Asymmetric Timeliness and Delayed Recognition of Bad News

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Abstract: This article examines whether the asymmetric timeliness measure captures delayed recognition of bad news and in which manner this delayed recognition occurs. I find that negative earnings changes of firms with high asymmetric timeliness have significant predictive power for future earnings changes of low-asymmetric-timeliness firms in the same industry. In contrast, the negative earnings changes of firms with low asymmetric timeliness do not have predictive power for future earnings changes of high-asymmetric-timeliness firms in the same industry. Moreover, neither type of firm has predictive power for the other group when earnings changes are positive. This result suggests that high-asymmetric-timeliness firms recognize the effects of a common negative shock before low-asymmetric-timeliness firms. Further, low-asymmetric-timeliness firms have more frequent and smaller negative earnings changes, suggesting that the eventual recognition of negative news "trickles out" as opposed to being recognized in an "earnings bath."

Keywords: asymmetric timeliness, conservatism, earning prediction

INTRODUCTION

Asymmetric timeliness (AT) is defined as the requirement for a higher standard for the recognition of good news than bad news in earnings (Basu, 1997). An implication of this definition is that firms with low AT delay the recognition of bad news in earnings. This article provides evidence for the existence of this delayed recognition and the manner in which it occurs using an AT measure suggested by Kahn and Watts (2009). This evidence lends support to the validity of an AT measure based on Basu's (1997) nonlinear regression of earnings on returns.

I find that negative earnings changes of firms with high AT have significant predictive power for future earnings changes of low-AT firms in the same industry. In con-

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trast, the negative earnings changes of firms with low AT do not have significant predictive power for future earnings changes of high-AT firms in the same industry. Moreover, neither type of firm has predictive power for the other group when earnings changes are positive. This result suggests that high-AT firms recognize the effects of a common negative shock before low-AT firms. In addition, I find that low-AT firms have more frequent and smaller negative earnings changes, suggesting that the eventual recognition of negative news "trickles out" as opposed to being recognized in an "earnings bath."

AT is one of the key characteristics of accounting. Research relates Basu (1997)'s measure of AT to contracting efficiency, persistence of special items, cost of capital, and corporate governance (Frankel & Roychowdhury, 2007; Zhang, 2008; LaFond & Watts, 2008; Francis & Martin, 2010). Recent studies, however, raise questions about the reliability of this measure, arguing that it is biased by economic events and disclosure policy (Givoly, Hayne, & Natarajan, 2007). Dietrich, Mueller, and Riedl (2007) also question whether this measure captures delayed recognition of earnings. Using a test that does not employ stock returns, I provide evidence that Basu's measure captures the tendency to delay the recognition of bad news in earnings following the definition of AT.

Unrecognized bad news will eventually affect earnings, because cash flows are more highly correlated with earnings over long windows (e.g., Dechow, 2004). An effective AT measure should be able to detect this delayed recognition of common bad news across firms. Thus, I predict that negative earnings changes of high-AT firms will precede negative earnings changes of low-AT firms in the same industry if the measure is effective.

Following Khan and Watts (2009), I measure firm-specific AT based on Basu's nonlinear regression of earnings on returns. Using this measure, I find negative earnings changes of high-AT firms predict earnings changes of low-AT firms in the next period within the same industry. However, I find that negative earnings changes of low-AT firms do not predict earnings changes of high-AT firms. These results provide evidence that the AT measure detects cross-sectional differences in the speed of recognition of bad news.

Given that firms with low AT delay recognition of bad news, I investigate how this retained bad news makes its appearance in earnings. Firms can choose either to recognize the accumulated bad news at one time ("earnings bath") or to recognize it slowly ("trickling out"). The method chosen has implications for earnings forecasts. "Earnings bath" firms will have less frequent but greater-magnitude negative earnings changes, while "trickling out" firms will have more frequent and smaller-magnitude negative earnings changes. These results suggest that low-AT firms trickle out the past unrecognized bad news. I also provide evidence that this "trickling out" is driven by accruals.

This study contributes to the literature in two ways. First, it provides evidence that AT measured by nonlinear regression of earnings on returns captures firms' differential timeliness in recognizing bad news. Given the recent debate on the validity of the Basu measure (Givoly et al., 2007; Dietrich et al., 2007), it is important to document whether this measure captures the differential timeliness of recognizing bad news following the definition of AT. Second, the study also contributes to the conservatism literature by providing evidence that low-AT firms tend to recognize accumulated bad news slowly rather than all at once. Understanding how firms ultimately recognize the accumulated bad news has implications for the prediction of future earnings and suggests an explanation for why firms choose not to recognize bad news promptly.

The remaining sections of the article develop testable hypotheses, describe research design and sample, provide empirical results of hypotheses tests, and offer conclusions.

HYPOTHESES DEVELOPMENT

Conservatism is defined as the differential verifiability required for recognition of profits versus losses (Watts, 2003a, 2003b). In the empirical literature, this is interpreted as representing "the accountant's tendency to require a higher degree of verification to recognize good news as gains than to recognize bad news as losses" (Basu, 1997). This definition implies that conservative firms will have greater timeliness in recognizing bad news than in recognizing good news, a phenomenon known as asymmetric timeliness (AT) (Frankel & Roychowdhury, 2007). Using the AT measure suggested by Basu (1997), literature shows that AT provides firms with benefits such as contracting efficiency, reduced cost of capital, and better governance (Zhang, 2008; LaFond & Watts, 2008; Francis & Martin, 2010). However, recent literature argues that this AT measure does not properly capture firms' differential timeliness and has an econometric issue (Givoly et al., 2007; Dietrich et al., 2007).

One way to verify the validity of the AT measure is to test whether it correctly captures firms' cross-sectional difference in the speed of recognizing bad news. Given common bad news, low-AT firms are expected to recognize bad news later than high-AT firms. In other words, a valid AT measure should be able to predict bad news recognition by low-AT firms following bad news recognition by high-AT firms. However, recognition of bad news by low-AT firms will not predict recognition of bad news by high-AT firms.

I use negative earnings changes as proxy for recognition of bad news. This proxy has been used by Basu (1997) and other researchers, including Ball, Robin, and Wu (2003) and Ball and Shivakumar (2005). As Ball and Kothari (2007) discuss, negative earnings change has an advantage over negative earnings as a proxy for recognition of bad news because it is less susceptible to survivor bias, and negative earnings cannot capture the event of recognition of bad news when firms recognize bad news but still have positive earnings. Therefore, assuming firms in the same industry share common bad news, I predict the following:

> **Hypothesis 1:** Negative earnings changes of high-AT firms have a positive correlation with future earnings changes of low-AT firms in the same industry.

Because AT implies timeliness in recognizing bad news but not good news, this study does not predict any association between high-AT firms and low-AT firms in recognizing good news, or positive earnings changes. I also do not expect to find any predicting power of low-AT firms for high-AT firms' earnings changes, regardless of the sign of earnings changes. Therefore, I predict the following:

> **Hypothesis 1a:** Positive earnings changes of high-AT firms are not associated with future earnings changes of low-AT firms in the same industry.
> **Hypothesis 1b:** Positive or negative earnings changes of low-AT firms are not associated with future earnings changes of high-AT firms in the same industry.

I further investigate in which way low-AT firms recognize accumulated unrecognized bad news, which has implications for the earnings persistence of a firm, which is of interest to investors and debt holders. There are two ways for low-AT firms to recognize bad news. They can recognize the accumulated bad news all at once, to maximize future positive income increases (the earnings bath hypothesis). Or they can recognize it slowly in a trickle, to minimize the magnitude of negative earnings changes (the trickling-out hypothesis).

The earnings-bath hypothesis can be explained by managers' incentive to maximize their compensation in the future by recognizing accumulated bad news all at once in years when current bad news is too obvious not to recognize, and managers are disqualified for the current year's bonus payment regardless of recognition of bad news. The trickling-out hypothesis can be warranted, for instance, by the incentive to avoid debt covenant breaches, because spreading out recognition of bad news prolongs the timing of the debt covenant breach, other things being equal. Therefore, whether a firm adopts the earnings-bath or trickling-out approach to recognizing accumulated bad news is an empirical question.

These two hypotheses have a diverging prediction on cross-sectional differences between high-AT and low-AT firms in the likelihood of negative earnings changes. In the big-bath world, low-AT firms will recognize accumulated bad news once after several instances, while high-AT firms recognize bad news whenever it occurs. Therefore, assuming there are multiple periods of bad news, the big-bath hypothesis predicts a lower frequency of recognition of bad news in low-AT firms than in high-AT firms. However, the trickling-out hypothesis predicts a higher likelihood of recognizing bad news by low-AT firms than by high-AT firms, because low-AT firms spread out recognition of the accumulated bad news through times of good news and bad news, while high-AT firms recognize bad news only in times of bad news. Therefore, assuming there are times of bad news and good news in any firm, the trickling-out hypothesis predicts a higher frequency of recognition of bad news in low-AT firms than in high-AT firms. Therefore my second hypothesis is (in the null hypothesis form):

> **Hypothesis 2:** The likelihood of future negative earnings changes is not associated with AT.

To further test how low-AT firms recognize accumulated bad news, I divide the sample into good news times and bad news times. In the times of good news, high-AT firms will not have any bad news (current or accumulated) to recognize, while low-AT firms may recognize previously unrecognized, accumulated bad news. In a trickling-out world, low-AT firms are more likely than high-AT firms to recognize bad news in times of good news, because they spread out the accumulated bad news through both good- and bad-news times.

In a big-bath world, two different predictions are possible. If low-AT firms take a big-bath approach to amplify bad news for future quick turn-around of earnings, they will not recognize the accumulated bad news during times of good news. In this case, there should not be any difference in the frequency of recognizing bad news between low-AT and high-AT firms. However, low-AT firms may recognize accumulated bad news even during times of good news, if an incoming CEO recognizes the accumulated bad news in a transition year (Murphy & Zimmerman, 1993; Pourciau, 1993). In this case, low-AT firms will have a higher frequency of recognizing bad news in times of good news than high-AT firms.

In times of bad news, the trickling-out hypothesis predicts no difference between low-AT firms and high-AT firms in the frequency of recognizing bad news, because low-AT firms spread out the recognition of bad news throughout bad- and good-news times. On the other hand, the big-bath hypothesis predicts that low-AT firms will have a lower frequency of recognizing bad news than high-AT firms, because low-AT firms recognize accumulated bad news once in several instances.

The big-bath hypothesis and the trickling-out hypothesis also have a departing prediction in cross-sectional difference between low-AT and high-AT firms in the magnitude of earnings changes. For negative earnings changes, the big-bath hypothesis predicts that low-AT firms will have a greater magnitude of earnings changes than high-AT firms, because low-AT firms recognize all the accumulated bad news at one time. However, the trickling-out hypothesis predicts that the magnitude of negative earnings changes will be smaller for low-AT firms than for high-AT firms. That is because high-AT firms recognize the bad news promptly and fully, while low-AT firms only recognize a small portion of the accumulated bad news and defer the remainder to the next period.

One may think, however, that the partial recognition of accumulated bad news by low-AT firms can be greater than the full recognition of contemporaneous bad news by high-AT firms. I argue, though, that the magnitude of bad news recognition by low-AT firms will be smaller than that of high-AT firms if the motivation of low-AT firms to trickle out bad news is to take benefits from contracts (for example debt covenants) by reducing the magnitude of negative earnings changes.

For positive earnings changes, neither hypothesis predicts any difference in the magnitude of earning changes between low-AT and high-AT firms. Therefore, my third hypothesis is (in the null hypothesis form):

> **Hypothesis 3:** The magnitude of negative earnings changes is not associated with AT.

RESEARCH DESIGN AND SAMPLE

Research Design

I follow Khan and Watts (2009) and Frankel and Roychowdhury (2007) in measuring firm-specific AT. Khan and Watts suggest a firm-specific AT measure modifying Basu's regression. Their measure allows coefficients to vary across firms and over time. The standard Basu (1997) regression is

$$X_{i,\,t} = \beta_{1,t} + \beta_{2,t}\, D_{i,t} + \beta_{3,i,t}\, R_{i,t} + \beta_{4,i,t}\, R_{i,t}\, D_{i,t} \qquad (1)$$

where i indexes the firm, t indexes time, X is earnings, R is returns (measuring news), D is a dummy equal to 1 when $R < 0$ and 0 otherwise. Basu interprets positive β_4 as evidence of AT. Based on this standard Basu regression, Kahn and Watts (2007) allow both β_3 and β_4 to vary with leverage (*LEV*), market-to-book (*MTB*), size (*Size*), and time as follows:

$$\beta_{3,i,t} = \mu_{1,t} + \mu_{2,t}\, Size_{i,t} + \mu_{3,t}\, MTB_{i,t} + \mu_{4,t}\, LEV_{i,t} \tag{2}$$
$$\beta_{4,i,t} = \lambda_{1,t} + \lambda_{2,t}\, Size_{i,t} + \lambda_{3,t}\, MTB_{i,t} + \lambda_{4,t}\, LEV_{i,t} \tag{3}$$

I substitute equation (2) and (3) in equation (1) and obtain the following empirical model to estimate firm-specific AT:

$$\begin{aligned} X_{i,t} = \beta_{1,t} + \beta_{2,t}\, D_{i,t} + R_{i,t}\,(\mu_{1,t} + \mu_{2,t}\, Size_{i,t} + \mu_{3,t}\, MTB_{i,t} + \mu_{4,t}\, LEV_{i,t}) + \\ R_{i,t}\, D_{i,t}\,(\lambda_{1,t} + \lambda_{2,t}\, Size_{i,t} + \lambda_{3,t}\, MTB_{i,t} + \lambda_{4,t}\, LEV_{i,t}) \end{aligned} \tag{4}$$

Equation (4) is estimated using annual cross-sectional regressions, and a firm-specific annual AT measure, $\beta_{4,i,t}$ is then computed using equation (3).

Hypothesis 1 predicts that negative earnings changes of high-AT firms will precede negative earnings changes of low-AT firms in the same industry. To test it, I first divide the sample into a high-AT group and a low-AT group for each year within each industry group defined by a two-digit SIC code, depending on whether a firm is above or below the median industry AT level. Then, I calculate the mean of earnings changes for each group. Finally, I run the following pool of time and industry regression:

$$\Delta X_{LAT,j,t+1} = \beta_0 + \beta_1 {*}\, \Delta X_{HAT,j,t} + e_t \tag{5}$$

where $\Delta X_{LAT,j,\, t+1}$ is mean earnings change of the low-AT group for industry *j* at time *t+1* and $\Delta X_{HAT,j,t}$ is the mean earnings change of the high-AT group for industry *j* at time *t*.

I use income before extraordinary item (data18 in Compustat) as earnings. Hypotheses 1 and 1a predict that β_1 will be positive when $\Delta X_{HAT,j,t}$ is negative but β_1 will not be significantly different from zero when $\Delta X_{HAT,j,t}$ is positive. This implies that recognition of bad news by firms in the high-AT group precedes recognition of bad news by firms in the low-AT group in the same industry. By running this industry pool regression, I expect to capture differential speed in recognizing industry-common bad news and minimize any effect from earnings changes of an individual firm caused by measurement error.[1] See figure 1 in the Appendix for an illustration of how I calculate

1. As Ball and Kothari (2007) argue, it is hard to differentiate whether transient negative earnings changes come from AT or from prior measurement errors. Positive measurement errors in the prior period can cause negative earnings changes in this period. However, this

$\Delta X_{LAT,j,\,t+1}$ and $\Delta X_{HAT,j,t}$.

I also run the following regression to test hypothesis 1b:

$$\Delta X_{HAT,j,t+1} = \beta_0 + \beta_1 * \Delta X_{LAT,j,t} + e_t \tag{6}$$

where $\Delta X_{HAT,j,t+1}$ is the mean earnings change of the high-AT group for industry *j* at time *t+1* and $\Delta X_{LAT,j,t}$ is the mean earnings change of the low-AT group for industry *j* at time *t*. Hypothesis 1b predicts that β_1 will not be significantly different from zero whether $\Delta X_{LAT,j,t}$ is positive or negative.

To model the likelihood of negative earnings changes, I run the following logistic regression model:

$$\begin{aligned} Neg\_\Delta X_{t+1} = {} & \beta_0 + \beta_1 * AT_t + \beta_2 * ROA_t + \beta_3 * EDF_t + \beta_4 * Industry\ ROA_t + \\ & \beta_5 * StdRet_t + \beta_6 * MVE_t + \beta_7 * MTB_t + \beta_8 * LEV_t + \\ & \beta_9 * Bad\_News_{t+1} + e_t \end{aligned} \tag{7}$$

where $Neg\_\Delta X_{t+1}$ is a dummy variable that equals 1 if change of income before extraordinary item (data18) from t to t+1 is negative, 0 otherwise. ROA_t is return on assets (data18/data6) at year *t*. EDF_t is implied probability of bankruptcy based on the KMV (Merton) bankruptcy model (Bharath & Shumway, 2004). *Industry* ROA_t is the median industry ROA for a firm’s four-digit SIC code. $StdRet_t$ is a standard deviation of stock returns over the window of 72 months with a minimum of 60 available months. MVE_t, MTB_t, and LEV_t are natural log of market value of equity (log[data25*data199 + 1]), market-to-book ratio (data25*data199/data60) and leverage ratios of a firm (data181/data6). Bad_News_{t+1} is a dummy variable that equals 1 if stock returns at t+1 are negative, 0 otherwise.

The trickling-out hypothesis predicts that β_1 will be negative, but the big-bath hypothesis predicts that β_1 will be positive. In times of good news, the trickling-out hypothesis predicts that β_1 will be negative, but the big-bath hypothesis predicts that β_1 will be either not significant or negative, depending on when the accumulated bad news is released. In times of bad news, the trickling-out hypothesis predicts that β_1 will not be significantly different from zero, but the big-bath hypothesis predicts that β_1 will be positive because the big-bath hypothesis suggests that low-AT firms recognize accumulated bad news once after several instances. I use stock returns measured over 12 months as a proxy for news. Positive returns suggest that there is good news

effect will be less prominent when calculating a group mean instead of a firm-specific earnings change, due to the potential offsetting effect of measurement error.

during the period, and negative returns suggest that there is bad news.

In testing hypothesis 3, I replace $Neg\_\Delta X_{t+1}$ in model (7) above with ΔX_{t+1}, where ΔX_{t+1} is change in income before extraordinary item (data18) from t to t+1. I divide the full sample into subgroups depending on the sign of ΔX_{t+1}. In the negative earnings changes group, the big-bath hypothesis predicts that β_1 will be positive, because low-AT firms recognize all the accumulated bad news at one time. On the other hand, the trickling-out hypothesis predicts that β_1 will be negative, because low-AT firms only recognize a small portion of the accumulated bad news and defer the remainder to the next period. In the positive earnings changes group, neither hypothesis predicts that β_1 will be significantly different from zero.

Sample Selection

My sample consists of all firms on the intersection of 2008 Compustat and CRSP databases with sufficient data to compute the AT measure, earnings changes, and other control variables. To minimize any time series dependence concerns, I include time fixed effects in all my multivariate analyses. To control for any firm-level or industry-level clustering, I use cluster-adjusted standard errors for the statistical significance tests (Petersen, 2007).

Sample Descriptive Statistics

Panel A of table 1[2] summarizes the descriptive statistics for key variables used in this analysis. Firms in the sample are on average asymmetric timely (median: 2.55) and have positive earnings (median: 0.05). However, accruals have a decreasing impact on earnings (median: -0.05), while operating cash flow has an income-increasing impact (median: 0.10). These results are consistent with prior literature that shows firms are overall conservative and have negative accruals (Basu, 1997; Givoly & Hayn, 2000). Operating cash flow is data308 in Compustat if observation is after the year 1987, and is otherwise calculated as operating income before depreciation minus interest minus taxes minus changes in non-cash working capital (Dechow, Kothari & Watts, 1998).

Accruals are the difference between income before extraordinary item and operating cash flows. In an untabulated result, 35 percent of firms have negative stock return while 53 percent of firms have negative earnings changes in t+1. This implies that the sample is balanced between positive and negative earnings change sub-groups to test

2. All tables are in the appendix.

the third hypothesis, but is imbalanced between good news and bad news sub-groups for the test of the second hypothesis. I do not expect this to cause any significant issue, though, given that the sample size is sufficient. My sample covers 36 SIC-two-digit industries and 23 years (1983 to 2005). None of thesubgroup of industry code or year is greater than 8 percent of the total sample, which implies that the sample is not dominated by one specific industry or year.

Panel B of table 1 summarizes Pearson correlations among variables in the sample. The AT measure has a negative relation with the size of the firm, but a positive correlation with leverage. This is consistent with prior literature and implies that more diverse firms are less asymmetric timely and debt contract demands AT. However, AT has a negative association with market-to-book ratio (MTB), which sometimes is used as an alternative conservatism measure.

This negative association has been explained by prior literature, including Ball and Kothari (2007) and Roychowdhury and Watts (2007). Earnings have a positive relation with accruals and operating cash flows, which are two components of earnings. Accruals have a negative association with operating cash flow, which implies a typical contemporaneous negative association between the two (Dechow & Dichev, 2002). Accruals have a negative association with future accruals change but a positive association with future cash flow change. This can be explained by accruals reversal and accruals' role of mitigating the timing lag in cash flows. Overall, the table shows that the correlation among variables is consistent with prior literature.

EMPIRICAL ANALYSES

Empirical Results of the Test of Hypothesis 1

As explained above, I calculate mean earnings changes for the low-AT group and high-AT group for each industry.[3] Then I estimate equation (5) and (6) to test hypothesis 1. Panel A of table 2 shows that negative earnings changes of high-AT firms predict next-period negative earnings changes of low-AT firms in the same industry (β_1 is 0.108 with a p-value of 0.05). This relation does not hold when earnings changes of high-AT firms are positive (p-value: 0.22).

I also statistically test whether β_1 is greater in the negative earnings changes subgroup than in the positive earnings changes sub-group. The result, shown in the bottom of panel A of table 2, shows that β_1 in the negative earnings changes sub-group is

3. Using median instead of mean does not change the results.

statistically greater than in the positive earnings changes sub-group (p-value is 0.03). These results suggest that only negative earnings changes in high-AT firms can predict future earnings changes in low-AT firms, and predicting power is statistically greater when high-AT firms' earnings changes are negative. This asymmetric predicting power of high-AT firms supports both hypothesis 1 and hypothesis 1a, which predict a positive association between the negative earnings changes of high-AT firms and the future earnings changes of low-AT firms in the same industry, but no association between the positive earnings changes of high-AT firms and the future earnings changes of low-AT firms. Panel B of table 2 shows that neither negative earnings changes nor positive earnings changes of low-AT firms are associated with the future earnings changes of high-AT firms. None of the coefficients is significant, and there is no predicting power difference between the negative earnings change sub-group and the positive earnings change sub-group. This supports hypothesis 1b.

One may think that different characteristics of the high-AT and low-AT groups may drive the results in hypothesis 1. Before further investigating this concern, I compared firm characteristics between the low-AT and high-AT groups (panel A of table 3). While there is no difference between frequency of bad news and size of sales, the two groups are quite different in other characteristics. Firms in the low-AT group are more profitable and larger and have higher cash flow, MTB, and leverage ratio. Therefore, I include these different firm characteristic variables as control variables in equation (5) to confirm that the result shown in table 2 is not compounded by the difference in firm characteristics. The result is reported in panel B of table 3.

With these control variables, adjusted R-squares jump from 42 percent to 50 percent, and the predicting power of the high-AT group is even stronger and more statistically significant. In model (2), I include all the firm characteristics that are shown in panel A of table 3 and find that β_1 is still positive and significant. In model (3), I include a bad news dummy variable to address any concerns that difference of bad news at time t+1 in the low-AT and high-AT groups may drive the result. The result is still robust on this specification. R-squares were 47 percent, and β_1 is statistically significant at 1 percent or lower level. Magnitude of β_1 also more than doubled compared to the simple model, implying that the predicting power of the negative earnings changes of the high-AT group on the future earnings changes of the low-AT group becomes stronger with control variables. This suggests that the level of AT is useful in predicting the future earnings changes of firms in the same industry, over and beyond general firm characteristics such as size. In the last specification, I excluded the industries of finance and insurance from the sample to relieve concerns on whether these regulated industries drive the result. The result was still robust in this specification.

Empirical Results of the Test of Hypothesis 2

I run a logistic regression of equation (7) to test the relation between the likelihood of negative earnings changes and AT. The dependent variable in this model is $Neg\_\Delta X_{t+1}$, a dummy variable that equals 1 if change of income before extraordinary item (data18) from *t* to *t+1* is negative, 0 otherwise. The equation also includes year dummies to control for year effects, but coefficients are not reported to save space. The first specification of table 4 reports the result of logistic regression of equation (7) using the full sample. The model chi-square statistic is 1,912.9 and is highly significant ($p < 0.0001$).

The result shows that there is a negative association between AT and likelihood of future negative earnings changes (p-value: 0.03). This finding supports the trickling-out hypothesis, which predicts that low-AT firms spread out past bad news over time rather than taking a “big bath,” and as a result, have a higher likelihood of negative earnings changes than high-AT firms. This model includes a dummy variable, Bad_news_{t+1}, to control for potential difference of occurrence of bad news at time *t+1*. Bad_news_{t+1} is 1 if stock return at *t+1* is negative and 0 otherwise.

In the second and the third specification, I report the results of logistic regression of the equation (7) in two sub-groups. I subdivide the full sample into a bad news group and a good news group, depending on stock return at *t+1*. While β_1 in the bad news group is not significant, β_1 in the good news group is significantly negative. These results again support the trickling-out hypothesis. While there is no difference between low-AT and high-AT firms in the frequency of recognition of bad news during times of bad news, the trickling-out hypothesis predicts that low-AT firms will have a higher frequency of recognition of bad news in good news times, because low-AT firms spread out the recognition of bad news. In good news times, high-AT firms do not have bad news to recognize, but low-AT firms spill over the accumulated bad news and realize negative earnings changes. On the other hand, the big-bath hypothesis predicts positive β_1 in bad news times and negative or nonsignificant β_1 in good news times, as discussed above. The magnitude of β_1 is marginally greater and more significant in the good news sub-sample than in the full sample. Overall, the results in table 4 lend evidence that low-AT firms recognize accumulated bad news slowly rather than all at once.

Empirical Results of the Test of Hypothesis 3

To test an association of magnitude of earnings changes and AT, I subdivide the full sample into two sub-samples depending on the sign of earnings changes at *t+1*.

The trickling-out hypothesis predicts a negative association between AT and earnings changes in the negative earnings changes sub-sample but no association in the positive earnings changes sub-sample. The big-bath hypothesis predicts a positive association between AT and earnings changes in the negative earnings changes sub-sample but no association in the positive earnings changes sub-sample. That is because both low-AT and high-AT firms are expected to equally recognize good news in earnings during good news times.

Panel A of table 5 shows regression results for the negative earnings changes sub-sample. β_1 is negative and significant in model (1). In models (2) and (3), I include Bad_news_{t+1} and Neg_OCF_{t+1} to control negative shock at *t+1*, where Neg_OCF_{t+1} is 1 if operating cash flow at *t+1* is negative and 0 otherwise. β_1 continues to be negative and significant. Panel B of table 5 shows that β_1 is not significant in the positive earnings changes sub-sample. Overall the results in table 5 support the trickling-out hypothesis.

I further test whether the results of table 5 are driven by accruals or cash flows. If firms delay recognition of bad news and decide to incorporate it into earnings slowly, one would predict that managers smooth negative earnings changes through accruals, not through cash flows, because managers have flexibility over accruals but not over cash flows. I test this prediction, and the results support it. In table 6, I test association between AT and changes in accruals at *t+1*. β_1 is negative and significant for the negative earnings change sub-group but not significant for the positive earnings change sub-group. In table 7, I test an association between AT and changes in operating cash flows at *t+1*. β_1 is not significant in either the positive or the negative earnings changes sub-group. This confirms conjecture that managers recognize delayed bad news through accruals.

CONCLUSION

I provide evidence that negative earnings changes of high-AT firms predict future negative earnings changes of low-AT firms. However, I do not find evidence that earnings changes of low-AT firms predict future earnings changes of high-AT firms. I also find that the likelihood of negative earnings changes is greater for low-AT firms, especially when there is good news. My results also show that the magnitude of negative earnings changes is smaller for low-AT firms, and these negative earnings changes are mostly driven by accruals. These results suggest that low-AT firms trickle out the accumulated unrecognized bad news rather than taking an earnings bath.

This study has provided evidence that AT measured by nonlinear regression of earnings on returns captures firms' differential timeliness in recognizing bad news. It also contributes to the conservatism literature by providing evidence that low-AT firms tend to recognize accumulated bad news slowly rather than all at once. Understanding of how firms recognize accumulated bad news offers implications for predicting future earnings.

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APPENDIX

Figure 1. Calculating $\Delta X_{LAT,j,\ t+1}$ and $\Delta X_{HAT,j,\ t}$

The figure shows that how I calculate $\Delta X_{LAT,j,\ t+1}$ and $\Delta X_{HAT,j,\ t}$. X is earnings, defined as income before extra-ordinary items (data 18 in Compustat). $\Delta X_{LAT,j,\ t+1}$ is earnings change from year t to year t+1 for Low AT (LAT) group. $\Delta X_{HAT,j,\ t}$ is earnings change from year t to year t+1 for High AT (HAT) group. b4,i,t is a coefficient from the regression of $\beta_{4,i,t} = \lambda_{1,t} + \lambda_{2,t}\,Size_{i,t} + \lambda_{3,t}\,MTB_{i,t} + \lambda_{4,t}\,Lev_{i,t}$, where i indexes the firm, t indexes time.

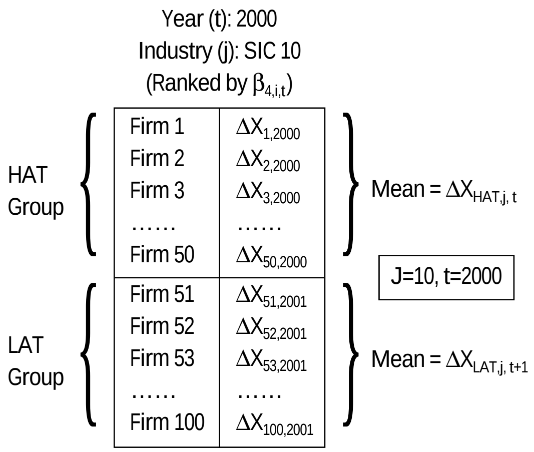

Table 1. Descriptive Statistics of the Key Variables in the Analysis

The sample consists of all firms in the 2008 CRSP/Compustat merged dataset with sufficiently available data. AT is Asymmetric Timeliness measured following Khan and Watts (2009). X is earnings, defined as income before extraordinary items (data 18 in Compustat). ACC is operating accruals, defined as the difference between earnings and operating cash flow. OCF is operating cash flow (data 308). MVE is natural log of market value of equity (log[data25*data199+1]). MTB is market-to-book ratio (data25*data199/data60). LEV is leverage ratio (data181/data6). StdRet is a standard deviation of stock returns over the window of 72 months with a minimum of 60 available months. ΔXt+1 is change of earnings from t to t+1. *, **, and *** indicate significance at the 10 percent, 5 percent and 1 percent level respectively.

Panel A. Univariate Statistics

Variable	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
AT	26,986	5.921	15.185	1.545	2.555	7.161
X	25,294	0.042	0.162	0.013	0.050	0.098
ACC	22,237	-0.0559	0.138	-0.093	-0.050	-0.012
OCF	22,237	0.099	0.145	0.047	0.101	0.162
MVE	26,986	6.665	1.613	5.485	6.605	7.765
MTB	26,986	3.0606	3.733	1.454	2.172	3.507
LEV	26,986	0.538	0.243	0.357	0.538	0.703
StdRet	25,794	0.127	0.064	0.084	0.111	0.153
ΔXt+1	25,991	-0.099	14957.000	-0.027	-0.001	0.016

Panel B. Pearson Correlations

	X	ACC	OCF	MVE	MTB	LEV	ΔXt+1	ΔACCt+1	ΔOCFt+1
AT	-0.09***	-0.04***	-0.07***	-0.15***	-0.08***	0.08***	-0.01	-0.01	0.01
X		0.59***	0.64***	0.10***	0.01*	-0.07***	0.00	0.00	0.00
ACC			-0.25***	-0.05***	-0.10***	0.02***	-0.02**	-0.02***	0.02***
OCF				0.18***	0.10***	-0.08***	0.02***	0.02***	-0.02***
MVE					0.22***	0.22***	0.01	0.01	-0.01
MTB						-0.12***	0.00	0.00	0.00
LEV							0.01**	0.01**	-0.01**
ΔXt+1								0.99***	-0.99***
ΔACCt+1									-1.00***

Table 2. OLS Regression Result of Association between Low-AT Earnings Changes and High-AT Earnings Changes

AT is Asymmetric Timeliness measured following Khan and Watts (2009). X is earnings, defined as income before extraordinary item (data 18 in Compustat). ΔXt+1 is change of earnings from t to t+1. ΔXt is change of earnings from t-1 to t. Subscript HAT means high-AT firms (defined as firms below mean of AT for each year and industry). Subscript LAT HAT means high-AT firms.

Panel A. Regression of Future Low-AT Earnings Changes on Current High-AT Earnings Changes

Variables	Dependent Variable: $\Delta X_{LAT,t+1}$			
	$\Delta X_{HAT,t} < 0$		$\Delta X_{HAT,t} > 0$	
	Coefficient	p-value	Coefficient	p-value
Intercept (β_0)	0.0011	0.7744	0.0109	0.0634
$\Delta X_{HAT,t}$ (β_1)	**0.1080**	**0.0527**	**0.0220**	**0.2274**
Industry fixed effects	yes		yes	
Year fixed effects	yes		yes	
Adj-R^2 (%)	9.4		7.4	
N	471		325	
Difference in β_1	F Value		p-value	
	4.61		0.0322	

Panel B. Regression of Future High-AT Earnings Changes on Current Low-AT Earnings Changes

Variables	Dependent Variable: $\Delta X_{HAT,t+1}$			
	$\Delta X_{LAT,t} < 0$		$\Delta X_{LAT,t} > 0$	
	Coefficient	p-value	Coefficient	p-value
Intercept (β_0)	-0.0120	0.0227	-0.0067	0.3722
$\Delta X_{LAT,t}$ (β_1)	**-0.1223**	**0.2459**	**0.0440**	**0.535**
Industry fixed effects	yes		yes	
Year fixed effects	yes		yes	
Adj-R^2 (%)	7.2		6.1	
N	407		390	
Difference in β_1	F Value		p-value	
	0.13		0.723	

Table 3. OLS Regression Result of Future Low-AT Earnings Changes on Current High-AT Earnings Changes with Control Variables

AT is Asymmetric Timeliness measured following Khan and Watts (2009). Bad_Newst+1 is a dummy equal to 1 if stock returns at t+1 are negative, 0 otherwise. ROA is return on asset (data18/data6). OCF is operating cash flow (data 308). MVE is natural log of market value of equity (log[data25*data199+1]). MTB is market-to-book ratio (data25*data199/data60). LEV is leverage ratio (data181/data6). ΔXt+1 is change of earnings from t to t+1. X is earnings defined as income before extraordinary item (data 18 in Compustat). Subscript LAT means low-AT firms (defined as firms below mean of AT for each year and industry). Subscript HAT means high-AT firms. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent level respectively.

Panel A. Descriptive Statistics for Low-AT Group and High-AT Group

Variable	LAT (N=797)			HAT (N=797)			Difference	
	Mean	Std Dev	Median	Mean	Std Dev	Median	t Value	Pr > |t|
AT	1.684	12.984	-1.042	8.978	13.519	5.090	-41.85	<.0001
Bad_News	0.369	0.224	0.333	0.379	0.213	0.361	-1.02	0.31
ROA	0.077	0.064	0.079	0.050	0.168	0.049	4.35	<.0001
OCF/Asset	0.125	0.071	0.126	0.079	0.215	0.092	5.40	<.0001
Sales/Asset	1.414	0.850	1.330	1.619	3.264	1.456	-1.80	0.07
MVE	7.315	1.090	7.346	5.778	1.129	5.610	31.70	<.0001
MTB	3.151	1.670	2.752	2.307	1.150	2.028	13.80	<.0001
LEV	0.513	0.162	0.493	0.565	0.145	0.551	-11.28	<.0001
ΔXt+1	-0.008	0.035	-0.005	-0.012	0.179	-0.004	0.65	0.51

Panel B. Regression of Future Low-AT Earnings Changes on Current High-AT Earnings Changes with Control Variables

Variables	Dependent Variable: $\Delta X_{LAT,t+1}$							
	Model (1)		Model (2)		Model (3)		Except SIC 60's	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Intercept (β_0)	0.0011	0.77	-0.0020	0.92	0.0089	0.63	0.0058	0.80
$\Delta X_{HAT,t}$ (β_1)	0.1080	0.05	0.1069	0.04	0.2840	0.00	0.2791	0.00
$LEV_{LAT,t}$ (β_2)			-0.0035	0.88	-0.0149	0.49	-0.0145	0.51
$MVE_{LAT,t}$ (β_3)			0.0015	0.70	0.0037	0.36	0.0067	0.06
$MTB_{LAT,t}$ (β_4)			-0.0005	0.78	-0.0009	0.62	-0.0010	0.58
$X_{LAT,t}$ (β_5)			-0.4231	0.00	-0.4039	0.00	-0.4268	0.00
$Sale_{LAT,t}$ (β_6)			0.0103	0.03	0.0064	0.16	0.0000	0.99
$OCF_{LAT,t}$ (β_7)			0.1224	0.05	0.1421	0.01	0.1933	0.01
$LEV_{HAT,t}$ (β_8)			0.0049	0.80	0.0083	0.64	0.0000	1.00
$MVE_{HAT,t}$ (β_9)			0.0026	0.60	0.0006	0.91	-0.0046	0.26
$MTB_{HAT,t}$ (β_{10})			0.0017	0.27	0.0014	0.41	0.0008	0.69
$X_{HAT,t}$ (β_{11})			-0.0455	0.30	-0.1348	0.01	-0.1139	0.07
$SALE_{HAT,t}$ (β_{12})			-0.0017	0.56	0.0024	0.37	0.0095	0.02
$OCF_{HAT,t}$ (β_{13})			-0.0668	0.01	-0.0724	0.00	-0.0873	0.02
$Bad\_News_{LAT,t+1}$ (β_{14})					-0.0117	0.14	-0.0161	0.06
$Bad\_News_{HAT,t+1}$ (β_{15})					-0.0123	0.09	-0.0061	0.32
Industry fixed effects	yes		yes		yes		yes	
Year fixed effects	yes		yes		yes		yes	
Adj-R^2 (%)	9.4		42.5		47		50	
N	471		365		347		317	

Table 4. Asymmetric Timeliness and Likelihood of Negative Earnings Changes

AT is Asymmetric Timeliness measured following Khan and Watts (2009). X is earnings defined as income before extraordinary item (data 18 in Compustat). Neg_ΔXt+1 is a dummy equal to 1 if change of earnings from t to t+1 is negative, 0 otherwise. ROA is return on asset (data18/data6). EDF is implied probability of bankruptcy based on KMV (Merton) bankruptcy model. Industry ROA is median industry ROA for a firm's four-digit SIC code. StdRet is standard deviation of stock returns over the window of 72 months. MVE is natural log of market value of equity (log[data25*data199+1]). MTB is market-to-book ratio (data25*data199/data60). LEV is leverage ratio (data181/data6). Bad_Newst+1 is a dummy equal to 1 if stock returns at t+1 are negative, 0 otherwise.

Variables	Dependent Variable: $Neg\_\Delta X_{t+1}$					
	Full Sample		Bad News		Good News	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
Intercept (β_0)	-0.2999	0.03	0.6312	0.01	-0.3973	0.01
$AT_t(\beta_1)$	-0.0061	0.03	0.0020	0.70	-0.0083	0.02
$ROA_t(\beta_2)$	4.7860	0.00	4.5478	0.00	5.0045	0.00
$EDF_t(\beta_3)$	-0.4033	0.02	-0.0644	0.83	-0.5980	0.01
Industry $ROA_t(\beta_4)$	-1.1987	0.00	-0.6859	0.07	-1.3877	0.00
$StdRet_t(\beta_5)$	2.0364	0.00	2.3103	0.00	1.9504	0.00
$MVE_t(\beta_6)$	-0.0583	0.00	-0.0811	0.00	-0.0452	0.00
$MTB_t(\beta_7)$	-0.0319	0.00	-0.0335	0.00	-0.0328	0.00
$LEV_t(\beta_8)$	0.2727	0.00	-0.1304	0.33	0.4770	0.00
$Bad\_News_{t+1}(\beta_9)$	0.8601	0.00				
Model chi-square	1,912.90		529.6		840.9	
p-value	0.0001		0.0001		0.0001	
N	22,952		8,237		14,715	
Obs. where $Neg\_\Delta X_{t+1} = 1$	12,173		5,336		6,837	
Obs. where $Neg\_\Delta X_{t+1} = 0$	10,779		2,901		7,878	

Table 5. Asymmetric Timeliness and Magnitude of Earnings Changes

AT is Asymmetric Timeliness measured following Khan and Watts (2009). X is earnings defined as income before extraordinary item (data 18 in Compustat). ∆Xt+1 is change of earnings from t to t+1. ROA is return on asset (data18/data6). EDF is implied probability of bankruptcy based on KMV (Merton) bankruptcy model. Industry ROA is median industry ROA for a firm's four-digit SIC code. StdRet is standard deviation of stock returns over the window of 72 months. MVE is natural log of market value of equity (log[data25*data199+1]). MTB is market-to-book ratio (data25*data199/data60). LEV is leverage ratio (data181/data6). Bad_Newst+1 is a dummy equal to 1 if stock returns at t+1 are negative, 0 otherwise. Neg_OCFt+1 is a dummy equal to 1 if operating cash flow at t+1 is negative, 0 otherwise. Operating cash flow is data308 in Compustat. Negative (positive) earnings change sub-sample is composed of firms for which ∆Xt+1 is negative (positive).

Panel A. Negative Earnings Change Sub-sample

Variables	Dependent Variable: Neg_ΔX_{t+1}					
	Model (1)		Model (2)		Model (3)	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept(β_0)	0.0156	0.22	0.0237	0.06	0.0321	0.02
$AT_t(\beta_1)$	-0.0005	0.02	-0.0004	0.03	-0.0005	0.02
$ROA_t(\beta_2)$	-0.1045	0.05	-0.1101	0.04	-0.1466	0.01
$EDF_t(\beta_3)$	-0.0203	0.07	-0.0193	0.08	-0.0171	0.14
Industry $ROA_t(\beta_4)$	0.1152	0.00	0.1168	0.00	0.0969	0.01
$StdRet_t(\beta_5)$	-0.4793	0.00	-0.4834	0.00	-0.4498	0.00
$MVE_t(\beta_6)$	0.0017	0.04	0.0016	0.06	0.0001	0.93
$MTB_t(\beta_7)$	-0.0039	0.00	-0.0039	0.00	-0.0037	0.00
$LEV_t(\beta_8)$	0.0311	0.00	0.0003	0.00	0.0449	0.00
Bad_$News_{t+1}(\beta_9)$			-0.015	0.00	-0.0146	0.00
Neg_$OCF_{t+1}(\beta_{10})$					-0.047	0.00
Firm fixed effects	yes		yes		yes	
Year fixed effects	yes		yes		yes	
Adj-R^2 (%)	11.22		11.5		13	
N	11,337		11,337		11,337	

Panel B. Positive Earnings Change Sub-sample

Variables	Dependent Variable: ΔX_{t+1}					
	Model (1)		Model (2)		Model (3)	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept(β_0)	0.0711	0.00	0.0762	0.00	0.0783	0.00
$AT_t(\beta_1)$	0.0001	0.44	0.0001	0.43	0.0001	0.33
$ROA_t(\beta_2)$	-0.5963	0.00	-0.5996	0.00	-0.6162	0.00
$EDF_t(\beta_3)$	-0.0028	0.69	-0.0036	0.61	-0.0023	0.74
Industry $ROA_t(\beta_4)$	0.1147	0.02	0.1121	0.02	0.0936	0.03
$StdRet_t(\beta_5)$	0.0354	0.50	0.0322	0.54	0.0358	0.47
$MVE_t(\beta_6)$	0.0027	0.02	0.0026	0.02	0.0018	0.07
$MTB_t(\beta_7)$	0.0031	0.00	0.0031	0.00	0.0032	0.00
$LEV_t(\beta_8)$	-0.0899	0.00	-0.0894	0.00	-0.0741	0.00
Bad_$News_{t+1}(\beta_9)$			-0.0159	0.00	-0.0153	0.00
Neg_$OCF_{t+1}(\beta_{10})$					-0.0372	0.00
Firm fixed effects	yes		yes		yes	
Year fixed effects	yes		yes		yes	
Adj-R^2 (%)	69.7		70.1		71.1	
N	10,779		10,779		10,779	

Table 6. Asymmetric Timeliness and Accruals Changes

AT is Asymmetric Timeliness measured following Khan and Watts (2009). X is earnings defined as income before extraordinary item (data 18 in Compustat). ΔACCt+1 is change of accruals from t to t+1, where accruals are defined as difference between earnings and operating cash flow (data308). ROA is return on asset (data18/data6). EDF is implied probability of bankruptcy based on KMV (Merton) bankruptcy model. Industry ROA is median industry ROA for a firm's four-digit SIC code. StdRet is standard deviation of stock returns over the window of 72 months. MVE is natural log of market value of equity (log[data25*data199+1]). MTB is market-to-book ratio (data25*data199/data60). LEV is leverage ratio (data181/data6). Bad_Newst+1 is a dummy equal to 1 if stock returns at t+1 are negative, 0 otherwise. Neg_OCFt+1 is a dummy equal to 1 if operating cash flow at t+1 is negative, 0 otherwise. Sub-sample is composed of either positive or negative earnings change at t+1.

Variables	Dependent Variable: ΔACC_{t+1}			
	$\Delta X_{t+1} < 0$		$\Delta X_{t+1} > 0$	
	Coefficient	p-value	Coefficient	p-value
Intercept (β_0)	-0.0005	0.63	0.0305	0.10
$AT_t(\beta_1)$	-0.0005	0.08	-0.0002	0.50
$ROA_t(\beta_2)$	-0.0973	0.13	-0.4593	0.00
$EDF_t(\beta_3)$	-0.0481	0.02	0.0224	0.19
Industry $ROA_t(\beta_4)$	0.1154	0.01	0.1766	0.01
$StdRet_t(\beta_5)$	-0.3059	0.00	-0.0808	0.23
$MVE_t(\beta_6)$	0.0045	0.00	0.0050	0.01
$MTB_t(\beta_7)$	-0.0017	0.15	0.0014	0.01
$LEV_t(\beta_8)$	0.0001	0.99	-0.0577	0.01
$Bad\_News_{t+1}(\beta_9)$	-0.0100	0.00	-0.0110	0.01
$Neg\_OCF_{t+1}(\beta_{10})$	0.0072	0.57	0.0398	0.04
Firm fixed effects	yes		yes	
Year fixed effects	yes		yes	
Adj-R^2 (%)	4.4		35.6	
N	9,395		8,802	

Table 7. Asymmetric Timeliness and Operating Cash Flow Changes

AT is Asymmetric Timeliness measured following Khan and Watts (2009). X is earnings defined as income before extraordinary item (data 18 in Compustat). ∆OCFt+1 is change of operating cash flow (data308) from t to t+1. ROA is return on asset (data18/data6). EDF is implied probability of bankruptcy based on KMV (Merton) bankruptcy model. Industry ROA is median industry ROA for a firm's four-digit SIC code. StdRet is standard deviation of stock returns over the window of 72 months. MVE is natural log of market value of equity (log[data25*data199+1]). MTB is market-to-book ratio (data25*data199/data60). LEV is leverage ratio (data181/data6). Bad_Newst+1 is a dummy equal to 1 if stock returns at t+1 are negative, 0 otherwise. Neg_OCFt+1 is a dummy equal to 1 if operating cash flow at t+1 is negative, 0 otherwise. Sub-sample is composed of either positive or negative earnings change at t+1.

Variables	Dependent Variable: ΔOCF_{t+1}			
	$\Delta X_{t+1} < 0$		$\Delta X_{t+1} > 0$	
	Coefficient	p-value	Coefficient	p-value
Intercept (β_0)	0.0283	0.03	0.0487	0.00
$AT_t(\beta_1)$	0.0012	0.63	0.0035	0.14
$ROA_t(\beta_2)$	-0.0747	0.05	-0.1723	0.00
$EDF_t(\beta_3)$	0.0458	0.01	-0.0209	0.18
Industry $ROA_t(\beta_4)$	-0.0208	0.32	-0.0872	0.00
$StdRet_t(\beta_5)$	-0.0917	0.04	0.1342	0.00
$MVE_t(\beta_6)$	-0.0041	0.00	-0.0031	0.01
$MTB_t(\beta_7)$	-0.0020	0.00	0.0017	0.00
$LEV_t(\beta_8)$	0.0226	0.03	-0.0208	0.05
$Bad\_News_{t+1}(\beta_9)$	-0.0057	0.02	-0.0068	0.02
$Neg\_OCF_{t+1}(\beta_{10})$	-0.0855	0.00	-0.0985	0.00
Firm fixed effects	yes		yes	
Year fixed effects	yes		yes	
Adj-R^2 (%)	7.5		14.3	
N	9,395		8,802	