; (iii) price per share and number of shares outstanding available at the end of periods  $t - 1$ , and  $t - 2$ , and (iv) market adjusted stock return available for year  $t$ . To compute market adjusted returns, raw stock returns are compounded over 12 month periods ending 3 months after

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<sup>10</sup> The sample construction in PT is based on an older version of Compustat, but we closely replicate their results.

the fiscal year end and are subsequently adjusted by subtracting the 12-month return on a value-weighted market index compounded over the same period.

To perform further tests we impose additional data requirements as necessary. Our analysis in Table 3 employs control variables, which requires non-missing values for book value of shareholders equity and total liabilities measured at the end of year  $t - 1$  as well as the standard deviation of 12 monthly stock returns measured over the year  $t - 1$ . This reduces the number of observations, but does not materially affect the basic results.

The analysis in Table 4 further requires non-missing proxies for unexpected returns and unexpected earnings. A proxy for unexpected returns is computed based on 5×5 reference portfolios formed by sorting observations annually on market capitalization at the end of year  $t - 1$  and then on book-to-market ratio. We calculate monthly value weighted average returns for each portfolio to estimate the expected return for stocks in this portfolio, and require a minimum of 10 non-missing return observations per portfolio in a given month. Unexpected returns are calculated by subtracting the estimated expected returns from raw returns, with both compounded over 12-monthly periods ending 3 months after the firm's fiscal year end. To estimate unexpected earnings we follow the industry-based procedure described in Section 2 and require a minimum of 10 observations per industry each year. The fixed effect analysis in Table 5 no longer requires non-missing control variables, but instead requires non-missing earnings in year  $t - 3$  to ensure a minimum of at least two observations per firm in all specifications.

All tests are based on variables that are truncated at both tails of the distribution using 1% cutoff values. Our analysis is based on samples ranging between 133,237 and 162,119 firm-year observations, depending on the data requirements described above. The number of observations is reported in each table, and is limited to the most restrictive model within that table to hold the

sample constant across different model specifications. Table 1 reports descriptive statistics for the variables used in subsequent analyses.

#### 4. Evaluation of scale as a source of bias.

We first replicate the basic results reported by PT in our slightly larger sample, and observe the same evidence consistent with scale-related effects. We then provide a refutable test of the scale effects hypothesis, which it fails, so we conclude that the explanation must lie elsewhere.

*4.1. Replicating the basic results.* The first intriguing result in PT occurs when they replace period price-deflated earnings per share as the dependent variable in the Basu regression with the inverse of lagged price (the scalar for both earnings and returns), and show that the “bad news” proxy exhibits a significantly negative incremental coefficient. This result is attributed to a “variance effect.” The second intriguing result comes when past earnings is substituted for current earnings in the pooled Basu regression, and the estimated coefficient on “bad news” is positive. That is, past earnings predict future returns, and the relation depends on the sign of future returns. This seemingly-anomalous result is attributed to a combination of the “variance effect” and an additional “loss effect” due to a positive correlation between price and the level of price-deflated earnings.

To replicate these results, we run the following regression using pooled cross-sectional and time series data:

$$\text{Dependent variable} = \alpha_0 + \alpha_1 D(\text{Ret}_t < 0) + \beta_0 \text{Ret}_t + \beta_1 D(\text{Ret}_t < 0) \text{Ret}_t + \varepsilon_t \quad (9)$$

where *Dependent variable* is one of the dependent variables, such as current (lagged) earnings deflated by price,  $X_t/P_{t-1}$  ( $X_{t-1}/P_{t-1}$ );  $\text{Ret}_t$  is market-adjusted 12-month return; and  $D(\cdot)$  is an indicator variable. We omit the subscript  $i$  that identifies individual companies for brevity.

Table 2 reports the results, which correspond to Table 3 in PT. Test statistics are based on the Fama-MacBeth (1973) procedure, hence the table shows mean coefficients and their corresponding t-statistics from the distribution of yearly coefficient estimates. The model in row (1) of the table shows coefficients based on the Basu specification with  $X_t/P_{t-1}$  as the dependent variable in Equation (9). The estimated coefficients  $\beta_0$  and  $\beta_1$  are statistically significant, and equal 0.017 and 0.249 (giving a total loss-year effect of 0.265), respectively. The magnitudes of the coefficients are similar to those in Basu (1997).

Row (2) of Table 2 presents an analogous model with the dependent variable replaced by lagged earnings,  $X_{t-1}/P_{t-1}$ . The estimated coefficients  $\beta_0$  and  $\beta_1$  in this specification are -0.036 and 0.148 (total effect of 0.112), respectively. Both are statistically significant, with Fama-MacBeth t-values of -10.7 and +14.5. Similarly, when the dependent variable is replaced by  $X_{t-2}/P_{t-2}$ , in row (3) of Table 2, the coefficients  $\beta_0$  and  $\beta_1$  are -0.035 and 0.135 (total effect of 0.10), respectively, and remain significant, with Fama-MacBeth t-values of -12.1 and +12.6. While the total effect  $\beta_0 + \beta_1$  in the lagged model is economically significant and over 40 percent of its equivalent for the original Basu model in row (1), the R-squared is only 4 percent. This suggests that R-squareds, which in some cases are used to evaluate the overall timeliness of earnings with respect to economic news, are relatively immune to the bias. Nevertheless, the findings in rows (2) and (3) are anomalous, and consistent with bias in the Basu estimator of conditional conservatism.

To support their argument that scale effects drive these results, PT make two steps. First, they fix earnings at 1 and use  $1/P_{t-1}$  as the dependent variable in model (9) to test the variance effect hypothesis.<sup>11</sup> Row (4) of Table 2 reports coefficient estimates  $\beta_0$  and  $\beta_1$  for this model of 0.078 and -0.218, respectively, which are statistically significant with Fama-MacBeth t-values of

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<sup>11</sup> This substitution is not meaningful under the null hypothesis that the Basu (1997) model is well specified, because the error term then includes  $(1 - X_t)/P_{t-1}$ , which is correlated with the regressors under the null. This may partly render the findings in PT spurious rather than indicative of bias.

+13.2 and -13.0. This evidence is consistent with the variance effect, suggesting that beginning of period stock price and the variance of returns are inversely related.<sup>12</sup> Moreover, higher positive returns are more indicative of a lower stock price than are negative returns of similar magnitude. Second, it is argued that combining this pattern with an inverse relation between loss frequency and price is likely to explain the spurious evidence of conservatism in rows (2) and (3) of the table. We evaluate this explanation in the following subsection.

*4.2. Do scale-related loss and variance effects explain the bias?* To examine whether the combination of scale effects explains a positive (negative) coefficient on "bad news" ("good news") in a regression of lagged price-deflated earnings  $X_{t-1}/P_{t-1}$  on current period "good" and "bad news," we isolate variation in scale and repeat the analysis. If scale effects are a primary reason for the bias, then it should *not* be present in a group of companies of the same scale. This reasoning forms the basis of our tests of the scale effects explanation. We sort observations annually by scale (beginning of period price  $P_{t-1}$ ) into 50 portfolios of equal size. This creates 50 sub-samples, each of which consists of companies of similar scale, because almost all of the scale variation is across (as distinct from within) the sub-samples. In fact, an analysis of variance indicates that this procedure eliminates approximately 99% of the total variation in scale, measured as  $\log(P_{t-1})$  or  $1/P_{t-1}$ , leaving only 1% of the total variance within the formed portfolios. We then re-estimate the benchmark lagged-earnings specification within each of the 50 portfolios, and test whether bias continues to be observed.

This analysis is summarized in Figure 1. The figure plots the sum of the coefficients  $\beta_0 + \beta_1$  estimated from variation within each of 50 portfolios, for both the current and lagged earnings specifications. The line denoted by 'stars' depicts the coefficients  $\beta_0 + \beta_1$  based on the original Basu (1997) estimator. The majority of estimates across the 50 portfolios are in the

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<sup>12</sup> To see this note that the estimates imply that greater deviations of stock returns from the market in either direction are on average associated with higher  $1/P_{t-1}$  and hence lower price.

range of 0.1 to 0.3. The magnitude of the coefficients is declining as we move towards portfolios with higher prices. Such evidence, however, is not surprising as it is well known that price and market capitalization are closely related (e.g., Hawawini and Keim, 2000) and that timely loss recognition is expected to be declining in firm size (e.g., Basu 2001; Khan and Watts, 2010). The line denoted by ‘dots’ depicts the estimates from Equation (10), where the dependent variable is lagged earnings  $X_{t-1}/P_{t-1}$ . Given that we have isolated variation in scale and hence largely eliminated the scale effects within each portfolio, the coefficients on negative returns in this regression should be approximately equal to zero, if loss and variance effects explain the bias. Nevertheless, we find that bias persists in notable magnitudes. Based on this evidence we conclude that scale effects provide an unsatisfactory explanation for the documented irregularity.

## **5. Effect of heterogeneity in earnings and return expectations.**

We argue that the expected components of returns and earnings are heterogeneous (primarily in cross-section but also in time-series), and that earnings-returns regression slopes are affected by the structure of the correlation between expected earnings and expected returns.

*5.1. Predictability of future market-adjusted returns.* We first demonstrate that future market adjusted returns can be predicted by both current market adjusted returns and current price-deflated earnings. Figures 2A and 2B plot the respective results. Observations are sorted annually into 50 portfolios based on current-period market-adjusted returns in Figure 2A and price-deflated earnings in Figure 2B. In each of these two figures, we plot the average year-ahead market adjusted return for each of the 50 portfolios.

The evidence indicates that market-adjusted returns are not a good measure of unexpected (abnormal) returns because they are predictable based on prior earnings (Ball 1978) and based on prior period stock performance (Jegadeesh and Titman, 1993). This implies that the expected components in earnings are likely to play an important role in the relation between

returns and earnings. Furthermore, earnings and returns based “momentum” in returns (Chan, Jegadeesh and Lakonishok, 1996) implies that the anomalously significant coefficients in the model using lagged earnings as the dependent variable could be a manifestation of a wider earnings pricing anomaly (e.g., Ball and Brown, 1968; Bernard and Thomas, 1989).<sup>13</sup>

Figures 2A and 2B also provide a strong indication that the expected levels of earnings and market-adjusted returns indeed are related in a non-linear fashion in cross section. This evidence is consistent with the argument in Ball (1978) that expected returns and expected earnings (scaled by number of shares and by price) share common underlying economic determinants. More specifically, the figures suggest that  $cov(\mu_{it}, \eta_{it}) \neq 0$  and that the effect is more pronounced for companies with low returns and earnings. We explore this further in the following sub-section.

*5.2. Non-linear relation between expected earnings and expected returns.* To demonstrate more directly the non-linearity in the cross-sectional relation between the expected components of earnings and returns, we induce cross-sectional variation in expected values using known important risk factors: size and book-to-market ratio (Fama and French 1992, 1993). Each year we partition observations into 5×5 (or 10×5) portfolios based on beginning of period market capitalization and book-to-market ratio. For each portfolio we then compute average earnings and market-adjusted returns across all years, and provide times-series means as estimators of the portfolios’ expected earnings and expected returns (in excess of the market).

Forming portfolios on the basis of important *ex ante* risk factors is designed to induce cross-sectional variation in expected returns but not in unexpected returns. This design differs from the commonly-used firm-level regression of returns on earnings (Freeman and Tse, 1992; Das and Lev, 1994; Burgstahler and Dichev, 1997; Beneish and Harvey, 1998), which almost

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<sup>13</sup> See also Rusticus (2011), who shows a spurious relation between returns and implied cost of capital estimates due to return predictability.

entirely reflects the relation between the unexpected components of the variables. Our design averages earnings outcomes within portfolio, and over time, for portfolios that are not formed on the basis of earnings, and hence removes most of the variation in unexpected earnings in order to isolate mean effects.

Using these portfolio-level data, we run a non-parametric regression of estimated expected earnings on estimated expected return. This regression accommodates arbitrary non-linearity in the relation. The estimated regression function is presented in Figure 2C and indicates a pronounced non-linearity. For low levels of expected returns, expected earnings and expected return are positively related, with slope coefficients close to 1. However, this relation reverses for companies with high expected returns.

We conjecture that this non-linear pattern occurs due to a combination of the offsetting effects described in Section 2.2: a positive relation (dominant in mature firms) occurs because scaled earnings and average stock return reflect similar underlying economic factors (Ball 1978); and a negative relation (dominant in firms making substantial new investment) occurs because these are earnings-decreasing activities under accounting rules but are associated with increased expected stock returns (Penman and Zhang, 2002; Eberhart, Maxwell and Siddique, 2004). We conjecture that these opposing effects combine to produce a non-linear relation between expected earnings and expected returns.

The evidence in Figure 2 implies that the non-linear cross-sectional correlation between the expected components of earnings and returns leads to non-zero confounding parameters  $\theta_0$  and  $\theta_1$  in equations (5a) and (5b).<sup>14</sup> This in turn imparts a bias in conventional Basu estimates.

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<sup>14</sup> Strictly speaking, Figure 2 reveals a non-linear relation between the sample means of returns and earnings, not their population means. Nevertheless, this is the relation that holds in the sample data and which underlies the anomalous evidence of a non-linear relation between returns and lagged earnings.



5.3. *Correcting the cross-sectional heterogeneity bias.* We implement three relatively simple and widely-used approaches to isolate the expected components in earnings, and show empirically that these methods substantially reduce or eliminate the bias. We also implement several methods of isolating the expected components of returns, which has a lesser effect (due largely to the greater unpredictability of returns).

*Approach 1: Control for firm characteristics.* In Section 2 we propose that without controls for the expected components in earnings and returns, estimates of conditional conservatism can exhibit bias due to an omitted variables problem. To examine whether this is indeed the case, our first approach augments the Basu regression with ex ante determinants of expected earnings and expected returns as proxied by several control variables commonly used in the literature (e.g., Ball and Shivakumar, 2005; Roychowdhury and Watts, 2007; Khan and Watts, 2009):

$$\begin{aligned} \text{Dependent variable} = & \alpha_0 + \alpha_1 D(\text{Ret}_t < 0) + \beta_0 \text{Ret}_t + \beta_1 D(\text{Ret}_t < 0) * \text{Ret}_t \\ & + \sum \delta_k \text{Controls}_{t-1} + \varepsilon_t \end{aligned} \quad (10)$$

where *Controls* are *scale*, proxied by natural logarithm of price ( $\log(P)$ ) and market capitalization ( $\log(MktCap)$ ), book-to-market ratio ( $b/m$ ), *Leverage*, and return *Volatility*, all of which are measured as of year  $t - 1$ . This model controls for the expected components of earnings and returns in a parsimonious fashion (the controls are not interacted with the negative return indicator variable) without directly relying on proxies for unexpected returns or earnings, but as we report below it performs reasonably well in addressing the bias.

Table 3 presents results from re-estimating the specifications presented earlier in Table 2, with the controls added. In this augmented Basu (1997) model, presented in row (1) of Table 3, the estimated coefficients  $\beta_1$  and  $\beta_0 + \beta_1$  remain both sizable in magnitude (0.183 and 0.224) and statistically significant (Fama-MacBeth t-statistics of 15.7 and 16.4). Arguably, the coefficient

estimates are more consistent with reasonable priors than those obtained from standard Basu regressions, as in Table 2. For example, in Table 2 the  $\beta_0 + \beta_1$  estimate of timely loss recognition is 15.6 times the  $\beta_0$  estimate of timely gain recognition, which seems unreasonably high, but the ratio falls to 5.5 times when controls are added in Table 3. The ratio falls even further with better controls for the expected components of returns and earnings, reported below.

In rows (2) and (3), where the dependent variable is lagged earnings, the estimates of  $\beta_1$   $\beta_0 + \beta_1$  are reduced substantially by adding these few control variables. For the model based on  $X_{t-1}/P_{t-1}$  the sum  $\beta_0 + \beta_1$  falls from 0.112 in Table 2 to only 0.043 when controls are added, while for the model based on  $X_{t-2}/P_{t-2}$  it reduces from 0.10 to 0.033. While statistically significant, the coefficients are substantially reduced in economic significance. Furthermore, the inclusion of control variables almost fully eliminates the “variance effect” in row (4): with  $1/P_{t-1}$  as the dependent variable, adding controls reduces the magnitude of  $\beta_1$  from -0.218 in Table 2 to -0.006 in Table 3, and  $\beta_0 + \beta_1$  from -0.141 to -0.004, rendering them economically and (in case of the total effect) statistically insignificant.

Based on these findings, we conclude that adding a small number of control variables commonly used in the literature successfully deals with any scale effects and to large extent removes the bias in standard Basu (1997) estimates. This implies that bias is largely driven by cross-sectional heterogeneity. Because these control variables are only proxies for the unknown true determinants of expected earnings, a more comprehensive or more descriptive set of controls could be expected to remove even more of the bias. Next, we examine alternative ways to deal with the issue.

*Approach 2: Expectations model to control for expected earnings and expected returns.*

Under this approach, as well as *Approach 3* discussed further, we attempt to isolate the expected components of both earnings and returns. In both approaches, returns are adjusted for two risk

factors, size and book-to-market, based on the evidence of Fama and French (1992, 1993). While these factors are unlikely to fully eliminate return expectations, the evidence is that they are powerful explanatory variables for mean returns and thus we expect them to lower the degree of bias in estimating the Basu model.

To demonstrate that this in fact occurs, we specify  $X_{t-1}/P_{t-1}$  as the dependent variable in model (9), which we then estimate successively using raw returns, market-adjusted returns, and finally size and book-to-market adjusted returns, while holding scale constant to isolate its effects. We expect these adjustments to returns to provide progressively better measurements of unexpected returns and, if our hypothesis that failure to control for cross-sectional differences in expected returns and earnings biasing the standard Basu estimator is correct, we expect the bias to progressively fall. The results are summarized graphically in Figure 3, which depicts the total effect  $\beta_0 + \beta_1$ . The figure indicates the bias is most pronounced when the Basu model uses raw returns (denoted by ‘stars’). The bias falls somewhat using market adjusted returns (denoted by ‘stars’) and falls even further as returns are adjusted for the two risk factors. The results in Figure 3 are after adjusting in various ways for expected returns only.

Table 4, Panel A then reports results after also adjusting earnings for its expected component by estimating Equation (7) within each year and 2-digit SIC industry code, and then using the residuals from this model to measure unexpected earnings. We use this measure of unexpected earnings and its lagged counterpart as dependent variables. Returns are adjusted for the two risk factors, as discussed above.

The additional data requirements reduce the sample size, so to facilitate comparison we first re-estimate the contemporary and lagged earnings specifications reported earlier in rows (1) and (2) of Table 2, replacing raw returns with size and book-to-market adjusted returns. These estimates are presented in rows (1) and (2) of Table 4. As expected, in comparison with their

equivalents in Table 2 the slope coefficients are somewhat lower when the expected component of returns is removed by adjusting for size and book-to-market factors.

Rows (3) and (4) of Table 4 then demonstrate the additional effect of removing the expected component of earnings. Using size and book-to-market adjusted returns as in row (1), row (3) presents results where the dependent variable is contemporaneous earnings less its expected component,  $(X_t - E[X_t])/P_{t-1}$ , estimated from the industry-based model. The estimated coefficients  $\beta_1$  and  $\beta_0 + \beta_1$  are 0.117 and 0.157, respectively, and are statistically significant. The magnitudes are lower than the Basu specification estimates of 0.229 and 0.251 in row (1), consistent with bias due to failure to isolate expected earnings. Row (4) presents results where the dependent variable is lagged earnings adjusted for its expected component,  $(X_{t-1} - E[X_{t-1}])/P_{t-2}$ . The coefficients  $\beta_1$  and  $\beta_0 + \beta_1$  now are only 0.031 and 0.028, respectively. The estimate for  $\beta_1$  is one-fifth of its equivalent in row (2) when earnings is not adjusted for its expected component and, while it is statistically significant, its economic magnitude is small.

Finally, Panel B of Table 4 estimates a model with additional controls for firm characteristics. The dependent variable in row (5) of Panel B is  $(X_t - E[X_t])/P_{t-1}$ , which corresponds to the results in rows (1) and (3) of Panel (A) in the absence of control variables. The asymmetric timeliness estimates of  $\beta_1$  and  $\beta_0 + \beta_1$  (0.124 and 0.162, respectively) are largely unchanged from their comparable row (3) estimates. In the lagged-earnings specification with  $(X_{t-1} - E[X_{t-1}])/P_{t-2}$  as the dependent variable presented in row (6),  $\beta_1$  and  $\beta_0 + \beta_1$  decrease to 0.013 and 0.014, respectively, when controls are added. Economically, these magnitudes hardly compare to that of the estimated asymmetric timeliness coefficient, and exhibit little bias. Overall, our analysis again suggests that the bias in Basu estimates can be attributed largely to

the cross-sectional correlation between expected earnings and expected returns and can be addressed in the usual way with appropriate controls.

*Approach 3: Using unexpected returns and using firm fixed effects to control for expected earnings.* Similar results are observed when firm fixed effects are used to control for expected earnings, either through differencing or fixed effects regression. These methods have an advantage over our second approach in that they do not rely on a parameterized expectation model. Instead they control for cross-sectional differences in expected earnings by making the simplifying assumption that expectations are time invariant. In this case panel data techniques, including differencing and fixed effects regressions, can be used to isolate the effect of expected earnings when estimating asymmetric timeliness. We follow this approach and present the results in Table 5. Because we do not require control variables and industry based measures of unexpected earnings, the sample size increases. The first two rows of the table replicate the main prior results for this sample.

We begin by differencing earnings as one way of eliminating their fixed effect components (note that we do not difference returns as they are already adjusted). Results are presented in rows (3) and (4) of Table 5. Row (3) presents estimates when the dependent variable is contemporaneous change in earnings scaled by beginning price,  $(X_t - X_{t-1})/P_{t-1}$ . The estimated coefficients  $\beta_1$  and  $\beta_0 + \beta_1$  are 0.093 and 0.152. While remaining statistically significant, these coefficient magnitudes are substantially lower than their counterparts of 0.234 and 0.254 for the standard (undifferenced) Basu regression in row (1). Row (4) presents the analogous model employing the lagged earnings benchmark, with the dependent variable specified as lagged change in earnings,  $(X_{t-1} - X_{t-2})/P_{t-2}$ . The estimated coefficients  $\beta_1$  and  $\beta_0 + \beta_1$  of -0.001 and 0.006 now are economically tiny and statistically indistinguishable from

zero. In other words, the bias does not survive differencing of earnings as a means of controlling for expected earnings.

We next exploit fixed effect regression analysis. Instead of including firm-dummies, which can be computationally intensive for a large panel, we perform a simple transformation where we subtract each firm's own mean from its earnings observations.<sup>15</sup> This also allows computation of Fama-MacBeth test statistics, as in prior tests. Specifically, from annual cross-sectional regressions of earnings deviations from their firm-specific means on size and book-to-market adjusted returns, we compute average regression coefficients and their standard errors. The estimates based on this procedure are presented in rows (5) to (7) of Table 5. Similar to the above analysis based on earnings changes, when the dependent variable is deviations of contemporary earnings from the firm-specific means, the coefficients  $\beta_1$  and  $\beta_0 + \beta_1$  are statistically significant and equal 0.093 and 0.137. However, when the dependent variable is one year lagged earnings and fixed effects are eliminated, row (6) indicates that the coefficients are close to zero in magnitude and the total effect is no longer statistically significant (Fama-MacBeth t-statistics of 2.75 and 1.42). Row (7) shows the model when the dependent variable is two year lagged scaled earnings less firm fixed effects. The estimated coefficients are somewhat lower than in row (6) and hardly exhibit any bias. This analysis confirms our earlier conclusion that the bias is explained by the presence of a correlated omitted mean effects, which are comparatively straightforward to remove.

*5.4. Summary.* Bias in the standard Basu regression estimator of conditional conservatism is substantially reduced by controls for commonly-used firm characteristics and is further reduced by controls for expected earnings and expected returns. A simple firm fixed-effects regression essentially eliminates the bias. Because these results are obtained in a panel of pooled

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<sup>15</sup> A fixed effects estimator by construction subtracts from each observation of the dependent variable its firm/subject specific mean value. Doing so eliminates *between* firms/subjects cross-sectional variation and identifies the effect of changes in the variable.

cross-section and time-series observations, the success of the firm fixed effects specification implies that the bias is primarily cross-sectional in nature, due mainly to variation in risk across firms rather than to variation in risk or in risk premia over time. This helps explain why the practice of adjusting earnings and returns by subtracting their market components, as in Ball and Brown (1968) and Basu (1997, Table 1 Panel B), is not sufficient, because it implicitly assumes the variation in expected returns is entirely cross-temporal and not cross-sectional in character.

## **6. Additional Analyses.**

*6.1. Time-series variation in conditional conservatism.* In their Figure 3, PT show that estimated Basu (1997) coefficients are correlated over time with the equivalent coefficients when the dependent variable is lagged earnings. They conclude from this co-movement that much of the variation in asymmetric timeliness estimates must be spurious. We believe such a conclusion is premature for three main reasons. First, co-movement can be partly driven by failure to properly control for omitted variables. Second, some co-movement takes place mechanically, by construction of OLS estimates using the same set of regressors. For example, mere randomness in the regressors' common denominator (notably, noise in the share price) introduces a degree of co-movement between estimates from the contemporaneous and lagged earnings specifications. Third, at a more basic level, it is straightforward to show that, because the residuals in the models for current and lagged earnings are correlated, the two sets of parameters will share a correlation of similar magnitude. To illustrate this point, Figure 4 plots time series of estimates of  $\beta_0 + \beta_1$  from two models: (1) a model based on the proxies for current unexpected earnings and unexpected returns (depicted with stars) and (2) a model based on unexpected lagged earnings (depicted by dots). While the model based on lagged earnings shows no evidence of systematic bias, the estimates from both models exhibit co-movement. Again, such co-movement

is fully expected from statistics viewpoint and thus we conclude that the evidence of co-movement is expected and does not invalidate the methodology discussed here.

*6.2. Bias and cross-sectional firm characteristics.* Our analysis in Section 2 suggests that bias in the estimates of asymmetric timeliness is likely to vary with firm characteristics. Indeed, PT find that three firm characteristics (size, market-to-book ratio, and leverage) seem to induce variation in the bias. They use this result to question the validity of the conditional conservatism scores developed by Khan and Watts (2010), as well as to question the inferences from prior studies that explain the variation of conditional conservatism with book-to-market, firm size and leverage based on agency theory arguments. In contrast, our arguments suggest that such findings are simply a result of failure to control for determinants of expected earnings. Thus we revisit the issue here.

We partition the sample into 50 equally sized portfolios by independent sorts on each of the three firm characteristics, measured as of the beginning of the current period. For each portfolio, we estimate the Basu (1997) model and its lagged earnings counterpart using proxies for *unexpected returns* and *unexpected earnings* (current and lagged), augmented for the basic control variables as in Table 4. For convenience, we present the results graphically. Figures 5A, 5B, and 5C provide estimates of the total effect  $\beta_0 + \beta_1$  based on Equation (10) for each of the 50 portfolios formed on size (market capitalization), book-to-market, and leverage, respectively. In all three figures, 'stars' and 'dots' depict estimates where the dependent variable is  $(X_t - E(X_t))/P_{t-1}$  and  $(X_{t-1} - E(X_{t-1}))/P_{t-2}$ , respectively.

We find that the coefficient estimates for contemporaneous unexpected earnings decrease in firm size, and increase in book-to-market and leverage, consistent with prior literature (Roychowdhury and Watts, 2007; Khan and Watts, 2009) and with the analytical arguments in Ball, Kothari and Nikolaev (2011). The estimates reach fairly high magnitudes in some



portfolios, substantially in excess of the original Basu (1997) whole-sample estimates. In contrast, when lagged unexpected earnings is the dependent variable, we do not observe systematic variation in the estimated coefficients  $\beta_0 + \beta_1$  across size, book-to-market, and leverage portfolios. Instead, the estimates fluctuate around their means slightly above zero and exhibit no bias. Similar results are found when we use earnings changes to proxy for their unexpected component.

This evidence is consistent with the conclusion that asymmetric timeliness estimates vary with the firm characteristics of size, market-to-book ratio, and leverage because they are natural determinants of expected earnings and returns. Fortunately, controlling for firm characteristics correlated with expected earnings and returns is straightforward to deal with empirically.

## **7. Discussion and concluding remarks**

We show that conventional Basu (1997) regression coefficients are biased estimators of the relation between the *unexpected* “news” components of earnings and returns, due to a cross-sectional relation between their expected components. In particular, conventional estimates of asymmetry in how economic news is incorporated in earnings are biased by a non-linear relation between expected earnings and expected returns. For the researcher focusing on news, this relation confounds the Basu estimator unless controlled for.

This bias was identified by Patatoukas and Thomas (2011). They attributed the bias to scale-related effects and discouraged researchers from using Basu (1997) regression coefficients, which we regard as excessively alarmist. We provide evidence that scale is not the issue, and that the problem arises from a (non-linear) correlation between the expected (as distinct from news) components of earnings and returns. The nature of the bias therefore does not seem to be conceptually different from one arising from an omitted correlated variable. Omitted variables are a common and well-recognized issue in the empirical literature generally. How to deal with

this problem empirically also is well understood (Greene 2003, Chapter 13). We show that bias essentially disappears when firm-specific effects in earnings are taken into account or other simple methods are employed. Advising against using the Basu (1997) measure of asymmetric timeliness, without offering any meaningful alternative, is unlikely to positively benefit empirical research.

We offer several simple ways to improve on the standard Basu (1997) specification to address the bias. Both an uncomplicated control for a small number of well-known risk factors determining expected values, and a relatively crude way of removing the expected components of firms' earnings, substantially reduce bias and increase confidence in estimates of asymmetric timeliness. Furthermore, a simple inclusion of firm fixed effects essentially eliminates the bias, which becomes insignificant. After implementing these controls, the estimate of asymmetric timeliness remains statistically and economically significant. The estimates are reduced in magnitude, and arguably are more consistent with reasonable priors. They also behave as a predictable function of market-to-book, size and leverage. It would be surprising if these results did not occur. Conditional conservatism accords with the long-standing accounting principle of anticipating losses but not gains, with specific asymmetric accounting rules such as the lower-of-cost-or-market method for inventories and the rules for impairment of long term assets, and with loss recognition practices that occurred prior to the promulgation of formal rules.

Some previous annual-horizon research designs have implemented limited controls for expected returns and expected earnings. Ball and Brown (1968, pp. 161-163) attempt to control for expected earnings and returns by differencing earnings and by subtracting their respective market factors. Basu (1997, Table 1 Panel B) subtracts the market factor in returns for one set of

results.<sup>16</sup> We show that subtracting ex post market factors is not sufficient when estimating conditional conservatism, and that failure to control for cross-sectional differences in expected earnings and expected returns, under a fairly general set of assumptions, can indeed bias the estimate. However, we show empirically that differencing earnings works well in this context as a control for expected earnings.

The conclusion drawn in PT (p. 9 for example) that bias in the Basu estimator is a result of truncation, as advocated in Dietrich et al. (2007), in our view is not valid. First, it is at best unclear how the sample truncation argument in Dietrich et al. is related to the scale effects argument in PT, because they are different effects. Second, Ball, Kothari, and Nikolaev (2011) demonstrate that sample truncation does not give rise to bias in a context where the unexpected (news) components of earnings and returns have been isolated, and we conclude from the analysis and evidence reported in the present paper that the problem is due to correlation between the expected values of the variables, not truncation. Thus, the issue has little in common with sample truncation. Third, Ball, Kothari, and Nikolaev (2011) argue that the procedure Dietrich et al. employ to support the truncation bias hypothesis is invalid.<sup>17</sup>

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<sup>16</sup> These are the two prominent annual-horizon research designs in the literature; the issue is less relevant in short-window “announcement effect” studies. Basu (1997, p.10) motivates controlling for the market factor on efficiency grounds, rather than on the need to control for expected values.

<sup>17</sup> Dietrich et al. offer the following empirical procedure, which they refer to as a “simulation,” to test their sample truncation bias hypothesis. First, they regress returns  $R_{it}$  on earnings and save the residuals  $\tau_{it}$  and predicted values  $\hat{R}_{it}$ . Second, they construct synthetic returns by matching firms’ predicted values with randomly selected residuals of other firms, such that  $R_{it}^S = \hat{R}_{it} + \tau_{kt}$  and  $k \neq i$ . Third, using these synthetic returns they obtain significant coefficients on negative returns in the Basu regression, which they argue is direct evidence of bias. This procedure is not strictly a simulation, and is akin to bootstrapping. It can be expected to show similar results to those obtained from actual returns, and does not provide new evidence of truncation bias. Because earnings is left-skewed under conditional conservatism, in their regression of returns on earnings the residual  $\tau_{it}$  is overrepresented by large positive values and underrepresented by negative values. Therefore, positive synthetic returns  $R_{it}^S$  are less likely to be true “good news” for firm  $i$  but more likely to be due to positive values of  $\tau_{kt}$ . In contrast, negative synthetic returns are more likely to be due to true “bad news” for firm  $i$  than to negative values of  $\tau_{kt}$ . In other words, the procedure uses actual rather than simulated earnings and retains the distributional properties of actual earnings that are due to conditional conservatism, and the values of the synthetic returns are still informative about the sign and magnitude of (“bad” and “good”) economic news for firm  $i$  in year  $t$ . Hence, the procedure does not permit a conclusion that estimates are biased.

The data patterns documented by PT and replicated herein are fully consistent with the conclusion of Ball, Kothari and Nikolaev (2011) that the Basu estimator provides a valid measure of conditional conservatism in the form of asymmetric incorporation of the *news* in stock returns (a proxy for economic income). The typical research objective is to estimate how accounting rules and reporting practices filter the stream of value-relevant information (“news”) to determine accounting earnings, and in particular the extent to which the accounting filter is asymmetric in its timeliness. The entire Ball et al. (2011) analysis therefore is carried out on the unexpected components of earnings and returns. Our result that the bias in the Basu estimator is driven by failing to control for expected returns and expected earnings therefore reconciles with the conclusion of Ball, Kothari and Nikolaev (2011) because, by definition, news has no expected value.

Finally, we note that the research objective does not always require the separation of changes in economic value into expected and news components. This is more likely to be the case when researching the role of conservatism in contracting contexts. For example, for the purpose of implementing a leverage covenant, lenders would seem to be indifferent between changes in firm value that are expected and those that are not.<sup>18</sup> The original Basu regression is well-specified when the research objective does not require separation of the news and expected components of returns.

Overall, we conclude that researchers interested in the incorporation of economic news in accounting earnings need to be aware of cross-sectional bias in estimates of conditional conservatism and we recommend several straightforward remedies to deal with it. Omitted variables are a standard problem in empirical research, and do not imply that all evidence of asymmetric timeliness is spurious or that the concept of conditional conservatism in Basu (1997) is conceptually flawed. Hopefully, further research will provide a more solid economic

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<sup>18</sup> See also Dechow (1994, p.14).

explanation for the observed relation between the expected components of returns and earnings, and of its effect on components of earnings (notably, cash flow versus accruals) and as a function of the measurement interval (quarterly, annual, or longer horizons).

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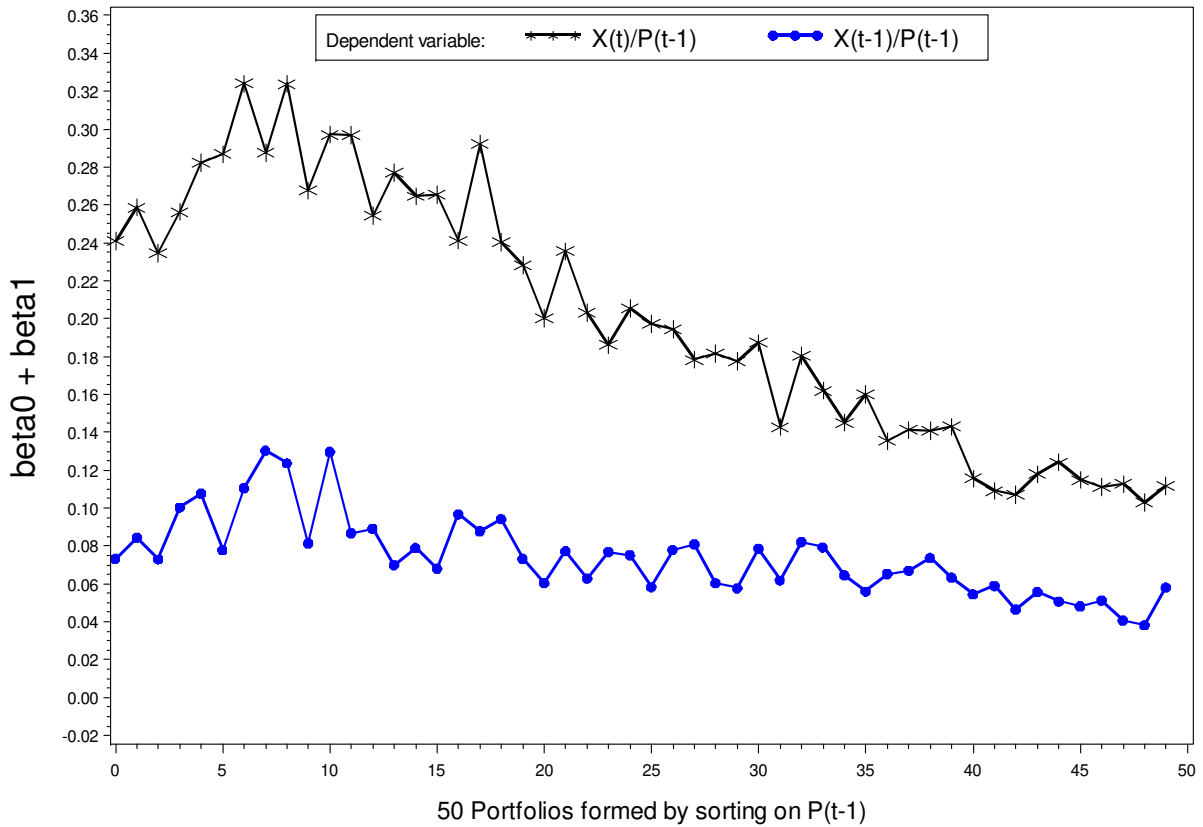
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**Figure 1: Coefficient estimates from regressions of current and lagged earnings on signed returns, holding scale effects constant**

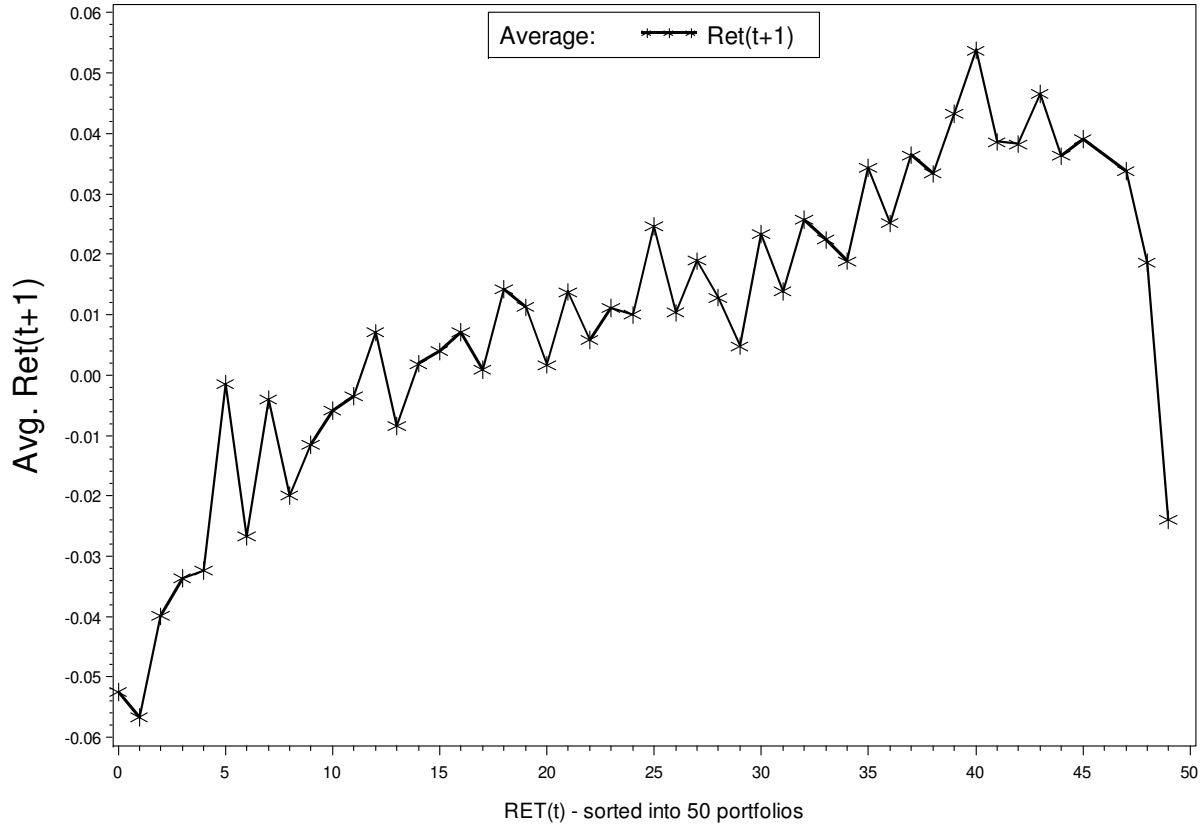
The figure presents the estimated total effect  $\beta_1 + \beta_2$  based on the model in Equation (9) estimated from pooled time series and cross-sectional data for each of 50 portfolios formed by annually sorting observations on beginning of period price  $P_{t-1}$ . The lines represented by 'stars' and 'dots' are based on a model where the dependent variable is current period price-deflated earnings ( $X_t/P_{t-1}$ ) and one period lagged price deflated earnings ( $X_{t-1}/P_{t-1}$ ), respectively.



## Figure 2: Important properties of expected returns and expected earnings

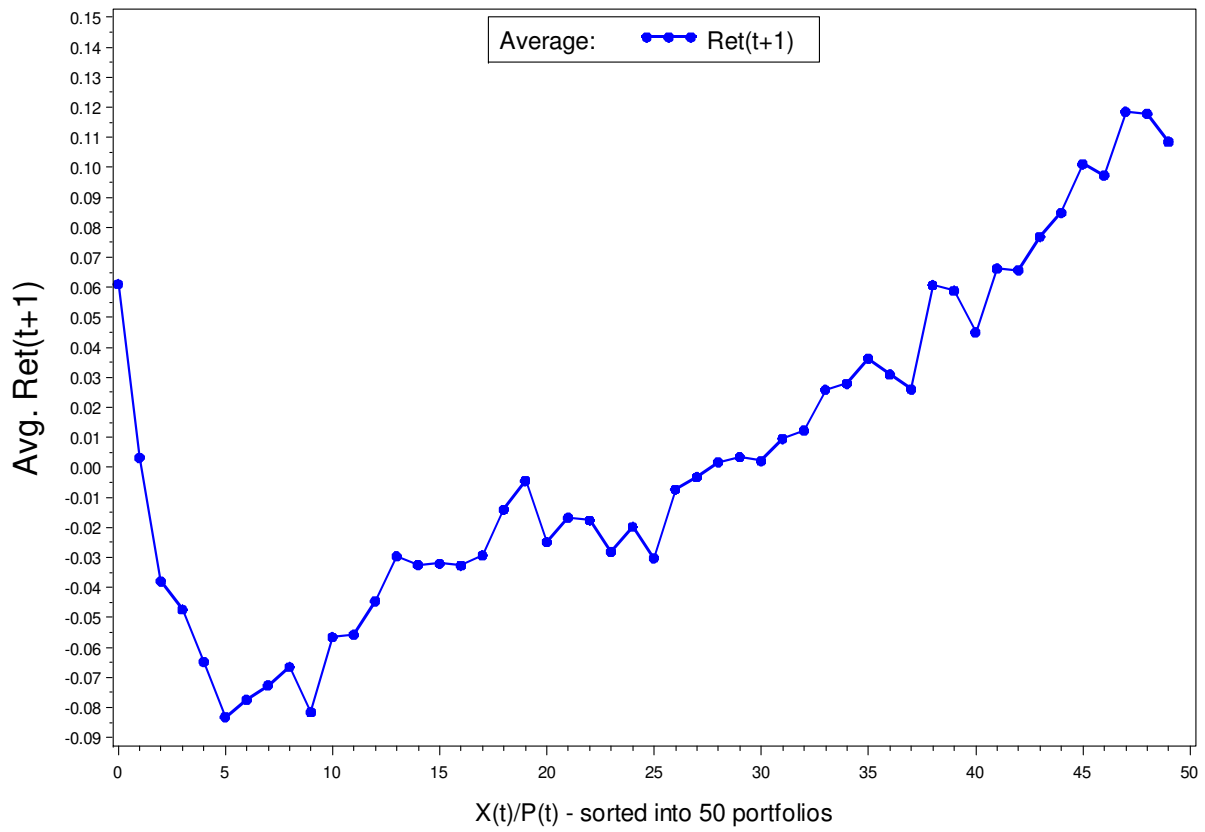
### Figure 2A: Future market adjusted returns conditional on current returns

Period  $t + 1$  average market adjusted returns ( $Ret_{t+1}$ ) for each of 50 portfolios formed by annually sorting on current-period market adjusted return ( $Ret_t$ ). Averages are estimated from pooled time series and cross-sectional data for each portfolio.



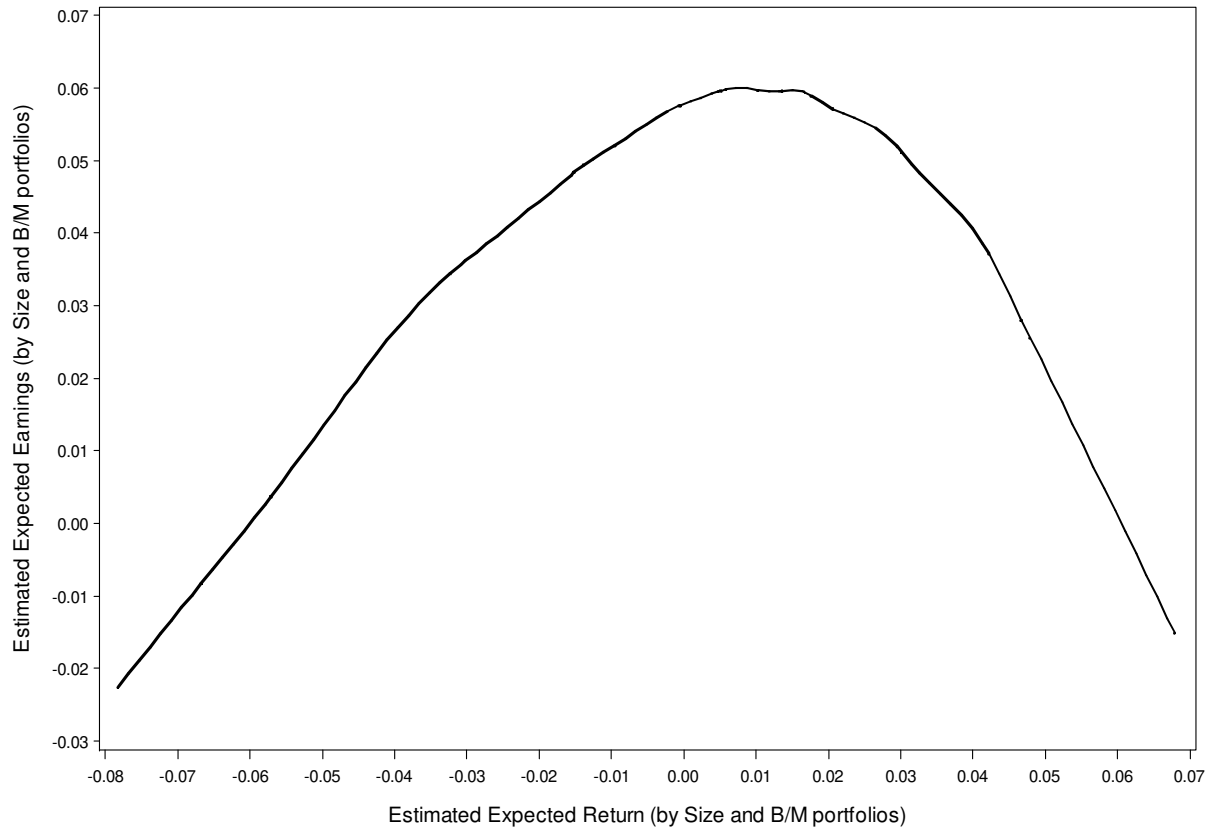
**Figure 2B: Future market adjusted returns conditional on current earnings**

Period  $t+1$  average market adjusted returns ( $Ret_{t+1}$ ) for each of 50 portfolios formed by annually sorting on current-period earnings ( $X_t/P_{t-1}$ ). Averages are estimated from pooled time series and cross-sectional data for each portfolio.



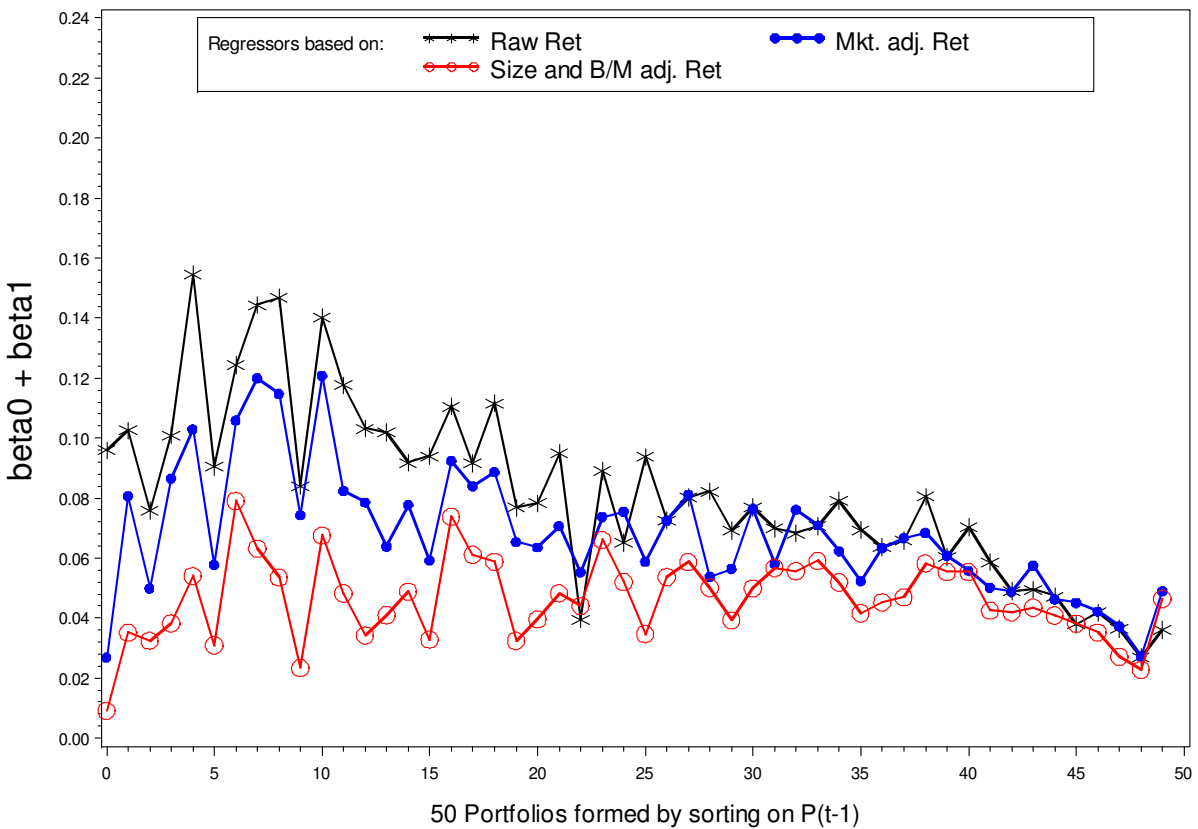
**Figure 2C: Non-linearity in the relation between expected returns and expected earnings**

To induce cross-sectional variation in expected values, we annually partition observations into 5×5 portfolios based on beginning of period market capitalization and book-to-market ratio. Time-series average earnings and average market adjusted returns for each portfolio are presented as estimates of the portfolio's expected earnings and expected returns. We estimate a non-parametric regression of estimated expected earnings on estimated expected return to accommodate arbitrary non-linearity in the relation between them. The regression line is plotted in this figure. Note that average return here is displaced to the left by the market average return.



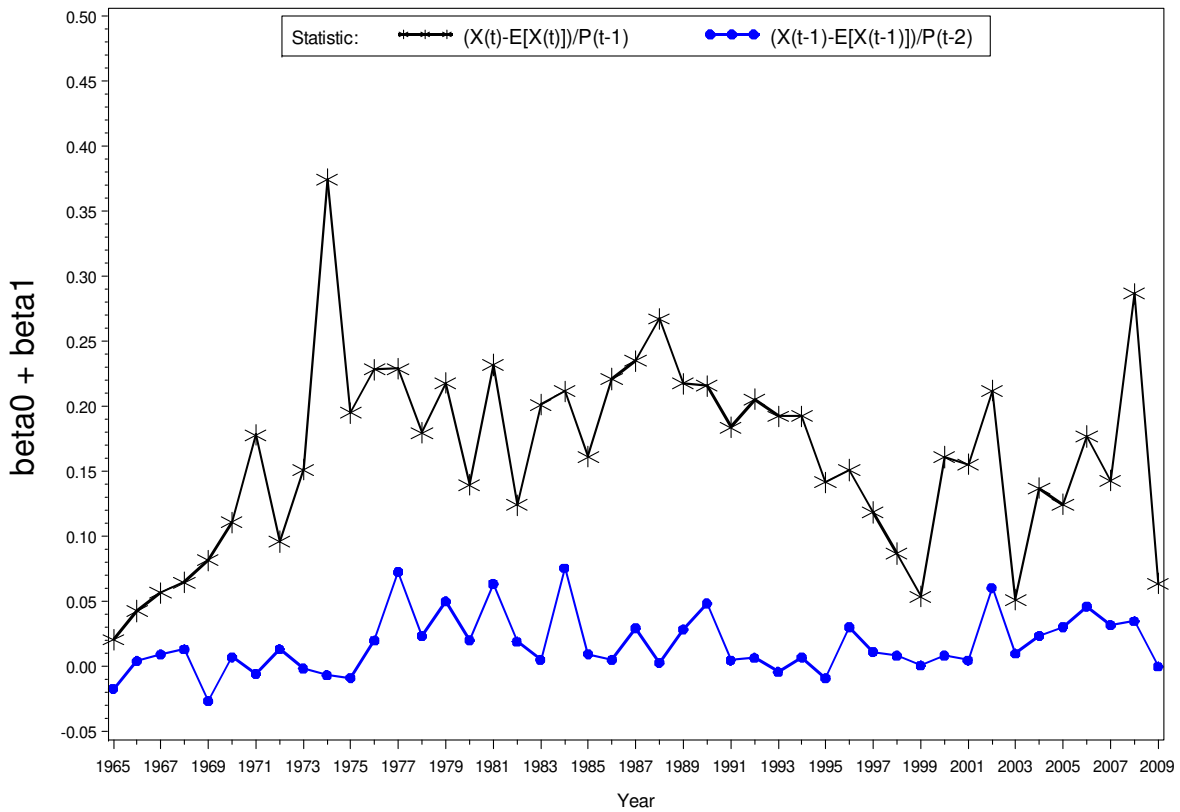
**Figure 3: The effect of adjusting returns for their expectation on the bias.**

The figure presents the estimated total effect  $\beta_1 + \beta_2$  based on the model in Equation (9) estimated for each of 50 portfolios formed by annually sorting on beginning of the period price  $P_{t-1}$ . The dependent variable is one period lagged price deflated earnings  $X_{t-1}/P_{t-1}$ ; the explanatory variables are constructed based on three measures of returns ( $Ret_t$ ): raw returns, market adjusted returns, and size and book-to-market adjusted returns. The lines represented by 'stars', 'dots', and 'circles' present estimates where  $Ret_t$  is raw returns, market adjusted returns, and size and book-to-market adjusted returns, respectively. Regressions are estimated from pooled time series and cross-sectional data for each portfolio.



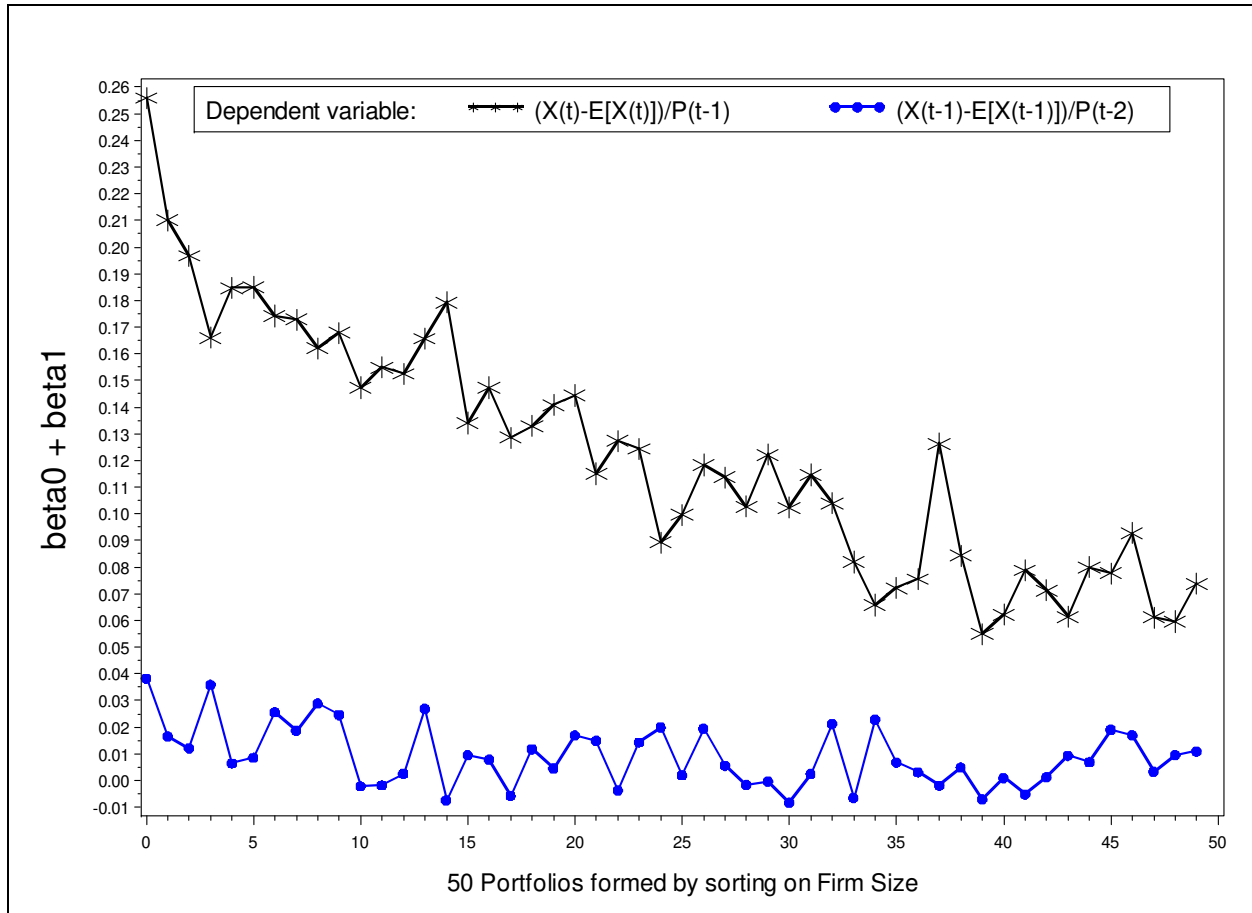
**Figure 4: Time series of estimates: Controlling for determinants of earnings.**

The lines represented by 'stars' and 'dots' present the time series of annual cross-sectional estimates of the total effect  $\beta_1 + \beta_2$  from Equation (10) where the dependent variable is current period unexpected earnings and one period lagged unexpected earnings, respectively. Unexpected earnings are estimated using the 2-digit SIC industry-based model discussed in Section 2 (*Approach 2*). The explanatory variable  $Ret_t^e$  is size and book-to-market adjusted return. Control variables include scale, book-to-market, leverage, and volatility



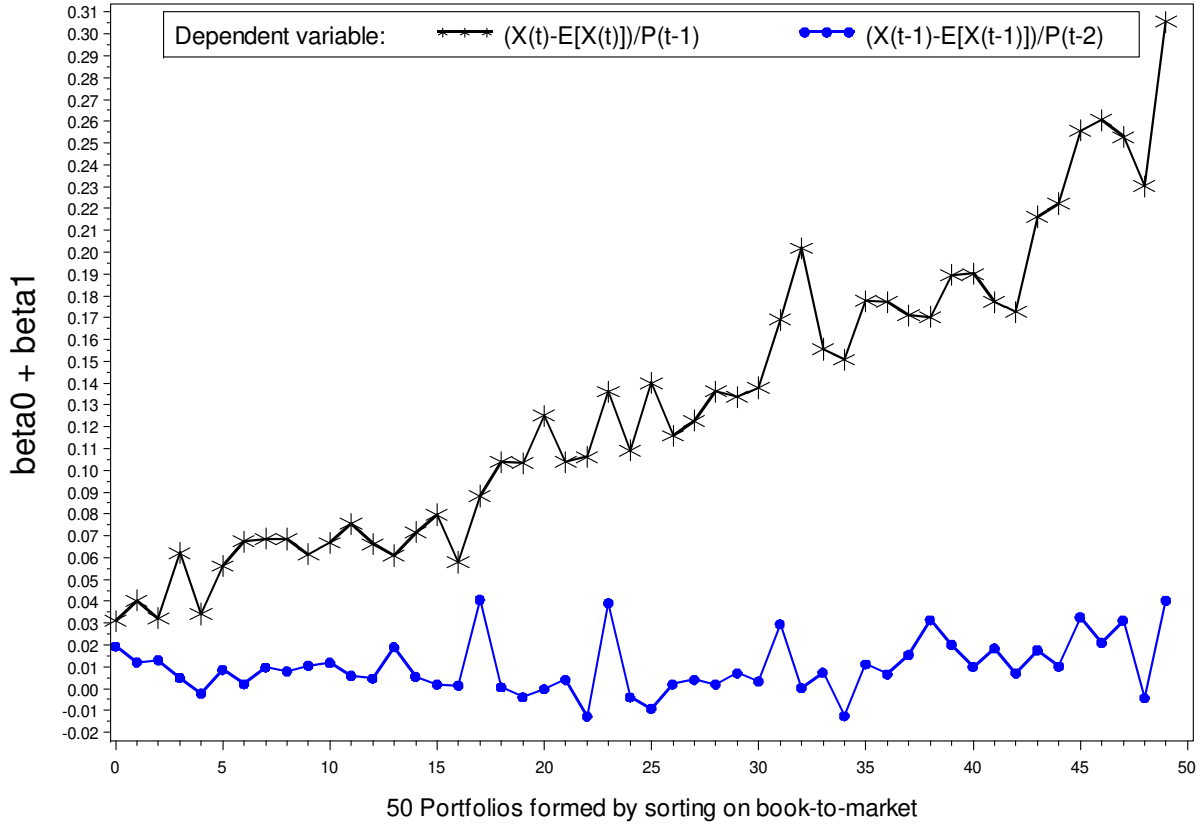
**Figure 5A: Slope coefficients from a regression of current and lagged earnings on signed returns, estimated across 50 portfolios based on firm size.**

The figure presents estimated coefficients for each of 50 portfolios formed by sorting on beginning of the period market capitalization. Regressions are estimated from pooled time series and cross-sectional data for each portfolio. ‘Stars’ and ‘dots’ represent estimates of  $\beta_1 + \beta_2$  from Equation (10) where the dependent variable is current period unexpected earnings and one period lagged unexpected earnings, respectively. Unexpected earnings are estimated using the 2-digit SIC industry-based model discussed in Section 2 (*Approach 2*). The explanatory variable  $Ret_t^a$  is size and book-to-market adjusted return. Control variables include scale, book-to-market, leverage, and volatility.



**Figure 5B: Slope coefficients from a regression of current and lagged earnings on signed returns, estimated across 50 portfolios based on market-to-book ratio.**

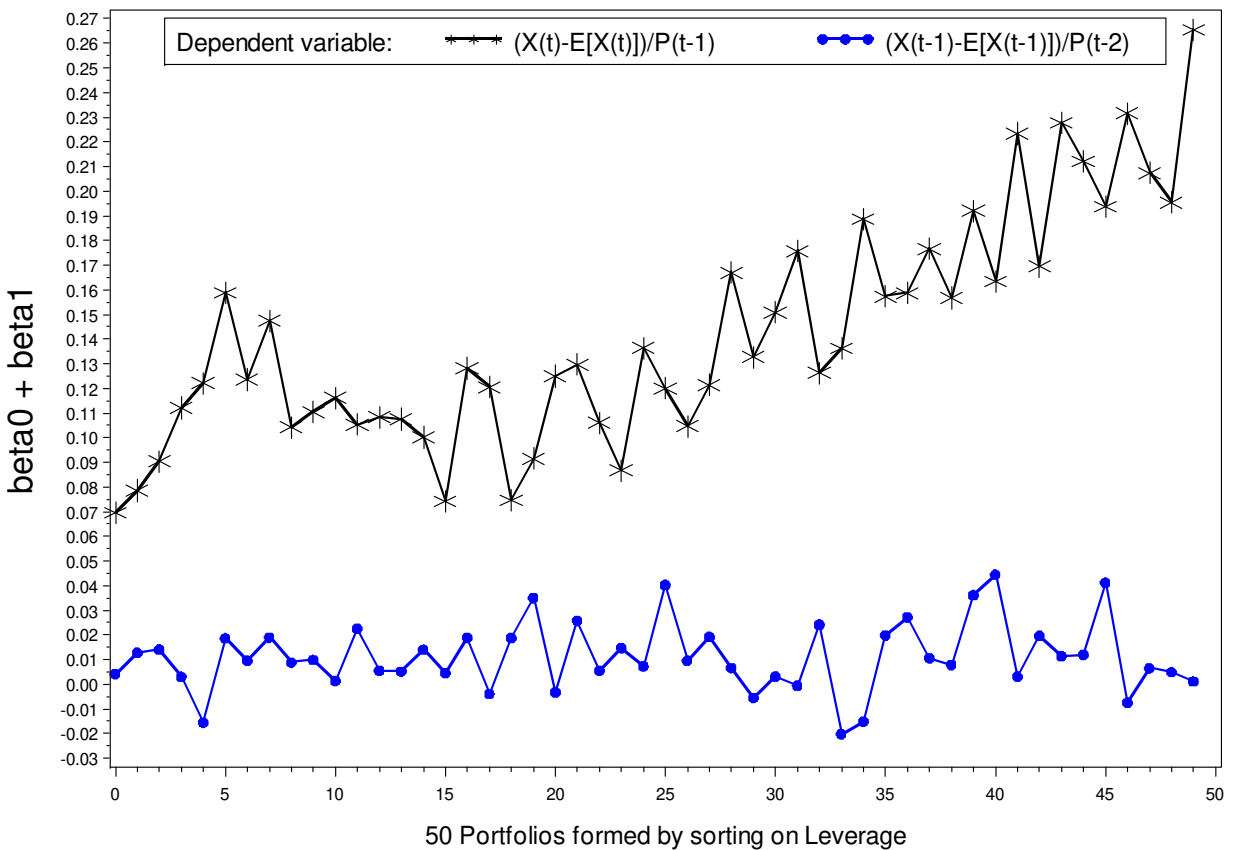
The figure presents estimated coefficients for each of 50 portfolios formed by sorting on beginning of the period book-to-market ratio. Regressions are estimated from pooled time series and cross-sectional data for each portfolio. ‘Stars’ and ‘dots’ represent estimates of  $\beta_1 + \beta_2$  from Equation (10) where the dependent variable is current period unexpected earnings and one period lagged unexpected earnings, respectively. Unexpected earnings are estimated using the 2-digit SIC industry-based model discussed in Section 2 (*Approach 2*). The explanatory variable  $Ret_t^a$  is size and book-to-market adjusted return. Control variables include scale, book-to-market, leverage, and volatility.





**Figure 5C: Slope coefficients from a regression of current and lagged earnings on signed returns, estimated across 50 portfolios based on leverage.**

The figure presents estimated coefficients for each of 50 portfolios formed by sorting on beginning of the period long-term debt-to-assets ratio. Regressions are estimated from pooled time series and cross-sectional data for each portfolio. ‘Stars’ and ‘dots’ represent estimates of  $\beta_1 + \beta_2$  from Equation (10) where the dependent variable is current period unexpected earnings and one period lagged unexpected earnings, respectively. Unexpected earnings are estimated using the 2-digit SIC industry-based model discussed in Section 2 (*Approach 2*). The explanatory variable  $Ret_t^a$  is size and book-to-market adjusted return. Control variables include scale, book-to-market, leverage, and volatility.



**Table 1: Descriptive statistics.**

Table 1 provides summary statistics for variables used in subsequent analysis. The data are based on the intersection of the Compustat and CRSP databases. We limit the sample to the period 1964-2010 and exclude observations that have beginning-of-period price under \$1. We require non-missing observations for (i) earnings before extraordinary items in years  $t$  to  $t-2$ ; (ii) common shares outstanding and beginning-of-period price for periods  $t-1$  and  $t-2$ ; (iii) market adjusted stock return in the current period  $t$ . Stock returns are compounded over the 12 months ending 3 months after the fiscal year end and are subsequently adjusted by subtracting the 12 month return on a value-weighted market index compounded over the same period. *MktCap* is market capitalization as of the beginning of the fiscal year; *b/m* is the ratio of book value of equity to its market value as of the beginning of the fiscal year; *Leverage* is the ratio of long term debt to total market value of assets as of the beginning of the fiscal year; *Volatility* is the standard deviation of monthly stock returns; *Ret* is market adjusted stock return;  $Ret^a$  is size and book-to-market adjusted stock return;  $X$  is earnings per share (earnings before extraordinary items divided by the number of shares outstanding);  $P$  is stock price per share.  $D(\cdot)$  is an indicator function and  $E[\cdot]$  is the expectation operator. The expectation model is estimated based on 2-digit SIC industry groups and is described in Section 2. Subscripts denote time at (over) which variables are measured. To remove outliers and data errors, variables are truncated at both tails using 1% a cutoff value.

*Panel A: Summary Statistics.*

<b>Variable</b>	<b># Obs.</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Q1</b>	<b>Median</b>	<b>Q3</b>
$Ret_t$	162119	0.005	0.451	-0.277	-0.047	0.206
$Ret_t^a$	159137	-0.021	0.420	-0.280	-0.059	0.174
$X_t/P_{t-1}$	162119	0.040	0.144	0.013	0.062	0.106
$X_{t-1}/P_{t-1}$	162119	0.036	0.132	0.019	0.058	0.094
$X_{t-2}/P_{t-2}$	162119	0.042	0.121	0.021	0.058	0.095
$X_t - E[X_t]/P_{t-1}$	162119	0.000	0.105	-0.019	0.008	0.039
$X_{t-1} - E[X_{t-1}]/P_{t-2}$	162119	0.000	0.087	-0.020	0.005	0.033
$X_t - X_{t-1}/P_{t-1}$	162119	0.004	0.133	-0.021	0.007	0.032
$X_{t-1} - X_{t-2}/P_{t-2}$	162119	0.010	0.117	-0.017	0.008	0.033
$\log(P_{t-1})$	162119	2.615	0.996	1.964	2.741	3.331
$\log(MktCap_{t-1})$	162119	5.081	2.121	3.517	4.923	6.492
$b/m_{t-1}$	158419	0.760	0.558	0.365	0.624	1.001
$Leverage_{t-1}$	158523	0.144	0.149	0.013	0.098	0.234
$Volatility_{t-1}$	141121	0.116	0.061	0.071	0.102	0.146

Panel B: Pearson correlations.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	$Ret_t$	1.00													
2	$Ret_t^a$	0.91	1.00												
3	$X_t/P_{t-1}$	0.28	0.27	1.00											
4	$X_{t-1}/P_{t-1}$	0.05	0.04	0.54	1.00										
5	$X_{t-2}/P_{t-2}$	0.06	0.04	0.35	0.45	1.00									
6	$X_t - E[X_t]/P_{t-1}$	0.27	0.28	0.73	0.00	0.05	1.00								
7	$X_{t-1} - E[X_{t-1}]/P_{t-2}$	0.02	0.03	0.29	0.62	0.00	-0.01	1.00							
8	$X_t - X_{t-1}/P_{t-1}$	0.26	0.25	0.55	-0.41	-0.06	0.79	-0.30	1.00						
9	$X_{t-1} - X_{t-2}/P_{t-2}$	0.02	0.02	0.17	0.41	-0.48	-0.03	0.75	-0.22	1.00					
10	$\log(P_{t-1})$	-0.01	0.05	0.27	0.32	0.28	0.10	0.18	-0.03	0.03	1.00				
11	$\log(Mkt. Cap_{t-1})$	-0.01	0.03	0.07	0.10	0.07	0.06	0.09	-0.02	0.00	0.71	1.00			
12	$b/m_{t-1}$	0.11	-0.01	0.09	0.11	0.18	-0.07	-0.09	-0.01	-0.06	-0.29	-0.37	1.00		
13	$Leverage_{t-1}$	0.04	0.00	0.05	0.05	0.07	-0.02	-0.05	0.01	-0.02	-0.06	-0.05	0.33	1.00	
14	$Volatility_{t-1}$	-0.02	-0.05	-0.25	-0.30	-0.30	-0.05	-0.06	0.03	0.03	-0.44	-0.28	-0.04	-0.08	1.00

**Table 2: Replication of the main findings in Patatoukas and Thomas (2010).**

The data are based on the intersection of the Compustat and CRSP databases. We limit the sample to the period 1963-2010 and exclude observations that have beginning-of-period price under \$1. We require non-missing observations for (i) earnings before extraordinary items in years  $t$  to  $t-2$ ; (ii) common shares outstanding and beginning-of-period price for periods  $t-1$  and  $t-2$ ; (iii) market adjusted stock return in the current period  $t$ . For comparability, we also require an equal number of observations for each model in a given table.  $Ret$  is *market adjusted* stock return compounded over the 12 months ending 3 months after the fiscal year end;  $X$  is earnings per share (earnings before extraordinary items divided by the number of shares outstanding);  $P$  is stock price per share.  $D(\cdot)$  is an indicator function. Subscripts denote time at (over) which variables are measured. To remove outliers and data errors, variables are truncated at both tails using a 1% cutoff value. The table reports average annual cross-sectionally estimated coefficients and their standard errors based on the Fama-MacBeth (1973) procedure. The model specification is as follows (*Dependent variable* is stated in the second column):

$$Dependent\ variable = \alpha_0 + \alpha_1 D(Ret_t < 0) + \beta_0 Ret_t + \beta_1 D(Ret_t < 0) Ret_t + \varepsilon_t$$

Row	Dependent Variable	Statistic	$\alpha_0$	$\alpha_1$	$\beta_0$	$\beta_1$	$\beta_0 + \beta_1$	R-squared	Number Obs.
(1)	$X_t/P_{t-1}$	Estimate t Value Pr >  t	0.081 13.468 0.000	0.011 4.581 0.000	0.017 3.853 0.000	0.249 17.805 0.000	0.265 18.074 0.000	0.170	162119
(2)	$X_{t-1}/P_{t-1}$	Estimate t Value Pr >  t	0.065 11.626 0.000	0.003 1.507 0.139	-0.036 -10.732 0.000	0.148 14.534 0.000	0.112 13.518 0.000	0.041	162119
(3)	$X_{t-2}/P_{t-2}$	Estimate t Value Pr >  t	0.070 13.135 0.000	0.001 0.458 0.649	-0.035 -12.057 0.000	0.135 12.649 0.000	0.100 11.006 0.000	0.038	162119
(4)	$1/P_{t-1}$	Estimate t Value Pr >  t	0.081 20.248 0.000	-0.001 -0.604 0.549	0.078 13.235 0.000	-0.218 -13.036 0.000	-0.141 -11.523 0.000	0.064	162119

**Table 3: The effect of controlling for ex ante determinants of expected earnings on bias in asymmetric timeliness.**

Table 3 replicates the main results in PT (2010) using unadjusted (raw) returns. The data are based on the intersection of the Compustat and CRSP databases. We limit the sample to the period 1964-2010 and exclude observations that have beginning-of-period price under \$1. We require non-missing observations for (i) earnings before extraordinary items in years  $t$  to  $t-2$ ; (ii) common shares outstanding and beginning-of-period price for periods  $t-1$  and  $t-2$ ; (iii) market adjusted stock return in the current period. The use of control variables further restricts the sample to non-missing book-value of equity, total liabilities, and standard deviation of 12 monthly returns during the annual period  $t-1$ . For comparability, we also require an equal number of observations for each model in a given table.  $Ret$  is market adjusted stock return compounded over the 12 months ending 3 months after the fiscal year end;  $X$  is earnings per share (earnings before extraordinary items divided by the number of shares outstanding);  $P$  is stock price per share.  $D(\cdot)$  is an indicator function. Control variables are measured as of beginning of the year  $t$  and include natural logarithm of beginning of period stock price and market capitalization (*scale* proxies), *book-to-market* ratio, *leverage* (total liabilities divided by market value of equity plus total liabilities), *volatility* (standard deviation of returns over prior year). Subscripts denote time at (over) which variables are measured. To remove outliers and data errors, variables are truncated at both tails using a 1% cutoff value. The table reports average annual cross-sectionally estimated coefficients and their standard errors based on the Fama-MacBeth (1973) procedure. The model specification is as follows (*Dependent variable* is stated in the second column):

$$Dependent\ variable = \alpha_0 + \alpha_1 D(Ret_t < 0) + \beta_0 Ret_t + \beta_1 D(Ret_t < 0) Ret_t + \sum \delta_k Controls_{kt-1} + \varepsilon_t$$

Row	Dependent Variable	Statistic	$\alpha_0$	$\alpha_1$	$\beta_0$	$\beta_1$	$\beta_0 + \beta_1$	R-squared	Number Obs.
(1)	$X_t/P_{t-1}$	Estimate	0.046	0.012	0.041	0.183	0.224	0.266	136894
		t Value	8.292	6.412	9.572	15.694	16.420		
		Pr >  t	0.000	0.000	0.000	0.000	0.000		
(2)	$X_{t-1}/P_{t-1}$	Estimate	0.018	0.002	-0.006	0.049	0.043	0.188	136894
		t Value	2.990	1.905	-3.298	8.457	7.523		
		Pr >  t	0.004	0.063	0.002	0.000	0.000		
(3)	$X_{t-2}/P_{t-2}$	Estimate	0.023	0.000	-0.009	0.042	0.033	0.177	136894
		t Value	3.692	0.334	-4.885	7.375	6.277		
		Pr >  t	0.001	0.740	0.000	0.000	0.000		
(4)	$1/P_{t-1}$	Estimate	0.388	-0.001	0.003	-0.006	-0.004	0.752	136894
		t Value	25.915	-1.287	2.200	-2.028	-1.401		
		Pr >  t	0.000	0.204	0.033	0.048	0.168		

**Table 4: Unexpected earnings, unexpected returns, and the magnitude of bias in asymmetric timeliness.**

Model specifications in PT (2010) are contrasted to specifications isolating the expected components of returns and earnings. Panels A and B present estimates with and without controls for firm level determinants of expected earnings. Expected earnings are estimated from the 2-digit SIC industry-based model described in Section 2 (*Approach 2*). Expected returns are estimated as the value weighted returns on 5x5 portfolios constructed by sorting annually on beginning of period market capitalization and then market-to-book ratio. The data are based on the intersection of the Compustat and CRSP databases. We limit the sample to 1964-2010 and exclude observations that have beginning-of-period price under \$1. We require non-missing observations for (i) earnings before extraordinary items in years  $t$  to  $t-2$ ; (ii) common shares outstanding and beginning-of-period price for periods  $t-1$  and  $t-2$ ; (iii) size and book-to-market adjusted stock return in period  $t$ ; and (iv) a minimum of 10 observations per industry in a given year, to estimate expected earnings. The use of control variables further restricts the sample to non-missing book-value of equity, total liabilities, and standard deviation of 12 monthly returns during the annual period  $t-1$ . For comparability, we also require an equal number of observations for each model reported in the table.  $Ret^a$  is size and book-to-market adjusted (unexpected) return, adjusted by subtracting from return compounded over the 12 months (ending 3 months after the fiscal year end) the 12 month return on a value-weighted portfolio compounded over the same period; we require 12 non-missing monthly returns for each firm and further require a minimum of 10 non-missing return observations for each portfolio in a given year.  $X$  is earnings per share (earnings before extraordinary items divided by the number of shares outstanding);  $P$  is stock price per share.  $D(\cdot)$  is an indicator function and  $E[\cdot]$  is the expectation operator. Control variables are measured as of beginning of the year  $t$  and include natural logarithm of beginning of period stock price and market capitalization (scale proxies), *book-to-market* ratio, *leverage* (total liabilities divided by market value of equity plus total liabilities), *volatility* (standard deviation of returns over prior year). Subscripts denote time at (over) which variables are measured. To remove outliers and data errors, variables are truncated at both tails using a 1% cutoff value. The table reports average annual cross-sectionally estimated coefficients and their standard errors based on the Fama-MacBeth (1973) procedure. The model specification is as follows (*Dependent variable* is stated in the second column):

**Panel A: Without control variables**

$$Dependent\ variable = \alpha_0 + \alpha_1 D(Ret_t^a < 0) + \beta_0 Ret_t^a + \beta_1 D(Ret_t^a < 0) Ret_t^a + \varepsilon_t$$

Row	Dependent Variable	Statistic	$\alpha_0$	$\alpha_1$	$\beta_0$	$\beta_1$	$\beta_0 + \beta_1$	R-squared	Number Obs.
(1)	$X_t/P_{t-1}$	Estimate	0.082	0.015	0.022	0.229	0.251	0.165	133237
		t Value	13.335	7.248	5.949	14.728	15.742		
		Pr >  t	0.000	0.000	0.000	0.000	0.000		
(2)	$X_{t-1}/P_{t-1}$	Estimate	0.066	0.004	-0.035	0.132	0.097	0.033	133237
		t Value	12.147	2.384	-11.068	11.855	10.736		
		Pr >  t	0.000	0.021	0.000	0.000	0.000		
(3)	$X_t - E[X_t]/P_{t-1}$	Estimate	0.013	0.011	0.040	0.117	0.157	0.136	133237
		t Value	11.239	7.686	15.144	12.698	14.645		
		Pr >  t	0.000	0.000	0.000	0.000	0.000		
(4)	$X_{t-1} - E[X_{t-1}]/P_{t-2}$	Estimate	0.005	0.001	-0.004	0.031	0.028	0.011	133237
		t Value	7.775	1.988	-1.988	6.643	7.049		
		Pr >  t	0.000	0.053	0.053	0.000	0.000		

**Panel B: Controlling for common determinants of expected earnings and returns**

$$\text{Dependent variable} = \alpha_0 + \alpha_1 D(\text{Ret}_t^a < 0) + \beta_0 \text{Ret}_t^a + \beta_1 D(\text{Ret}_t^a < 0) \text{Ret}_t^a + \sum \delta_k \text{Controls}_{kt-1} + \varepsilon_t$$

Row	Dependent Variable	Statistic	$\alpha_0$	$\alpha_1$	$\beta_0$	$\beta_1$	$\beta_0 + \beta_1$	R-squared	Number Obs.
(5)	$X_t - E[X_t]/P_{t-1}$	Estimate	0.019	0.011	0.038	0.124	0.162	0.161	133237
		t Value	4.081	7.518	14.217	13.787	15.254		
		Pr >  t	0.000	0.000	0.000	0.000	0.000		
(6)	$X_{t-1} - E[X_{t-1}]/P_{t-2}$	Estimate	-0.020	0.001	0.001	0.013	0.014	0.071	133237
		t Value	-4.688	1.073	0.954	2.626	3.459		
		Pr >  t	0.000	0.289	0.345	0.012	0.001		

**Table 5: Earnings changes, fixed effects, and bias in asymmetric timeliness.**

Table 5 provides model specifications which isolate the expected component of earnings and returns. This analysis follows *Approach 3* in Section 2, which assumes that expected earnings can be approximated by the fixed-effects. Expected returns are assumed to be equal to average value weighted portfolio return in a particular year. We use 5x5 portfolios are constructed annually by sorting observations on beginning of period market capitalization and, subsequently, market-to-book ratios. The data are based on the intersection of the Compustat and CRSP databases. We limit the sample to 1963-2010 and exclude observations that have beginning-of-period price under \$1. We require non-missing observations for (i) earnings before extraordinary items in years  $t$  to  $t-3$ ; (ii) common shares outstanding and beginning-of-period price for periods  $t-1$  to  $t-3$ ; (iii) size and book-to-market adjusted stock return in the current period. The last requirement imposes non-missing book-value of equity as of the end of  $t-1$  (we already require market capitalization to be available). For comparability, we also require an equal number of observations for each model reported in the table.  $Ret^a$  is size and book-to-market adjusted return computed by taking stock return compounded over the 12 months (ending 3 months after the fiscal year end) and adjusting it by subtracting the 12 month return on a value-weighted portfolio return compounded over the same period; we require 12 non-missing monthly returns for each firm and further require a minimum of 10 non-missing observations for each portfolio in a given year.  $X$  is earnings per share (earnings before extraordinary items divided by the number of shares outstanding);  $P$  is stock price per share.  $D(\cdot)$  is an indicator function and  $E[\cdot]$  is the expectation operator. Subscripts denote time at (over) which variables are measured. To remove outliers and data errors, variables are truncated at both tails using 1% cutoff value. The table reports average annual cross-sectionally estimated coefficients and their standard errors based on the Fama-MacBeth (1973) procedure. The model specification is as follows (*Dependent variable* is stated in the second column):

$$Dependent\ variable = \alpha_0 + \alpha_1 D(Ret_t^a < 0) + \beta_0 Ret_t^a + \beta_1 D(Ret_t^a < 0) Ret_t^a + \varepsilon_t$$

Row	Dependent Variable	Statistic	$\alpha_0$	$\alpha_1$	$\beta_0$	$\beta_1$	$\beta_0 + \beta_1$	R-squared	Number Obs.
(1)	$X_t/P_{t-1}$	Estimate	0.081	0.015	0.020	0.234	0.254	0.160	142255
		t Value	13.073	7.119	5.378	15.204	16.026		
		Pr >  t	0.000	0.000	0.000	0.000	0.000		
(2)	$X_{t-1}/P_{t-1}$	Estimate	0.078	0.002	-0.029	0.120	0.091	0.031	142255
		t Value	13.194	1.260	-9.576	10.924	10.348		
		Pr >  t	0.000	0.214	0.000	0.000	0.000		
(3)	$X_t - X_{t-1}/P_{t-1}$	Estimate	0.016	0.011	0.059	0.093	0.152	0.103	142255
		t Value	7.215	7.523	16.753	8.479	13.184		
		Pr >  t	0.000	0.000	0.000	0.000	0.000		
(4)	$X_{t-1} - X_{t-2}/P_{t-2}$	Estimate	0.010	0.001	0.007	-0.001	0.006	0.007	142255
		t Value	4.700	0.763	3.337	-0.251	1.596		
		Pr >  t	0.000	0.449	0.002	0.803	0.117		
(5)	$X_t/P_{t-1} - f.e.(\eta_i)$	Estimate	0.010	0.008	0.044	0.093	0.137	0.097	142255
		t Value	2.234	4.471	12.225	8.728	12.298		
		Pr >  t	0.030	0.000	0.000	0.000	0.000		
(6)	$X_{t-1}/P_{t-1} - f.e.(\eta_i)$	Estimate	0.002	-0.001	-0.012	0.020	0.009	0.009	142255
		t Value	0.515	-0.628	-4.542	2.750	1.427		
		Pr >  t	0.609	0.533	0.000	0.008	0.160		
(7)	$X_{t-2}/P_{t-2} - f.e.(\eta_i)$	Estimate	0.003	-0.003	-0.010	0.014	0.004	0.009	142255
		t Value	0.843	-2.966	-4.061	2.139	0.845		
		Pr >  t	0.404	0.005	0.000	0.038	0.402		



