The Implications Of Accounting Conservatism For The Relation Between Earnings And Stock Returns

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ABSTRACT

Characterizing accounting conservatism as the accountants' tendency to require a higher degree of verification for recognizing good news than bad news, Basu (1997) predicts that the slope coefficient and R^2 in a regression of earnings on concurrent stock returns will be higher for bad news (negative stock returns) than for good news (positive stock returns). However, standard econometric analysis indicates that the R^2 is a function of the sensitivity of earnings to returns and the noise ratio, which is defined as the ratio of the variance of noise in earnings to the variance of noise in returns. I show that the R^2 from the regression of earnings on stock returns is not necessarily higher for bad news than for good news. So the test of R^2 is not a robust test of accounting conservatism. Consistent with the prediction, I find that the slope coefficient is higher for bad news firms reporting losses than for good news firms reporting profits, but R^2 is lower for bad news firms reporting losses than for good news firms reporting profits.

Keywords: accounting conservatism; earnings; returns; reverse regression

1. INTRODUCTION

This paper examines the empirical implications of accounting conservatism for the relation between earnings and stock returns. Accounting conservatism characterized as differential verifiability requirements for recognizing gains versus losses (Basu 1997; Watts 2003) implies that accounting recognizes bad news (negative stock returns) in earnings on a timelier basis than it does good news (positive stock returns). Given that there is no generally accepted definition of accounting conservatism[1], many studies (Basu 1997; Pope and Walker 1997; Givoly and AHayn 2000; Ball, Kothari, and Robin 2000; Ryan and Zarowin 2003; Pae 2007) use the test of differential timeliness of earnings between good and bad news to examine the existence and magnitude of accounting conservatism. These studies examine the slope coefficient and R^2 in a regression of earnings on stock returns, and interpret a higher slope coefficient and/or R^2 for bad news firms than for good news firms as evidence of accounting conservatism. This paper revisits the issue of the effect of accounting conservatism on the relation between earnings and returns: the sensitivity of earnings and the R^2 in the regression of earnings on returns.[2]

Basu (1997) posits and finds that the slope coefficient and R^2 in the regression of earnings on returns are greater for bad news firms than for good news firms. Basu's (1997) prediction on the asymmetric sensitivity of earnings (the slope coefficient) between good and bad news rests on the two assumptions: (1) the R^2 in the

[1] Feltham and Ohlson (1995, 1996) characterize accounting conservatism as the book value of equity being on average less than the market value of equity in the long run. Pae et al. (2005) refer to Basu's (1997) characterization of the relation between earnings and returns as earnings conservatism and Feltham and Ohlson's characterization of the relation between the book value and market value of equity as balance sheet conservatism.

[2] This paper does not examine under what conditions firms will optimally choose a conservative reporting. See Kwon, Newman, and Suh (2001), Gigler and Hemmer (2001), and Ahmed et al. (2002) for analytical modeling of conservative accounting, and Watts (2003) for a good review on the demand for accounting conservatism.

regression of earnings on returns is greater for bad news than for good news, and (2) the ratio of variance of earnings to variance of returns is greater for bad news than for good news. These two assumptions lead to a higher slope coefficient for bad news than for good news.[3] Empirical evidence is generally consistent with his slope coefficient prediction; however, the R^2 prediction seems less robust compared to the slope coefficient prediction. For example, Hayn (1995) examine the relation between earnings and returns in the liquidation option context. By partitioning firms into firms reporting profits ("profit" firms) and firms reporting losses ("loss" firms), Hayn (1995) reports that the slope coefficient in a regression of returns on earnings is much smaller (almost zero) for loss firms than for profit firms, and that the R^2 is much lower (almost zero) for loss firms than for profit firms. Since the regression of earnings on returns in Basu (1997) is the reverse regression of Hayn (1995) or vice versa, the lower slope coefficient for loss firms in Hayn (1995) is consistent with the predicted higher slope coefficient for bad news firms in Basu (1997). However, the R^2 result in Hayn (1995) appears inconsistent with the prediction of Basu (1997) since there should be no difference in R^2 between the direct and reverse regressions.[4] On the other hand, Ball, Kothari, and Robin (2000) examine the impact of the origin of legal system on the timeliness of earnings of seven countries using the reverse regression of Basu (1997). Their table 3 reports that code-law countries, in particular France and Japan, have a higher slope coefficient for bad news than for good news, but have a lower R^2 for bad news than for good news. Based on the R^2 result, which conflicts with the slope coefficient result, one cannot assert that accounting in France and Japan is less conservative or less timely for bad news than for good news.

Consistent with more robust empirical evidence on the slope coefficient, my model is based on the assumption that the more fundamental feature of accounting conservatism is that the sensitivity of earnings with respect to stock returns (the slope coefficient in the regression of earnings on returns) is greater for bad news than for good news, which is contrasted to Basu (1997) who starts with the conjecture that the R^2 is greater for bad news than for good news. My model is based on the assumption that the relative leniency in the recognition of bad news as compared to good news leads to a more timely recognition of bad news than good news and a possibly greater measurement error with bad news than good news due to inherent difficulty in estimating future cash flows in bad news situations. The timely recognition of bad news and delayed recognition of good news ensures that the slope coefficient in the regression of earnings on concurrent stock returns is higher for bad news than for good news. However, standard econometric analysis shows that R^2 is not necessarily higher for bad news than for good news. R^2 is shown to be a function of the sensitivity of earnings and the noise ratio, which is defined as the ratio of the variance of noise in earnings to the variance of returns. A timely recognition of bad news increases the R^2 of bad news while a potentially greater measurement error with bad news will decrease the R^2. If the noise ratio is relatively high for bad news, it is quite possible that the R^2 is lower for bad news than for good news. This paper emphasizes that the R^2 is not a robust test of accounting conservatism or timeliness of earnings so that we should not put too much emphasis on the comparison of R^2 between the good and bad news in assessing accounting conservatism and timeliness of earnings in a cross-sectional and time-series analysis.

To explore the possibility that the slope coefficient is greater, but the R^2 is lower for bad news than good news, I partition the samples of good news and bad news into the profit and loss sub-samples. I focus on firms in which the sign of earnings matches the sign of stock returns: good news firms reporting profits and bad news firms reporting losses. Empirical tests of the relation between earnings and returns on this restricted sample show that the slope coefficient is higher for bad news firms reporting losses than for good news firms reporting profits, but the R^2 is lower for bad news firms reporting losses than for good news firms reporting profits, corroborating the prediction of the econometric analysis that the R^2 is not necessarily greater for bad news firms than for good news firms. This empirical result, however, should be interpreted with caution because partitioning on the dependent variable, earnings, may lead to biased estimates (Hausman and Wise 1977). On the other hand, Dietrich, Muller, and Riedl

[3] Using the following relationship between the slope coefficient (β) and R^2: $\beta^2 = R^2 \frac{\text{var(Eamigns)}}{\text{var(Returns)}}$, Basu (1997, footnote 7) notes that a higher R^2 and a greater variance ratio for bad news than good news implies a greater slope coefficient for bad news than good news.

[4] Basu (1997) argues that the R^2 result in Hayn (1995) is sensitive to specification issues such as risk adjustment. Note that there is a subtle difference between Basu (1997) and Hayn (1995) in partitioning firms into two distinct groups. However, the two partitioning schemes are related because bad news firms are more likely to report losses than profits, and good news firms are more likely to report profits than losses.

(2003) argue that when accounting information drives stock returns, the correct specification is the regression of returns on earnings. In that case, partitioning on returns is also subject to the same econometric problems. Given that there is no consensus on the correct specification, both earnings and returns are not free from this potential econometric issue. However, it appears that the slope coefficient result is consistent regardless of the specification, whereas R^2 is not. As a practical matter, the test of the slope coefficient would be a more robust test of accounting conservatism than the test of R^2.

The remainder of the paper is organized as follows. Section 2 presents an analytical model that incorporates asymmetric sensitivity of earnings between good news and bad news, and examines the impact of accounting conservatism on the relation between earnings and returns. Section 3 reports sample selection and descriptive statistics. Section 4 presents empirical findings. A summary is reached in section 5.

2. MODEL

A firm's earnings reports can be viewed as a signal generated by the firm's accounting system, incorporating the news that the firm has received for the reporting period.[5] In an efficient capital market, the stock price impounds all value relevant information without delay. Since the change in firm value or returns represents the implications of news to future prospects of the firm, I assume that the mapping of news into earnings is equivalent to mapping of current stock returns into earnings. For simplicity and consistency with extant empirical studies, I partition news into good or bad, and assume that the mapping is influenced by whether the news is good or bad.

$$\begin{aligned} X_t &= f(R_t, R_{t-1}, \cdots) \\ &= \begin{cases} \omega R_t + \varepsilon_t + \Phi(R_{t-1}, R_{t-2}, \cdots), & \text{if the current news is good.} \\ \omega_B R_t + \varepsilon_{Bt} + \Phi(R_{t-1}, R_{t-2}, \cdots), & \text{if the current news is bad.} \end{cases} \end{aligned}$$

where X_t and R_t are earnings and stock returns for period t, respectively. The model assumes that current reported earnings is a function of current and past stock returns. It is consistent with extensive empirical evidence that stock returns precede accounting earnings for several periods (e.g., Kothari and Sloan 1992; Kothari and Zimmerman 1995). The coefficients on stock returns (ω and ω_B) represent the sensitivity of earnings in recognizing good news as profits and bad news as losses. I assume that there is asymmetry in the sensitivity of earnings depending on whether news is good or bad. Consistent with the notion of conservative accounting in Basu (1997), I assume that bad news is more quickly recognized in the concurrent earnings than good news, that is, $1 \geq \omega_B > \omega > 0$. That is, accounting earnings reflects concurrent bad news in a timelier manner than it does concurrent good news. I assume that the coefficient on returns is greater than zero, implying that at least some part of the current period's news is reported as earnings in the same period.[6] For simplicity and without loss of generality, ω_B is set to one, implying that bad news is immediately and fully recognized as losses in the concurrent period.[7] $\Phi(\cdot)$ represents the impact of past returns on current earnings. I do not specify how past returns are reflected in the current period's earnings. Under the assumption that bad news is immediately recognized as losses in the current period, only good news will affect future periods' earnings. Since returns are uncorrelated across periods under no-arbitrage opportunity condition in the capital markets, the regression of current earnings on only concurrent returns will not bias the estimate of the

[5] I do not model a possible information asymmetry between a firm and the market. That is, I do not consider the case in which the firm uses earnings report to signal her private information to the capital market or other related parties. It is beyond the scope of this study.

[6] The model excludes the case of "excessive" conservatism/timeliness by setting the upper bound to one. The exclusion of excessive conservatism/timeliness implies that auditors and other institutional factors limit firms' ability to overstate profits and losses. The relaxation of this constraint does not affect the analysis.

[7] Equivalently, one can think of ω as the ratio of the sensitivity of earnings for good news to the sensitivity of earnings for bad news. Alternatively, 1/ ω can be interpreted as the relative sensitivity of earnings for bad news compared to good news.

coefficient on concurrent stock returns. In the subsequent discussion, I will replace $\Phi(\cdot)$ with a constant, ϕ.[8] ε_t represents a noise affecting reported earnings, but uncorrelated with current and past returns. I do not assume that the variance of the noise in earnings is the same between good news and bad news. The variance of the noise in accounting earnings under bad news (ε_{Bt}) may be greater than the variance of the noise in accounting earnings under good news (ε_t) due to the inherent measurement errors associated with the estimation of future losses and some incentive issues associated with bad news. Finally, following Basu (1997), I use non-negative returns as a proxy for good news, and negative returns as a proxy for bad news, assuming that there is no measurement error in stock returns with respect to news, or the market is efficient with respect to news. The simplified model relating returns to earnings is

$$X_t = \begin{cases} \omega R_t + \varepsilon_t + \phi, & \text{if } R_t \geq 0 \quad (\text{"good news"}) \\ R_t + \varepsilon_{Bt} + \phi, & \text{if } R_t < 0 \; (\text{"bad" news}) \end{cases}$$

Consistent with the above model, Basu (1997) examines accounting conservatism by estimating the following regression separately for good news and bad news:

$$X_t = \alpha + \beta R_t + \varepsilon_t \tag{1}$$

The coefficient on stock returns is expected to be ω for good news firms ($\beta_G = \omega$) and one for bad news firms ($\beta_B = 1$). Since ω is assumed to be less than one, the slope coefficient of bad news is greater than that for good news (($\beta_B > \beta_G$), which is consistent with Basu (1997).

Basu (1997) also predict that the R^2 will be higher for bad news than for good news. The R^2s of regression (1) for good news (G) and bad news (B) are

$$\begin{aligned} R_G^2 &\equiv \frac{Cov^2(X_t, R_t \mid G)}{Var(X_t \mid G)Var(R_t \mid G)} \\ &= \frac{\omega^2 Var^2(R_t \mid G)}{[\omega^2 Var(R_t \mid G) + Var(\varepsilon \mid G)]Var(R \mid G)} = \frac{1}{1 + \left(\dfrac{\sigma_\varepsilon^2(G)}{\sigma_R^2(G)}\right)/\omega^2} = \frac{1}{1 + \xi(G)/\omega^2} \end{aligned} \tag{2}$$

$$R_B^2 \equiv \frac{Cov^2(X_t, R_t \mid B)}{Var(X_t \mid B)Var(R_t \mid B)} = \frac{1}{1 + \dfrac{\sigma_\varepsilon^2(B)}{\sigma_R^2(B)}} = \frac{1}{1 + \xi(B)} \tag{3}$$

The R^2 depends on the sensitivity of earnings (ω) and the ratio of the variance of the noise in earnings to the variance of returns ($\sigma_\varepsilon^2(news)/\sigma_R^2(news)$) conditional on news. I will refer to the latter as the "noise" ratio, and it will be denoted by $\xi(news)$. I define *the sensitivity adjusted noise ratio* as one plus the noise ratio deflated by the square of the sensitivity of earnings. The sensitivity adjusted noise ratios for good and bad news are ($1 + \xi(G)/\omega^2$)

[8] If there is a consistent application of conservative accounting, the expected impact of past returns on current earnings is more likely to be positive since good news is more likely to be delayed than bad news. That implies a positive intercept in the regression of earnings on concurrent returns (Basu (1995)).

and $(1+\xi(B))$, respectively.[9] In the presence of measurement error or noise in earnings, the ratio of R_B^2 to R_G^2 increases with the relative sensitivity of earnings for good news (ω), and decreases with the noise ratio for bad news ($\xi(B)$). It can be seen that the R^2 for bad news is higher (lower) than that for good news if, and only if, the sensitivity adjusted noise ratios for bad news is lower (higher) than that for good news. The discussion so far can be summarized in the following proposition.

Proposition 1: *Assume that accounting conservatism is characterized as in equation (1). The regressions of earnings on stock returns for good news and bad news will imply the following:*

(i) *The coefficient estimate on stock returns, which represents the sensitivity of earnings, is higher for bad news firms than that for good news firms, that is,* $\beta_B > \beta_G$.

(ii) *The R^2 is higher (lower) for bad news than for good new if, and only if, the sensitivity adjusted noise ratio is lower (higher) for bad news firms than for good news firms.*

$R_B^2 > (<) R_G^2$ *if, and only if,* $1+\xi(B) < (>) 1+\xi(G)/\omega^2$,

where ω *is the sensitivity of earnings for good news, and* $\xi(news \in \{G,B\}) \equiv \sigma_\varepsilon^2(news)/\sigma_R^2(news)$ *represents the ratio of the variance of noise in earnings to the variance of returns conditional on news("noise" ratio).*

Proposition 1 emphasizes that even if earnings is more sensitive to bad news than good news ($\omega < 1$), the R^2 is not necessarily greater for bad news than for good news. The prediction on the relative magnitude of R^2 between good and bad news is an empirical question. Under the maintained position that earnings for bad news is noisier than earnings for good news ($\xi(B) > \xi(G)$), if the noise ratio is sufficiently greater for bad news than good news and the sensitivity of earnings for good news (ω) is not close to zero, then the R^2 can be lower for bad news than for good news. That is, asymmetric sensitivity of earnings between good and bad news does not necessarily imply a higher R^2 for bad news than good news.

Observe that R^2 will be perfect if there is no noise in reported earnings.[10] For example, a firm may report earnings that equals the decrease of the market value of equity for the fiscal period for bad news or 10 per cent of the increase of the market value of equity for good news. In this case, earnings becomes a sufficient statistics with respect to stock returns even if the sensitivity of earnings differs between good and bad news. That is, the noise in earnings or the reporting error is critical in specifying the differences in R^2 between good news and bad news.[11] I will exclude the cutting edge case of no noise in earnings. Consider cases in which the sensitivity of earnings is low for good news compared to bad news (i.e., ω is close to zero), there is no difference in the noise ratio between good news and bad news, or the ratio is greater for good new than for bad news. In these cases, it is not guaranteed that the R^2 is higher for bad news than good news.

[9] In general, the sensitivity of earnings for bad news differs from unity. If the sensitivity of earnings for bad news is $\omega_B \neq 1$, the sensitivity adjusted noise ratio for bad news will be $(1+\xi(B)/\omega_B^2)$.

[10] Throughout the paper, I assume that the sensitivity of earnings is constant. If it is not the case, R^2 will be less than perfect.

[11] Even if the R^2 of an individual firm-specific regression is perfect, the use of cross-sectional regression can create a lower R^2 for good news firms than for bad news firms. If the variation of the sensitivity of earnings among good news firms is greater than the variation of the sensitivity of earnings among bad news, the R^2 will be lower for the good news firms than for bad news firms. Note that it is due to the cross-sectional variation of the sensitivity of earnings among good news firms, not due to the inherent lack of sensitivity of earnings signal for good news as compared to the sensitivity of earnings for bad news.

Corollary 1: *(1) If the sensitivity of earnings to good news (ω) is close to zero, or (2) the noise ratio is independent of the content of news ($\xi(G) = \xi(B) = \xi > 0$), or (3) the noise ratio is greater for good news than for bad news ($\xi(G) > \xi(B)$), then the R^2 is higher for bad news than for good news.*

Note that the last two conditions in Corollary 1 are against my maintained position that bad news is more likely to lead to noisier reported earnings than good news. In general, earnings will be noisier for bad news than good news. As earnings for bad news becomes noisier, the R^2 of bad news firms will decrease. Proposition 1 predicts that if the magnitude of the noise ratio of bad news firms is substantially large relative to that of good news firms, the R^2 of bad news firms could be less than the R^2 of good news firms. This case will be illustrated later in empirical tests. However, note that this condition is very stringent to meet because the sensitivity of earnings to bad news is generally substantially greater than that to good news, which means that the square of the ratio of the sensitivity of earnings to bad news to the sensitivity of earnings to good news, $(1/\omega)^2$ is very big. In that case, the sensitivity adjusted noise ratio is more likely to be greater for good news than for bad news, which means a higher R^2 for bad news than good news.

Next, I examine the impact of accounting conservatism on the regression of returns on earnings, which is contrasted to the regression of earnings on returns analyzed earlier. Hayn (1995) reports that the slope coefficient and R^2 are higher for firms reporting profits ("profit firms") than for firms reporting losses ("loss firms"). Since the regression of earnings on returns in Hayn (1995) is the reverse of the regression of returns on earnings in Basu (1997) or *vice versa*, the finding of the slope coefficient being higher for profits firms than for loss firms is consistent with Basu (1995). But, the finding of the R^2 being higher for profits firms than for loss firms is apparently inconsistent with Basu (1997) since there should be no difference in R^2 between the direct and reverse regressions. I examine the role of measurement error or noise in earnings on this seemingly conflicting result using the following regression of returns on earnings:

$$R_t = a + bX_t + \varepsilon_t . \qquad (4)$$

Note that there is a difference between Basu (1997) and Hayn (1995) in partitioning sample firms. Basu (1997) uses the sign of stock returns to partition the sample into good or bad news sub-samples, whereas Hayn (1995) uses the sign of earnings to partition the sample. To control for the effect of different partitioning variables and focus on the effect of measurement error or noise in earnings, I adopt the partitioning scheme of Basu (1997).[12] The R^2s of regression (4) for good and bad news are the same as those for the regression of earnings on returns in equations (2) and (3). The slope coefficients of regression (4) for good news and bad news are[13]

$$b_G \equiv \frac{Cov\ (X_t, R_t \mid G)}{Var(X_t \mid G)} = \frac{1}{\omega(1 + \xi(G)/\omega^2)} \qquad (5)$$

$$b_B \equiv \frac{Cov^2(X_t, R_t \mid B)}{Var(X_t \mid B)} = \frac{1}{1 + \xi(B)} \qquad (6)$$

Unlike the slope coefficients in Basu (1997), the slope coefficients in the regression of returns on earnings are a function of the relative sensitivity of earnings (ω) and the sensitivity adjusted noise ratio ($1+\xi(\cdot)/\omega^2$). Note that earnings are assumed to be measured with error.[14] The reverse regression of Basu (1997) is not influenced by the

[12] In empirical tests, I also present the regression results with the sign of earnings as the partitioning variable.

[13] The slope coefficient in the regression of returns on earnings (b) can be also inferred from the following relation using the slope coefficient (β) and R^2 in the regression of earnings on returns :

$b_{news} = R^2(news)/\beta_{news}$, where $news \in \{G, N\}$.

[14] If earnings are measured without error, i.e., $R^2=1$, the coefficient on earnings will be the inverse of the coefficient on returns. In that case, the higher coefficient on returns for bad news ensures the higher coefficient on earnings for good news, $\beta_B > \beta_G \Leftrightarrow b_G > b_B$.

noise in earnings since earnings is specified as the dependent variable, but the regression of Hayn (1995) is influenced by the noise in earnings. It can be seen that the estimate of the coefficient on earnings will be greater for good news than for bad news if the product of the sensitivity of earnings and the sensitivity adjusted noise ratio is higher for bad news than for good news.

Proposition 2: *The slope coefficient in the regression of returns on earnings is greater (smaller) for good news than for bad news if, and only if, the product of the sensitivity of earnings and the sensitivity adjusted noise ratio is smaller (greater) for good news than bad news.*

$b_G > (<)\, b_B$ *if, and only if,* $\omega(1+\xi(G)/\omega^2) < (>)\,(1+\xi(B))$.

When the noise ratio is independent of the content of news ($\xi(G) = \xi(B) = \xi$), the slope coefficient will be higher for good news than for bad news if, and only if, the common noise ratio (ξ) is smaller than ω. That is, $b_G > (<)\, b_B$ if, and only if, $\xi < (>)\, \omega$.[15]

Proposition 2 states that the ordering of the estimates of the coefficients on earnings depends on the sensitivity of earnings and the sensitivity adjusted noise ratio while proposition 1 states that the ordering of R^2 depends on the sensitivity adjusted noise ratio alone. Since the model assumes that the fundamental feature of conservative accounting is a greater sensitivity of earnings for bad than good news, the following relations follow

$$(1+\xi(G)/\omega^2) < (1+\xi(B)) \Rightarrow \omega(1+\xi(G)/\omega^2) < (1+\xi(B))$$

or

$$\omega(1+\xi(G)/\omega^2) > (1+\xi(B)) \Rightarrow (1+\xi(G)/\omega^2) > (1+\xi(B))$$

Now, it follows

$$R_G^2 > R_B^2 \Rightarrow b_G > b_B \text{ or } b_G < b_B \Rightarrow R_G^2 < R_B^2$$

By construction, the estimate of the coefficient on returns is always greater for bad news than for good news, that is, $\beta_B(=1) > \beta_G(=\omega)$. However, propositions 1 and 2 state that $\beta_B > \beta_G$ does not necessarily imply $R_B^2 > R_G^2$ and/or $b_G > b_B$. Due to the noise in earnings, the R^2 prediction of Basu (1997) does not necessarily hold, and the reverse regression of earnings on returns and the usual regression of returns on earnings are not the mirror image of each other.

So far, it is assume that the correct specification is the regression of earnings on returns. However, Dietrich, Muller, and Riedl (2003) argue that when information drives stock returns, the correct specification is the standard regression of returns on earnings. In that case, the reverse regression of earnings on returns coupled with partitioning on returns causes econometric problems associated with truncated samples (Hausman and Wise 1977): asymmetric sensitivity of earnings to bad versus good news could be an artifact of partitioning on returns. It is beyond the scope of the study to determine the correct specification. However, it seems that accounting and stock returns influence each other. It is well documented that stock prices react to news in earnings announcements. At the same time, firms' earnings reacts to the change in market values of firms. For example, the lower of cost or market rules in GAAP for inventories and marketable securities influences accounting earnings when the market value of an asset is lower than the book value of the asset. The more accurate picture will be the interaction between earnings and returns, rather than one influences the other. So, neither the regression of earnings on returns nor the regression of returns on earnings is free from the potential econometric problem associated with partitioning on the dependent variable. The empirical test results are reported for both the standard regression of returns on earnings and the reverse regression of earnings on returns.

[15] If the sensitivity of earnings for bad news (ω_B) is different from 1, the condition becomes $\xi < (>)\, \omega\omega_B$.

3. DATA AND DESCRIPTIVE STATISTICS

Earnings per share and stock prices are obtained from COMPUSTAT, and annual stock returns are calculated by compounding the CRSP monthly stock returns. I use the basic earnings per share (including extraordinary items and discontinued operations) deflated by beginning-of-fisca-year stock price as a measure of earnings (X_t). Annual stock returns (R_t) are measured for the year ending three months after the fiscal period end. Observations in the top and bottom one percent of earnings and returns in each year are deleted to mitigate the effect of extreme observations. The resulting sample consists of 138,880 firm-year observations over the sample period 1964 through 2001. I partition the sample into firms experiencing non-negative annual stock returns ("good news firms") and firms experiencing negative annual stock returns ("bad news firms"). The sample is also partitioned into firms reporting profits ("profit firms") and firms reporting losses ("loss firms"). Table 1 reports the distribution of the sample partitioned by the signs of stock returns and earnings. Bad news firms and loss firms are 44 percent and 23 percent of the sample firm-years, respectively. Consistent with other studies (Hayn 1995; Givoly and Hayn 2000), the proportion of firms reporting losses has increased in recent years.

Table 1: Distribution of the Sample by the Signs of Returns and Earnings
Good news represents firms with non-negative returns and bad news represents firms with negative returns

Year	No. of Obs.	Good News	Bad News	% of Bad News	Profits	Losses	% of Losses
1964	847	692	155	18%	821	26	3%
1965	929	643	286	31%	906	23	2%
1966	1,117	647	470	42%	1,096	21	2%
1967	1,270	923	347	27%	1,218	52	4%
1968	1,312	1,045	267	20%	1,269	43	3%
1969	1,424	267	1,157	81%	1,352	72	5%
1970	1,652	998	654	40%	1,455	197	12%
1971	1,860	1,040	820	44%	1,618	242	13%
1972	2,003	653	1,350	67%	1,846	157	8%
1973	2,939	672	2,267	77%	2,778	161	5%
1974	3,288	1,089	2,199	67%	2,973	315	10%
1975	3,268	2,767	501	15%	2,902	366	11%
1976	3,041	2,083	958	32%	2,822	219	7%
1977	3,218	2,306	912	28%	2,971	247	8%
1978	3,214	2,524	690	21%	3,028	186	6%
1979	3,349	1,798	1,551	46%	3,076	273	8%
1980	3,565	3,035	530	15%	3,154	411	12%
1981	3,625	1,256	2,369	65%	3,073	552	15%
1982	3,885	3,093	792	20%	2,994	891	23%
1983	3,968	2,362	1,606	40%	3,046	922	23%
1984	4,256	2,244	2,012	47%	3,257	999	23%
1985	4,264	2,772	1,492	35%	3,039	1,225	29%
1986	4,245	2,483	1,762	42%	2,932	1,313	31%
1987	4,498	1,438	3,060	68%	3,143	1,355	30%
1988	4,663	2,639	2,024	43%	3,285	1,378	30%
1989	4,537	2,283	2,254	50%	3,119	1,418	31%
1990	4,551	1,927	2,624	58%	3,088	1,463	32%
1991	4,560	2,919	1,641	36%	3,043	1,517	33%
1992	4,649	2,694	1,955	42%	3,175	1,474	32%
1993	4,936	2,743	2,193	44%	3,474	1,462	30%
1994	5,867	3,036	2,831	48%	4,390	1,477	25%
1995	6,116	4,327	1,789	29%	4,518	1,598	26%
1996	6,307	3,646	2,661	42%	4,636	1,671	26%
1997	6,551	4,523	2,028	31%	4,698	1,853	28%
1998	6,336	1,633	4,703	74%	4,358	1,978	31%
1999	6,012	3,130	2,882	48%	4,209	1,803	30%
2000	5,859	2,531	3,328	57%	3,890	1,969	34%
2001	899	431	468	52%	558	341	38%
Total (%)	138,880	77,292 (55.65%)	61,588 (44.35%)		107,210 (77.2%)	31,670 (22.8%)	

. Panel A of Table 2 reports descriptive statistics of the full sample. The mean and median market-to-book ratios, which are defined as the ratio of the market value of equity to the book value of equity, are 2.90 and 1.43, respectively, suggesting that accounting is on average conservative over the sample period if the market-to-book ratio is used as a measure of balance sheet conservatism (Pae, Welker, and Thornton 2005). The median annual stock returns and earnings per share deflated by the beginning stock price is 5.6% and 6.4%, respectively. Accruals (ACC) are calculated by the change in non-cash working capital plus depreciation. Cash flows from operations (CFO) are calculated by subtracting accruals from net income.[16] Accruals and cash flows from operations are deflated by beginning-of-fiscal-year market value of equity. Accruals are on average negative due to depreciation, and the median cash flows from operation are positive.

Panel B and C report the descriptive statistics of the good and bad news sub-samples and the profit and loss sub-samples. In terms of market capitalization and sales, the good news and profit firms are on average bigger than the bad news and loss firms. The median market-to-book ratio is greater for the good news and profit samples than for the bad news and loss samples. If accruals are used to expedite the recognition of bad news, the ratio of accruals to cash flows will be higher for bad news (Pae, Welker, and Thornton 2005;Pae 2007). Consistent with this argument, the ratio of the absolute value of the median accruals to the median cash flows is grater for bad news (0.67=0.035/0.052) than for good news (0.37=0.046/0.123).

Table 2: Descriptive Statistics

X is earnings per share deflated by the beginning stock price, and *R* is stock returns for the year ending three months after fiscal period-end. *MV* is the market value of equity at fiscal year end. *P/B* is the ratio of the market value of equity to the book value of equity at fiscal period end. *Sales* are annual sales. ACC is accruals measured by the change in working capital (excluding cash) plus depreciation. CFO is cash flow from operation measured by net income minus Acc. If cash flow statement is available, CFO is obtained from cash flow statement and accruals are calculated as net income minus CFO. ACC and CFO are deflated by the beginning market value of equity. Good (bad) news is represented by non-negative (negative) stock returns. Conservative (aggressive) accounting firms denote firms whose annual stock returns (*R*) are higher (lower) than earnings (*X*).

Panel A: Full Sample (#obs = 138,880)

Variable	Mean	Std. Dev.	Q1	Median	Q3	Min	Max
R	0.128	0.555	-0.203	0.056	0.347	-0.972	8.250
X	0.034	0.190	0.007	0.064	0.113	-3.085	0.961
MV	1,041.11	6,955.81	17.88	71.88	349.26	0.06	508,329
P/B	2.90	59.14	0.86	1.43	2.49	-3,008	10,474
Sales	1,038.60	4,957.78	26.60	106.37	443.80	-48.12	206,083
ACC	-0.083	0.457	-0.137	-0.041	0.013	-30.309	46.209
CFO	0.113	0.437	0.006	0.090	0.196	-45.997	27.619

Panel B: Good News versus Bad News

Variable	Good News (#obs = 77,292)				Bad News (#obs = 61,588)			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
R	0.456	0.139	0.305	0.587	-0.284	-0.422	-0.240	-0.109
X	0.078	0.045	0.086	0.139	-0.020	-0.053	0.034	0.077
MV	1,302.10	26.48	105.37	492.12	713.56	12.01	44.51	204.74
P/B	3.08	0.97	1.56	2.70	2.67	0.75	1.27	2.22
Sales	1,229.02	35.45	135.70	560.01	799.57	18.88	77.31	319.70
ACC	-0.081	-0.141	-0.046	0.012	-0.085	-0.131	-0.035	0.015
CFO	0.158	0.043	0.123	0.241	0.059	-0.029	0.052	0.138

Panel C: Profits versus Losses

Variable	Profit Firms (#obs = 107,210)				Loss Firms (#obs = 31,670)			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
R	0.186	-0.117	0.111	0.385	-0.069	-0.474	-0.210	0.128
X	0.104	0.051	0.083	0.132	-0.200	-0.254	-0.113	-0.047
MV	1,248.04	26.03	102.58	471.11	340.08	7.15	23.10	84.85
P/B	2.67	0.91	1.44	2.36	3.68	0.67	1.37	3.31
Sales	1,222.05	42.13	146.80	571.82	417.73	5.62	26.69	122.19
ACC	-0.042	-0.105	-0.030	0.024	-0.210	-0.278	-0.102	-0.016
CFO	0.150	0.044	0.113	0.218	0.000	-0.108	-0.018	0.089

[16] If cash flow statements are available (after 1986), cash flows from operations are directly obtained from cash flow statements. In that case, accruals are calculated as the difference between net income and cash flows from operations.

4. Empirical Results

4.1 The Impact Of Accounting Conservatism On The Relation Between Earnings And Returns

Table 3: The Relation between Earnings and Returns: Mean Estimates of Annual Cross Sectional Regressions

Regression 1: $X_{it} = \alpha_t + \beta_t R_{it} + \varepsilon_{it}$

Regression 2: $R_{it} = a_t + b_t X_{it} + \varepsilon_{it}$

X_{it} is earnings per share deflated by the beginning stock price, and R_{it} is stock returns for the year ending three months after fiscal period-end. Means of the estimates of the coefficients from the above annual cross-sectional regressions are reported. T-values in parentheses are calculated based on the estimates of the coefficients from annual regressions. Good (bad) news is represented by non-negative (negative) stock returns. Conservative (aggressive) accounting firms denote firms whose annual stock returns (R_t) are higher (lower) than earnings (X_t). The noise ratio (ξ) is the ratio of the variance of the residual of regression 1 to the variance of returns.

Panel A: The Full sample

	α	β	Adj. R^2	ξ	a	b
Mean of Annual regressions (t-value)	0.036 (3.99)	0.102 (11.51)	0.098	0.12	0.065 (2.10)	1.113 (7.87)

Panel B: Good News versus Bad News Samples

	α	β	Adj. R^2	ξ	a	b
Good News: Mean of Annual regressions (t-value)	0.074 (11.20)	0.025 (3.42)	0.020	0.13	0.372 (13.41)	0.299 (2.51)
Bad News: Mean of Annual regressions (t-value)	0.064 (7.95)	0.285 (12.44)	0.100	1.28	-0.253 (-20.98)	0.453 (6.88)

Panel C: Profit versus Loss Samples

	α	β	Adj. R^2	ξ	a	b
Profits: Mean of Annual regressions (t-value)	0.093 (16.35)	0.056 (9.83)	0.119	0.03	-0.045 (-1.80)	2.435 (14.74)
Losses: Mean of Annual regressions (t-value)	-0.186 (-14.18)	0.019 (3.28)	0.002	0.24	-0.064 (-1.62)	0.035 (0.96)

Panel D: News versus Signs of Earnings

	α	β	Adj. R^2	ξ	a	b
Good News and Profits (I) Mean of Annual regressions (t-value)	0.099 (17.00)	0.041 (7.22)	0.052	0.05	0.260 (13.86)	1.274 (9.50)
Good News and Losses (IV) Mean of Annual regressions (t-value)	-0.182 (-13.29)	-0.017 (-1.69)	0.005	0.26	0.465 (12.54)	-0.165 (-2.81)
Bad News and Losses (III) Mean of Annual regressions (t-value)	-0.170 (-15.36)	0.096 (3.51)	0.010	1.95	-0.345 (-20.74)	0.062 (3.65)
Bad News and Profits (II) Mean of Annual regressions (t-value)	0.092 (16.34)	0.081 (12.87)	0.062	0.18	-0.258 (-20.92)	0.836 (8.89)

See Figure 1 for the classification of firms into four categories.

To examine the impact of the content of news and the measurement error or noise in earnings on the relation between earnings and returns, I estimate the regression of returns on earnings and the reverse regression of earnings on returns separately. The estimate of the slope coefficient in the reverse regression of earnings on returns is used to infer the degree of sensitivity of earnings to stock returns. The adjusted R^2 and the regression of returns on earnings are used to examine the impact of noise in earnings. I estimate the two regressions each year from 1964 to 2001, and report the mean coefficient estimates and the mean adjusted R^2 (Fama and MacBeth (1973)). Panel A of Table 3 reports the results of annual cross-sectional regressions for the full sample. The mean of the adjusted R^2 is 0.098. The mean coefficient estimate on returns (β) is 0.102, which is significantly positive at the 0.01 level. The mean coefficient estimate on earnings (*b*) is 1.113, which is significantly different from the value expected (9.804 = 1/0.102, the inverse of β) under no measurement error in earnings, suggesting that a significant amount of measurement error or noise in earnings would influence the R^2 and would bias the estimated slope coefficient in the regression of returns on earnings.

Next, I partition the sample into good news and bad news sub-samples based on the sign of annual stock returns. Consistent with Basu (1997), Panel B reports that the mean coefficient estimate on returns is higher for bad news firms than for good news firms. If I interpret the coefficient on returns as the timeliness of earnings with respect to stock returns, I can state that earnings for bad news are more than eleven times as timely as earnings for good news (11.4 = 0.285/0.025). The mean adjusted R^2 is also higher for bad news firms than for good news firms. The noise ratio (ξ), which is defined as the ratio of the variance of noise in earnings to the variance of returns, is inferred from the (un-adjusted) R^2 and the estimate of the coefficient on returns (β) using the following relation: $\xi = \beta^2(1-R^2)/R^2$. As predicted, the noise ratio is higher for earnings for bad news (1.28) than for earnings for good news (0.13). However, the sensitivity adjusted noise ratio ($1+\xi/\beta^2$) is still higher for good news than that for bad news, which explains why the adjusted R^2 is higher for bad news than that for good news even if the noise in earnings is greater for bad news than for good news. These results are consistent with predictions in Basu (1997).

The regressions of returns on earnings show that the mean coefficient estimate on earnings is higher for bad news (0.453) than for good news (0.299). This result demonstrates that the reverse regression of earnings on returns is not the mirror image of the regression of returns on earnings, and *vice versa*. If they were the mirror image of each other, I would expect that the estimate of the coefficient on earnings is higher for good news than for bad news. Proposition 2 predicts that the coefficient on earnings is a function of the sensitivity of earnings and the noise ratio of earnings. If earnings are measured without noise or at least there is no difference in the sensitivity adjusted noise ratios between good news and bad news, the coefficient on earnings will be greater for good news than for bad news. Our regression results demonstrate that in the presence of measurement error in earning, the higher coefficient on returns and the higher adjusted R^2 for bad news do not assure the higher coefficient on earnings for good news than for bad news.

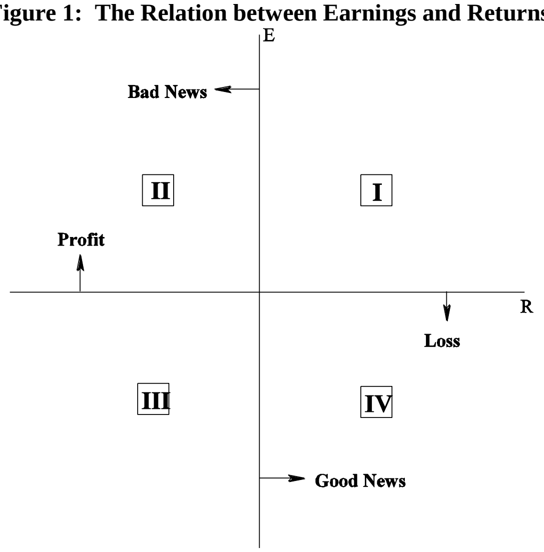
Panel C reports the regression results of profit versus loss firms. Consistent with Hayn (1995), the coefficient on earnings (*b*) is not significantly different from zero and the adjusted R^2 is close to zero for loss firms. The reverse regression of earnings on returns shows that the mean coefficient estimate on returns is higher for profit firms (0.056) than for loss firms (0.019). Once again, this demonstrates that the reverse regression and the direct regression are not the mirror image of each other.

The analyses so far corroborate the importance of the noise in earnings when one assesses the relation between earnings and returns. In order to examine the interaction between the sign of earnings and the content of news measured by the sign of annual stock returns, I partition the sample into four sub-samples based on the signs of earnings and returns: good news firms reporting profits, good news firms reporting losses, bad news firms reporting losses, and bad news firms reporting profits.[17] I examine whether Basu's (1997) predictions for good versus bad news hold for these samples further conditioned on the sign of earnings. This restriction will provide further insights into the effect of the signs of returns and earnings into the relation between earnings and returns.

[17] In calculating mean coefficients, I exclude years in which I have less than 30 observations (mostly in 1960s). I have used 33 years for quadrant III (bad news/loss partition), and 31 years for quadrant IV (good news/loss partition)

First, I focus on the sub-samples in which the sign of earnings matches the sign of returns, that is, firms in quadrants I and III in Figure 1. Quadrant I includes good news firms reporting profits, and quadrant III includes bad news firms reporting losses. The imposition of this restriction is made to test the robustness of the R^2 prediction by Basu (1997).

Figure 1: The Relation between Earnings and Returns



If earnings for bad news is noisier than earnings for good news, and the difference in sensitivity of earnings between bad news and earnings is modest, proposition 2 predicts that the coefficient on returns is higher for bad news than for good news, but the adjusted R^2 can be lower for bad news than for good news.[18] The results in Panel D support this prediction. The mean coefficient estimate on returns is higher for bad news/losses sample (0.096) than for good news/profits sample (0.041), but the adjusted R^2 is lower for bad news/losses sample (0.01) than for good news/profit sample (0.052).[19]

To summarize, inconsistent with Basu (1997), the adjusted R^2 can be lower for bad news firms than for good news firms. Consistent with Proposition 1, the empirical results indicate that a higher sensitivity of earnings for bad news than good news does not necessarily imply a higher R^2 for bad news than good news. However, the empirical result should be interpreted with caution because partitioning on the dependent variable, returns or earnings, may lead to biased estimates (Hausman and Wise 1977). If the correct specification is the regression of earnings on returns as in Basu (1997), it is problematic to partition on earnings. On the other hand, if the correct specification is the regression of returns on earnings (Dietrich, Muller, and Riedl 2003), partitioning on returns causes econometric problems. It is beyond the scope of this study to determine the correct specification in examining the relation between earnings and returns. So the empirical results presented in Panel D should be interpreted with this caveat.

I also estimate the regressions for the remaining firms in quadrants II and IV, in which the sign of stock returns differs from the sign of earnings. The mean coefficient estimate on returns is not significantly different from zero for good news firms reporting losses (quadrant IV) while the mean coefficient estimate on returns is significantly positive for bad news firms reporting profits (quadrant II), suggesting that earnings are timelier for bad news than for good news regardless of the sign of earnings. However, the adjusted R^2 is very low for the good news

[18] Note that the noise ratio for bad news/loss firms in quadrant III is 1.95, which is almost 40 times larger than the noise ratio for good news/profit firms in quadrant I.
[19] Note that the ratio of sensitivity of earnings to bad news/loss to sensitivity of earnings to good news/profit (2.34=0.096/0.041) on the restricted sample is lower than that in the full sample in Panel B of Table 3 (11.4=0.285/0.025).

firms reporting losses (quadrant IV). It seems that the observed low adjusted R^2 of the good news sample in Panel B is mainly due to good news firms reporting losses (quadrant IV). On the other hand, the adjusted R^2 for bad news firms reporting profits (quadrant II) is the highest in the four quadrants. The high adjusted R^2 for bad news reported in Panel B seems to be driven by bad news reporting profits firms rather than bad news firms reporting losses firms. The analysis presented in Panel D shows that the coefficient on returns is higher for bad news than for good news, but the adjusted R^2 is sensitive how bad news are further partitioned.

4.2 Sensitivity Tests

The descriptive statistics reported in Table 2 shows that the sample contains observations with extreme values of returns and earnings even after I delete the top and bottom one percent of observations in stock returns and earnings in each year. In order to assess the impact of these extreme observations on the results presented earlier, I further delete observations in which returns are greater than 3 or earnings per share deflated by beginning-of-fiscal-year stock price is less than -3. The results (not tabulated) are qualitatively similar to those reported in the previous section.

I use annual stock returns calculated for the year ending three months after the fiscal period end in order to make sure that all accounting information is available before the beginning of the return period. As an additional check, I repeated the analyses using annual stock returns calculated for the fiscal period. The results (not tabulated) are robust to the choice of the return period.

In the main analysis, I do not include past stock returns since the omission of past stock returns do not bias the coefficient on stock returns under the assumption that current stock returns are uncorrelated with past stock returns under no-arbitrage condition. As an additional check, I add four years of lagged stock returns as additional explanatory variables. The inclusion of past stock returns increases the adjusted R^2, however, the results (not tabulated) are qualitatively similar to those presented in the previous section.

5. SUMMARY

This paper examined the implications of accounting conservatism for the relation between earnings and stock returns. The econometric analysis shows that R^2 is not necessarily higher for bad news firms than for good news firms. In particular, the R^2 for bad news firms can be lower if earnings are substantially noisier for bad news firms than for good news firms. It is shown that the adjusted R^2 is lower for bad news firms reporting losses than for good news firms reporting profits. This study emphasizes that the test of R^2 is not a robust test of accounting conservatism.

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