How Well Do Investors Understand Loss Persistence?

Kevin Ke Li*

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Abstract: This paper examines investors' expectations of loss persistence. I develop a model to forecast loss firms' future earnings based on Joos and Plesko (2005). This model produces smaller forecast errors than random walk models or a model that assumes losses are transitory. The results suggest that investors do not fully distinguish the differences in loss persistence captured by the model, and instead appear to assume that all losses are transitory. Consequently, investors are surprised by future announcements of negative earnings for firms with predicted persistent losses, and these firms experience significantly negative abnormal returns over the following four quarters. Additional results indicate that the future negative returns of firms with predicted persistent losses are smaller in magnitude when these firms are followed by analysts. The results are robust to controls for various price anomalies and are not driven by short sales constraints.

Keywords: loss persistence; investor optimism; behavioral heuristics; stock returns

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* Kevin Li, Rotman School of Management, 105 St. George Street, Toronto, ON M5S1L2, Canada. Email: kevin.li@rotman.utoronto.ca

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1. INTRODUCTION

Firms reporting losses are prevalent in the U.S. economy. The proportion of loss firms on Compustat is 9.7% in 1976 and peaks at 45.2% in 2001 before it drops to 33.7% in 2007.[1] In theory, losses should not persist because returning to profitability is a maintained hypothesis of financial reporting, embodied in the going-concern assumption (Joos and Plesko, 2005; hereafter JP2005). In practice, firms can take actions to avoid persistent losses, such as liquidating loss-generating assets (Hayn, 1995). However, some firms do report persistent losses. For example, General Motors Corporation (GM) had four consecutive years of losses starting in 2005 and filed for Chapter 11 bankruptcy protection on June 1, 2009; Exelixis Inc., a biotech pharmaceutical company, has not reported profits since its initial public offering in 2000. These examples show that there is a large heterogeneity in loss persistence. However, anecdotal evidence suggests that investors may not fully understand the persistence of losses. For example, when discussing the future prospects of GM on MSN.com message board in July 2008, many people believed that the automaker could survive its persistent losses or even thrive.[2] In this paper, I examine whether investors can correctly anticipate loss persistence when they value loss firms.

Losses provide a unique setting to examine investors' expectations of the overall earnings persistence. Because losses on average are less persistent than profits (Hayn, 1995), loss firms

[1] Loss firms are defined as firms reporting negative earnings before extraordinary items and discontinued operations. The pattern before 2001 is similar to the results documented by prior studies, e.g., Hayn (1995), Givoly and Hayn (2000), Joos and Plesko (2005), and Klein and Marquardt (2006).

[2] See “Will General Motors survive and even thrive?”: http://moneycentral.msn.com/community/message/thread.asp?threadid=726399&boardname=Hide&header=SearchOnly&footer=Show&boardsparam=Page%3d1&linktarget=_parent&pagestyle =money1&forumid=18&board=MarketTalkwithJimJubak

are likely to experience large variations in earnings from the period they incur losses to future periods. The large variations in loss firms' earnings make it difficult for investors to correctly assess loss persistence, and thus may lead to incomplete market adjustments (Brown, 2001). The large variations in loss firms' earnings also allow researchers to use a parsimonious model to distinguish losses that are likely to persist from those that are likely to be transitory. In contrast to the large heterogeneity in loss persistence, the majority of profits have similar persistence. This has two effects. First, a similar earnings forecast model may not be powerful enough to distinguish the differences in the persistence of profits. Second, investors may have a better sense of profit persistence. Sloan (1996) finds that in a sample dominated by profit firms, stock prices correctly reflect the implications of current earnings for future earnings using annual data. Because of the aforementioned two effects, I do not find evidence indicating that investors misunderstand the overall persistence of profits.

To examine investors' expectations of loss persistence, it is necessary to have a proxy of the expected loss persistence. JP2005 propose a model to predict loss reversal probability using current and past financial information. Their model can distinguish loss firms that are more likely to return to profitability from those that are more likely to remain in loss. I adopt a modified version of JP2005 model, which predicts loss firms' earnings in the following quarter. Predicting the levels of future earnings instead of loss reversals makes it easier to compare the results in this paper with the findings in prior studies that use levels of earnings as reference points, e.g., Balakrishnan et al. (2010). To examine if stock prices fully impound the information about loss persistence, I focus on two groups of loss firms: predicted persistent and transitory losses. I use the quarterly distribution of the forecast earnings derived from the model to define these two groups: predicted persistent losses are loss observations with forecast earnings in the lowest quintile of the quarterly distribution, and predicted transitory losses are loss observations in the highest quintile of the distribution.[3]

Using the framework developed by Mishkin (1983), I find that investors do not fully distinguish the differences in loss persistence identified by the model; instead they appear to assume that all losses are transitory. Consequently, investors are surprised by future announcements of negative earnings for firms in the persistent loss group. The abnormal returns over the following four quarters are significantly negative for the persistent loss group, but close to zero for the transitory loss group. The overvaluation of firms with predicted persistent losses appears to be economically significant. A trading strategy that takes a long position in firms with predicted transitory losses and a short position in firms with predicted persistent losses yields hedge returns of 10.4% per annum. The hedge returns are clustered around future earnings announcement dates, consistent with the interpretation that they represent a delayed response to predictable changes in future earnings. I show that analyst forecasts reflect fairly accurate expectations of loss persistence. Consequently, the future negative returns of the persistent loss group are smaller in magnitude when these firms are followed by analysts.

I provide several robustness tests to support the inference that the negative abnormal returns of firms with predicted persistent losses are due to investors' incorrect assessment of loss persistence. First, the hedge returns based on forecast earnings are robust to controls for accruals, book-to-market ratio, standardized unexpected earnings (SUE), momentum, return volatility, earnings-to-price ratio and the level of current earnings. This suggests that investors'

[3] I follow the terminology in JP2005 because the forecast earnings derived from the model incorporate the likelihood of a loss firm to return to profitability, which is modeled in JP2005. Loss firms with higher forecast earnings have higher loss reversal probabilities, and hence those losses are more transitory. In addition, as the results in Section 5 shows, predicted persistent losses exhibit higher autocorrelations than predicted transitory losses, suggesting that the losses in the former group are more consistent over time. Finally, the model in this paper also helps investors identify "big bath" losses, which are extreme losses but not persistent. This indicates that the forecast earnings derived from the model do not simply predict how extreme the future earnings will be, but rather capture the expected persistence of the losses.

misunderstanding of loss persistence is largely uncorrelated with other price anomalies. Second, in a subsample of observations with positive short interest ratio (SIR), the negative abnormal returns of the persistent loss group are larger in magnitude when these firms have higher SIR. This suggests that the results are not driven by short sales constraints, because this alternative explanation implies that prices should deviate more from fundamental value in firms that are harder to short. Third, in a subsample of loss firms with zero special items, the hedge returns based on forecast earnings are similar to the results of the full sample. This suggests that the overvaluation of firms with predicted persistent losses is not driven by investors' failure to price the implications of special items for future earnings (e.g., Burgstahler et al., 2002; Dechow and Ge, 2006). Finally, I implement the least trimmed squares procedure and drop 1% of the observations that are the most influential. Future returns of the loss firms in the remaining sample are still positively associated with forecast earnings, and the hedge returns are even larger than the full sample results. This suggests that the results are not driven by a small number of extreme observations.

This paper contributes to the prior literature along the following dimensions. First, this study discovers a new area where stock markets may not be efficient. Prior studies of investors' expectations of earnings persistence primarily focus on the persistence of the components of earnings in a broader sample including both profit and loss observations (e.g., Sloan, 1996; Burgstahler et al., 2002; Richardson et al., 2005; Dechow and Ge, 2006). I examine investors' expectations of the overall earnings persistence in loss firms. Investors' misunderstanding of the overall earnings persistence appears to be a unique phenomenon to loss firms. It is likely due to the large variations in loss firms' earnings. The overvaluation of firms with predicted persistent losses is economically significant and becomes more costly to investors and capital markets as the proportion of loss firms in the U.S. economy increases over time.

Second, this paper offers a new explanation for the smaller market reaction to negative earnings than to positive earnings. Prior studies take the low earnings response coefficient (ERC) of loss firms as evidence that losses are less informative than profits about firms' future prospects (e.g., Hayn, 1995). In this paper, I offer an alternative explanation: investors underestimate loss persistence and do not penalize loss firms sufficiently for their poor performance. The finding that loss firms on average have negative future abnormal returns supports the misvaluation explanation.

The remainder of the paper is organized as follows. Section 2 discusses related research and develops the hypotheses. Section 3 presents the earnings forecast model. Section 4 describes the sample selection and variable measurement. Section 5 presents the main empirical results and robustness tests. Section 6 provides conclusions.

2. RELATED RESEARCH AND DEVELOPMENT OF HYPOTHESES

2.1 Investors react less to losses than to profits

Hayn (1995) examines the association between earnings and contemporaneous stock returns, i.e., the ERCs, in loss firms and profit firms. Hayn argues that losses indicate situations where the abandonment option could be attractive. Consequently, losses are less informative about firms' future prospects than profits, which is manifested in the lower ERC of loss firms. Basu (1997) examines the impacts of accounting conservatism on the persistence of earnings. Basu argues that accounting conservatism results in earnings reflecting "bad news" more quickly and fully, but recognizing "good news" over time. Consequently, negative earnings shocks are less persistent than positive earnings shocks. Basu finds that consistent with this asymmetric persistence, ERC is higher for positive earnings changes than for negative earnings changes.

Loss avoidance is important to managers (e.g., Degeorge et al., 1999; Graham et al., 2005), and is rewarded by investors (e.g., Brown and Caylor, 2005). Nevertheless, the potential to return to profitability varies across loss firms. JP2005 develop a model to estimate loss reversal probability and classify loss firms into persistent and transitory losses based on the estimated probability. JP2005 find that the ERC in transitory loss group is on average significantly positive, but the ERC in the persistent loss group becomes significantly negative over time, implying that larger persistent losses are related to higher returns over time. To understand this puzzling result, they examine the role of R&D component in the valuation of persistent losses. They find that when persistent losses do not include R&D, the ERC is still negative but becomes insignificant. When persistent losses include an R&D component, investors value the R&D component as an asset (higher R&D is associated with higher contemporaneous returns) and the remaining non-R&D component of losses as if it is transitory (the ERC on this component is significantly positive). The evidence in JP2005 indicates that loss firms' ERC varies with loss persistence. However, JP2005 do not examine if investors' valuation of loss firms *correctly* impounds information about loss persistence, which is the main research question of my study. Nevertheless, their finding that investors treat the non-R&D component of persistent losses as transitory indicates investors may underestimate loss persistence.[4]

2.2 Investors' inefficient pricing of losses and special items

[4] JP2005 do not provide evidence on the persistence of the non-R&D component of persistent losses. However, it is likely that this component of persistent losses is also persistent because the non-R&D component in persistent losses is much more negative than its counterpart in transitory losses (JP2005, p.865), and the level of losses is the most important predictor of loss persistence (JP2005, p. 859).

Balakrishnan et al. (2010) re-examine the post-earnings announcement drift (PEAD) using levels of earnings. The investment strategy in Balakrishnan et al. (2010) is very passive and only requires buying or selling a stock the day after earnings of quarter t are announced and place it into a portfolio based on its earnings' decile ranking from quarter t-1. They show that investors do not fully respond to quarterly profit/loss announcements. In an attempt to explain this mispricing, they show that the hedge returns are correlated with the differences between conditional and unconditional probabilities of losses and profits, as if investors do not rely fully on conditional probabilities, i.e., the probability of reporting losses/profits next quarter for loss/profit firms this quarter. Balakrishnan et al. make no attempt to distinguish whether firms in the low earnings deciles will have persistent losses. Their trading strategy does not require any type of forecasting. In contrast, I use the earnings forecast model to predict loss firms' earnings one quarter before they are announced and use the forecast earnings as a proxy for loss persistence. As results in Section 5 show, the forecast earnings are a more accurate measure of expected loss persistence than the levels of current losses. By examining the time-series characteristics of losses with different persistence and how investors evaluate loss persistence, I provide an explanation to the negative abnormal returns on loss firms observed in Balakrishnan et al. (2010).[5] In addition, by forecasting earnings one quarter ahead of their announcements, I provide an improved investment strategy that yields 20% higher hedge returns than the naïve classification in Balakrishnan et al. (2010).

Narayanamoorthy (2006) examines different behaviors of PEAD in profit and loss firms. Narayanamoorthy finds that the autocorrelations of SUEs are significantly lower in loss firms

[5] Although Balakrishnan et al. motivate their study by the different characteristics of profits and losses (e.g., loss firms have much bigger earnings forecast errors than profit firms), their investment strategy does not exploit these differences. Because their ranking variable is earnings, loss firms are likely to concentrate in the two lowest deciles. Hence, we can only infer that the average semi-annual abnormal returns on loss firms are about -5%, without knowing much of the cross-sectional variations.

than in profit firms, consistent with losses having a greater tendency to mean revert than profits (Basu, 1997). Consequently, PEAD is significantly smaller in loss firms than in profit firms.

Loss persistence and special items are closely related. Given the transitory nature of special items, losses caused by special items are expected to be transitory as well. The results of prior studies on the pricing of special items are largely contextual. Burgstahler et al. (2002) and Dechow and Ge (2006) show that investors fail to price the implications of negative special items for future earnings. Both studies find that negative special items lead to positive future abnormal returns. In contrast, Bartov et al. (1998) examine a sample of 315 write-offs in 1984 and 1985 and find that these firms have significantly negative abnormal returns over a two-year period following the announcements of the write-offs. Finally, Doyle et al. (2003) show that special items, which are constantly excluded from pro forma earnings, have no implications for firms' future cash flows from operations and are not associated with future stock returns.

2.3 Development of hypotheses

To investigate whether stock prices fully reflect available information about loss persistence, it is necessary to specify an alternative naïve expectation model against which to test the null of market efficiency. Prior studies on the value-relevance of losses provide some evidence of how investors price accounting losses. Hayn (1995) finds that ERC is lower for firms with more loss years in the past, an important predictor of loss persistence. JP2005 show that ERC is lower for the persistent loss group. These results suggest that contemporaneous stock returns are less associated with losses that are more likely to persist. Hayn (1995) and JP2005 take the results as evidence that the value-relevance of earnings decreases as the likelihood of exercising the abandonment option increases. Alternatively, these results can be interpreted as investors underreact to losses that are likely to persist, which raises the possibility that investors underestimate the persistence of these losses. Consequently, the naïve expectation model employed in this study is that investors fail to fully distinguish the differences in loss persistence and treat all losses as transitory.

H1(a): The earnings expectations embedded in loss firms' stock prices fail to fully reflect the different persistence of losses.

If investors treat all losses as transitory and underestimate the persistence of predicted persistent losses, then firms with predicted persistent losses will be overvalued and firms with predicted transitory losses will be valued at close to their fair value.

H1(b): Future abnormal returns are negative for firms with predicted persistent losses and close to zero for firms with predicted transitory losses.

Note that the prediction of H1(b) is different from the prediction of SUE-based strategy. Bernard and Thomas (1990) hypothesize that investors' expectations of future earnings follow a seasonal random walk model. If investors' expectations follow the seasonal random walk model, then they will expect loss firms to continue reporting the same level of losses in the future *regardless of the persistence of the losses*. Consequently, firms with predicted persistent losses will be valued at close to their fair value, while firms with predicted transitory losses will be undervalued because these firms have the highest forecast earnings and are the least likely to report losses in the future.

Prior studies on price anomalies use the abnormal returns over earnings announcement period to disentangle systematic valuation errors from risk compensation, e.g., La Porta (1996), La Porta et al. (1997), and Sloan (1996). If the abnormal stock returns of firms with predicted persistent losses represent a delayed response to predictable changes in future earnings, then they should be concentrated around information events that reveal those changes, such as future earnings announcements.

H2: The abnormal stock returns predicted in H1(b) are clustered around future earnings announcement dates.

If the optimistic bias about loss persistence is caused by investors' inability to process complicated financial information or other behavioral heuristics, such as the disposition effect, it should be concentrated in naïve investors and less pronounced among sophisticated market participants, such as sell-side analysts. Prior studies show that larger analyst coverage, measured as the number of analysts following the firm, corresponds to more information available about the firm, e.g., Lang and Lundholm (1996), Hong et al. (2000), and Gleason and Lee (2003). However, analyst forecasts are also known to be optimistic, e.g., Richardson et al. (2004), and Bradshaw et al. (2006). If analyst coverage helps investors correct their bias about loss persistence, then the negative abnormal returns of firms with predicted persistent losses would be smaller in magnitude when these firms are followed by analysts.

H3: The abnormal stock returns predicted in H1(b) are smaller in magnitude for loss firms with analyst coverage.

3. THE EARNINGS FORECAST MODEL FOR LOSS FIRMS

JP2005 develop a model to estimate the annual loss reversal probability. Their model is as follows:

$$\begin{aligned} REVERSAL_{t+1} = {} & \beta_1 EARN_t + \beta_2 PAST\_EARN_t + \beta_3 SIZE_t + \beta_4 SALESG_t \\ & + \beta_5 FIRSTLOSS_t + \beta_6 LOSS\_SEQ_t + \beta_7 DIVDUM_t + \beta_8 DIVSTOP_t + \varepsilon_{t+1} \end{aligned} \quad (1)$$

where $REVERSAL_{t+1}$ is an indicator variable that is equal to one if the loss firm becomes profitable next year, and zero otherwise (other variables will be defined later).

Building on the model of JP2005, I propose the following quarterly earnings forecast model for loss firms:

$$\begin{aligned} EARN_{t+1} = {} & \alpha + \beta_1 EARN_t + \beta_2 EARN_{t-3} + \beta_3 SIZE_t + \beta_4 SALESG_t + \beta_5 FIRSTLOSS_t \\ & + \beta_6 LOSS\_SEQ_t + \beta_7 DIVDUM_t + \beta_8 SPI_t + \beta_9 SPI_{t-3} + \beta_{10} Q3_t + \beta_{11} Q4_t + \varepsilon_{t+1} \end{aligned} \tag{2}$$

where $EARN_t$ is quarterly income before extraordinary items and discontinued operations, scaled by total assets at the beginning of quarter t; $SIZE_t$ is the logarithm of market value of equity at the end of quarter t; $SALESG_t$ is the percentage growth in sales over quarter t; $FIRSTLOSS_t$ is an indicator variable that is equal to one if the loss in quarter t is the first one in a sequence, and zero otherwise; $LOSS\_SEQ_t$ is the number of sequential quarterly losses over the four quarters prior to quarter t; $DIVDUM_t$ is an indicator variable that is equal to one if the firm pays dividends during quarter t, and zero otherwise; SPI_t is special items scaled by total assets at the beginning of quarter t; $Q3_t$ and $Q4_t$ are dummy variables indicating the third and the fourth fiscal quarters, respectively.

In this paper, I choose to forecast loss firms' future earnings because the forecast earnings contain information about the loss reversal probability as well as the expected earnings in the loss and profit outcomes. Although the forecast earnings and the estimated loss reversal probability are highly correlated (Pearson correlation is 0.760), the forecast earnings are more informative about loss firms' future performance. Consequently, the results based on the forecast earnings are stronger. In addition, predicting earnings instead of loss reversals makes it easier to compare the results in this paper with the findings in prior studies that use levels of earnings as reference points, e.g., Balakrishnan et al. (2010).

I extend the model of JP2005 in the following aspects. First, I change their annual loss reversal model to a quarterly earnings forecast model. Consequently, $EARN_t$, $SALESG_t$,

$FIRSTLOSS_t$, $LOSS\_SEQ_t$, and $DIVDUM_t$ are all measured using quarterly data, and $PAST\_EARN_t$, the average *EARN* over the past five years, is dropped from the forecast model. $DIVSTOP_t$, the dummy variable indicating that firms stop paying dividends during the loss period, is also dropped from the model because its coefficient changes from negative for annual results to positive for quarterly results, inconsistent with the prediction of JP2005.[6] According to the results of JP2005 (p. 859), loss firms' future earnings should be positively associated with $EARN_t$, $SIZE_t$, $FIRSTLOSS_t$ and $DIVDUM_t$, negatively associated with $LOSS\_SEQ_t$, and not significantly associated with $SALESG_t$.[7] To control for the well-documented seasonal effects of quarterly earnings, the earnings in the same quarter last year ($EARN_{t-3}$) are added to the model.[8] In addition, this model includes two dummy variables indicating the third and the fourth fiscal quarters. The fourth fiscal quarter results are backed out from annual results, which are audited and hence more conservative (Brown and Pinello, 2007). In addition, the majority of write-offs take place at the end of the fiscal year (Elliott and Shaw, 1988). Consequently, more firms report losses and the magnitude of losses is higher in the last fiscal quarter than in other interim quarters. This suggests that observations from the third fiscal quarter will have lower expected earnings in the following quarter (i.e., the fourth quarter) and observations from the fourth fiscal quarter will have higher expected earnings in the following quarter (i.e., the first quarter of the next fiscal year). Hence, ceteris paribus, future earnings should be negatively associated with $Q3_t$ and positively associated with $Q4_t$.

[6] The exclusion of $DIVSTOP_t$ does not change the results significantly because only 2% of the observations stop paying dividends.

[7] JP2005 do not have a specific prediction about the sign of $SALESG_t$. They argue that sales growth is expected to be positively associated with the likelihood of loss reversal. But the effect is weakened if high sales growth identifies young firms that have not yet achieved profitability. Their results show that the coefficient on sales growth is positive but statistically insignificant.

[8] The inclusion of other interim earnings, $EARN_{t-1}$ and $EARN_{t-2}$, does not change the results significantly.

Second, this model includes special items as predictors of future earnings. Fairfield et al. (1996) show that the disaggregation of earnings into operating earnings, special items, and other components improves earnings forecast. Firms with losses caused by one-time write-offs are likely to report profits in the next quarter. Hence, ceteris paribus, earnings in quarter t+1 should be negatively associated with special items in quarter t (SPI_t). To control for the seasonal effects of special items on earnings documented by Burgstahler et al. (2002), the special items in the same quarter last year (SPI_{t-3}) are added to the model.[9] According to Burgstahler et al. (2002, p. 596), earnings in quarter t+1 should be negatively associated with special items in quarter t-3.

Similar to JP2005, I estimate equation (2) by quarter and compute the forecast earnings of quarter t+1 using independent variables measured in quarter t and the mean of the coefficients of quarter t-4 to quarter t-1.[10] For example, to estimate the earnings of the second quarter of 1984 for the firms reporting losses in the first quarter, I first calculate the mean of the quarterly estimated coefficients of equation (2) over the four quarters of 1983, then multiply it by the independent variables measured in the first quarter of 1984. I classify loss observations into predicted persistent and transitory losses using the quarterly quintiles of the forecast earnings. Predicted persistent losses are loss observations with forecast earnings in the first quintile of the distribution, and predicted transitory losses are loss observations in the fifth quintile of the distribution.

I also use an alternative model to forecast loss firms' year-over-year earnings. The model is as follows:

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[9] The inclusion of other interim special items, SPI_{t-1} and SPI_{t-2}, does not change the results significantly.

[10] The results are similar if the coefficients are (1) averaged over the past eight or sixteen quarters, (2) weighted by the number of observations in each quarter, (3) weighted by a scheme that gives the highest weight to the coefficient of the most recent quarter and progressively lower weights to the coefficients of older quarters, or (4) estimated in pooled observations of the past four, eight or sixteen quarters.

$$EARN_{t+4} = \alpha + \beta_1 EARN_t + \beta_2 SIZE_t + \beta_4 SALESG_t + \beta_5 FIRSTLOSS_t + \beta_6 LOSS\_SEQ_t + \beta_7 DIVDUM_t + \beta_8 SPI_t + \varepsilon_{t+1} \qquad (3)$$

By comparing the forecasts derived from equation (2) and equation (3), I can assess the persistence of predicted persistent losses in a longer horizon. Because both models produce similar results, I only report the main test results based on equation (2).

4. SAMPLE SELECTION AND VARIABLE MEASUREMENT

I obtain quarterly financial statement data from the Compustat (Xpressfeed) database and daily stock returns from the CRSP database.[11] The sample period is from 1984 to 2006. To minimize data errors, I require that firm-quarter observations have positive total assets (ATQ), positive sales (SALEQ), and positive market value of equity (PRCCQ*CSHOQ) at the end of the fiscal quarter. Financial firms (SIC between 6000 and 6999) and utilities (SIC between 4900 and 4999) are excluded from the sample. To minimize the effects of thinly traded stocks, I exclude observations with stock prices below five dollars (measured in 2006 dollars) at the end of the quarter.[12] I replace missing values of special items (SPIQ) with zero.[13] All financial statement variables are winsorized at the 1% tails. Consistent with prior studies (e.g., Hayn, 1995; JP2005), I define loss firms as firm-quarter observations with negative income before extraordinary items and discounted operations (IBQ). Because the calculation of forecast earnings requires financial information for the past four quarters, financial data are collected starting from the first quarter of 1983. There are 64,539 loss observations from 1983 to 2006 with sufficient data to calculate forecast earnings. The final sample consists of 62,370 loss observations from 1984 to 2006 with

[11] Compustat (Xpressfeed) quarterly data are restated financial information, which introduces a peak-ahead bias in the test. To ensure that the results are not driven by this peak-ahead bias, I re-examine the results using Compustat annual data. The tenor of the results (untabulated) does not change when using annual instead of quarterly financial information.

[12] This criterion reduces the sample from 123,806 firm-quarter observations to 64,539 firm-quarter observations. However, the results are not sensitive to this selection criterion.

[13] The results are similar if observations with missing special items are excluded.

non-missing forecast earnings. To examine the effects of analyst coverage on investors' expectations of loss persistence, I collect analyst coverage and consensus earnings per share (EPS) forecasts (mean estimate) from the I/B/E/S Summary History files. Analyst coverage is the number of analysts that provide EPS forecasts for the firm.

Raw stock returns include dividends and other distributions. If a stock is delisted during the return window, then the CRSP delisting return is included in the buy-hold return, and the proceeds are reinvested in the CRSP size-matched decile portfolio for the remainder of the return window. If the delisting return is missing, I use the replacement values suggested by Shumway (1997) and Shumway and Warther (1999). Specifically, if the stock is traded on NYSE or AMEX prior to delisting, I replace the missing delisting return with -30% (Shumway, 1997; Shumway and Warther, 1999); if the stock is traded on NASDAQ prior to delisting, I replace the missing value with -55% (Shumway and Warther, 1999). Size-adjusted returns are computed by measuring the buy-hold return in excess of the buy-hold return on the CRSP size-matched decile portfolio. The portfolios are based on the size deciles of NYSE, AMEX and NASDAQ firms. The portfolio membership is determined using the market value of equity at the beginning of the calendar year in which the return cumulation period begins.

5. EMPIRICAL ANALYSES AND ROBUSTNESS TESTS

5.1 The prevalence of losses in U.S. firms

Figure 1 plots the percentage of Compustat (Xpressfeed) firms reporting quarterly losses (aggregated by calendar year) from 1976 to 2007. The percentage of loss firms increases from 9.7% in 1976 to 45.2% in 2001. The trend reverses after 2001. In 2007, 33.7% of firms report losses. Givoly and Hayn (2000) attribute the decrease in earnings over time to an increase in accounting conservatism. However, Klein and Marquardt (2006) show that accounting conservatism is not as significant as other non-accounting factors in explaining the increase in losses over time. The non-accounting factors they identify include Compustat coverage of small firms, real firm performance measured by cash flows from operations, and business cycle factors.

[Insert Figure 1 here]

The U.S. economy has experienced significant changes since the 1970s as it moves away from brick-and-mortar manufacturing industries to service and knowledge-based industries. Figure 1 shows that the percentage of Compustat firms in the "new economy" industries has increased steadily, from 7.3% in 1976 to 18.4% in 2007.[14] Firms in these industries invest heavily in intangible assets. Corresponding to the rise of new economy industries, investment in intangible assets in the U.S. economy increases from 4.4% of GDP in 1978 to 10.5% in 2000 (Nakamura, 2001). Under U.S. GAAP, many investments in intangibles are expensed, such as investments in R&D activities. Hence, firms in the new economy industries are more likely to report losses. For example, Figure 1 shows that 69.7% of new economy firms report losses in 2001, significantly higher than the 45.2% of the general population. The evidence suggests that structural changes in the U.S economy may also contribute to the increase in losses over time.

5.2 The different persistence of losses and profits

Losses on average are less persistent than profits (Hayn, 1995; Basu, 1997). The lower persistence of losses translates to larger variations in earnings in loss firms than in profit firms. Figure 2 plots the distributions of earnings changes from quarter t to t+1 (scaled by total assets at the end of quarter t) for firms reporting losses and profits in quarter t. I follow the same criteria discussed in Section 4 to select profit firms. There are 221,591 firm-quarter observations

[14] There is no standard definition of new economy. Many studies use SIC codes to classify new economy industries, e.g., Ittner et al. (2003). In this paper, new economy industries include pharmaceutical products, telecommunications, computers, and electronic equipment. Industry classification is based on Fama and French (1997) 48 industry groups.

reporting profits from 1983 to 2006. As Figure 2 shows, only 34% of loss firms have quarterly earnings changes within 1% of total assets. In contrast, 68% of profit firms have earnings changes within this range. The standard deviation of earnings changes in loss firms is much larger than that in profit firms (0.064 vs. 0.026). The larger variations in loss firms' earnings provide a unique setting to test investors' expectations of the overall earnings persistence.

[Insert Figure 2 here]

5.3 The earnings forecast model for loss firms

Table 1 Panel A reports the distribution of the sample's loss observations by the number of *sequential* quarterly losses. The results show that some losses are very persistent. For example, 15% of loss firms have more than eight quarters of sequential losses.[15] Panel A also reports the average loss reversal ($REVERSAL_{t+1}$) and the mean earnings in the next quarter ($EARN_{t+1}$). Both $REVERSAL_{t+1}$ and $EARN_{t+1}$ decrease monotonically in the length of loss sequence.

[Insert Table 1 here]

Panel B presents descriptive statistics of the variables in equation (2). On average, quarterly losses account for about 5% of total assets. Panel C shows that, on the univariate base, $EARN_{t+1}$ is positively correlated with $EARN_t$, $EARN_{t-3}$, $SIZE_t$, $FIRSTLOSS_t$, $DIVDUM_t$, SPI_{t-3}, and $Q4_t$, and negatively correlated with $SALESG_t$, $LOSS\_SEQ_t$, SPI_t, and $Q3_t$. All the variables except SPI_{t-3} have the predicted correlations with $EARN_{t+1}$.

Table 2 Panel A reports the Fama-MacBeth regression results of equation (2). On average, the model explains approximately 46% of the variations in loss firms' future earnings. All the predictors inherited from JP2005 have the coefficients consistent with their results (p. 859). All

[15] The longest loss sequence in the sample is 66 quarters or 16.5 years (untabulated), which belongs to RIBI ImmunoChem Research Inc, a biotechnology company acquired by Corixa Corporation in October 1999.

the new variables added to the model have significant coefficients in the predicted direction. The significantly positive coefficient on $EARN_{t-3}$ (t=25.86) is consistent with the seasonal effects of quarterly earnings. The coefficients on SPI_t and SPI_{t-3} are -0.604 (t=-27.93) and -0.344 (t=-11.33), respectively. This suggests that SPI_{t-3} has much less incremental effect on $EARN_{t+1}$ than SPI_t after controlling for other variables.[16] Consistent with the fourth fiscal quarter results being the most conservative, $EARN_{t+1}$ is positively associated with $Q4_t$ (t=13.69) and negatively associated with $Q3_t$ (t=-14.16).[17]

[Insert Table 2 here]

I use the mean of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and the independent variables measured in quarter t to compute the expected earnings of quarter t+1 ($FEARN_t$), where the subscript t denotes that the forecast is made at time t. Table 2 Panel B reports descriptive statistics of portfolios formed on $FEARN_t$. The third column of the results shows that, on average, firms with predicted persistent losses (the first quintile of $FEARN_t$) are expected to lose 11.3 cents per dollar of assets in the next quarter, while firms with predicted transitory losses (the fifth quintile of $FEARN_t$) are expected to earn 1.1 cents. The next three columns report the actual earnings in quarter t, quarter t+1, and quarter t+4, respectively. Moving from quarter t to quarter t+1, there is little change in earnings for firms with predicted persistent losses (from -0.117 to -0.114). After four quarters, these firms still report significant losses (mean $EARN_{t+4}$=-0.100). In contrast, the earnings of firms with predicted transitory losses

[16] Note that this finding does not conflict with the results of Burgstahler et al. (2002), who show a prominent effect of lag four special items on seasonally-differenced earnings. In their study (Table 2 Panel B), seasonally-differenced earnings in quarter t+1 to t+4 are separately tested against special items in quarter t, while in this study special items in quarter t-1 and t-3 are put together in one regression to test their incremental effects on total earnings in quarter t+1 after controlling for other variables. In addition, the sample in their study is not restricted to loss firms.

[17] I use a similar earnings forecast model for profit firms. I replace $FIRSTLOSS_t$ with $FIRSTPROFIT_t$ and $LOSS\_SEQ_t$ with $PROFIT\_SEQ_t$ (note that the signs of $FIRSTPROFIT_t$ and $PROFIT\_SEQ_t$ are opposite from those of $FIRSTLOSS_t$ and $LOSS\_SEQ_t$). The coefficients of the forecast model for profit firms are similar to those for loss firms. However, the adjusted R-square is only 22%, much lower than that for loss firms, which suggests that the model is less powerful in explaining future earnings of profit firms.

increase significantly from quarter t to t+1 (from -0.020 to 0.004). On average, these firms are profitable four quarters after their loss quarter (mean $EARN_{t+4}$=0.003). The seventh column shows that only 8.5% of firms with predicted persistent losses return to profitability in the next quarter. In contrast, 67.4% of firms with predicted transitory losses are profitable in the next quarter. The final column of Panel B shows that firms with predicted persistent losses have much smaller market capitalization than firms with predicted transitory losses.

Figure 3 Panel A plots the mean earnings of the persistent loss group and the transitory loss group over a nine-quarter window. Quarter t represents the time when firms are ranked into $FEARN_t$ quintiles. Firms with predicted transitory losses on average have positive earnings in the four quarters prior to the loss quarter and return to profitability immediately after the loss quarter. This suggests that the losses in quarter t are temporary deviations from these firms' normal performance. In contrast, firms with predicted persistent losses remain unprofitable for the entire nine quarters. In addition, the earnings of these firms are relatively stable over time. This suggests that the losses in quarter t for firms with predicted persistent losses represent the norm of their future performance. Panel B shows similar patterns for observations without special items, suggesting that the transitory nature of the predicted transitory losses is not purely driven by special items. Overall, the results in Table 2 Panel B and Figure 3 show that the forecast earnings derived from equation (2) capture the expected persistence of losses.

[Insert Figure 3 here]

Table 2 Panel C reports forecast errors of different earnings forecast models for loss firms. Forecast errors are defined as the difference between actual earnings of quarter t+1 and the expected earnings derived from each model. Model 1 is the earnings forecast model in equation (2). Model 2 is the random walk model, i.e., the expected earnings of quarter t+1 equal to the earnings of quarter t. Model 3 is the seasonal random walk model, i.e., the expected earnings of quarter t+1 equal to the earnings of quarter t-3. Model 4 assumes that losses are transitory, i.e., the expected earnings of quarter t+1 are zero. In the predicted persistent loss portfolio, the mean forecast errors of Model 1 and Model 3 are the smallest in magnitude and statistically insignificant. This suggests that both Model 1 and Model 3 produce unbiased earnings forecasts for firms with predicted persistent losses. Model 1 also produces the smallest mean forecast errors for loss firms in other portfolios, except for the transitory loss group. Finally, the forecast errors from Model 1 have smaller standard deviation than the forecast errors from the other three models. The evidence suggests that the predictors other than $EARN_t$ and $EARN_{t-3}$ in Model 1 improve forecast accuracy.

Balakrishnan et al. (2010, p.34) show that 77% of the firms with extreme losses, or High Loss, report losses in the following quarter. The evidence suggests that extreme losses can be persistent. Then a legitimate question is whether the levels of losses alone can provide sufficient information about loss persistence. To answer this question, I examine the firms in the lowest quintile of $EARN_t$. If the levels of current losses provide sufficient information about loss persistence, then the majority, if not all, of these firms should remain in the lowest quintile of $EARN_{t+1}$. Untabulated results show that only 59% of the 12,438 observations in the lowest quintile of $EARN_t$ remain in the lowest quintile of $EARN_{t+1}$. If based solely on the levels of losses, the remaining 41% or 5,072 observations would be misclassified as predicted persistent losses. In contrast, none of these 5,072 observations are classified as predicted persistent losses based on $FEARN_t$. Therefore, the model developed in this paper improves the prediction of loss persistence. It helps investors distinguish losses that are caused by “big baths” from those that are truly persistent.

Table 3 Panel A compares the quintile classifications based on the forecast earnings from equation (2) and equation (3). Equation (3) produces year-over-year forecast earnings ($FYOYEARN_t$). The results show that 75% of the firms with predicted persistent losses are in the lowest quintile of $FYOYEARN_t$, indicating that the majority of the firms with predicted persistent losses are expected to have poor performance one year later. Panel B reports serial correlations of future earnings in portfolios formed on $FEARN_t$. Future earnings of firms with predicted persistent losses exhibit high serial correlations. For example, the Pearson correlation is 0.565 between $EARN_{t+1}$ and $EARN_{t+2}$, and is 0.445 between $EARN_{t+1}$ and $EARN_{t+4}$. The serial correlations of earnings in the remaining four portfolios are much lower. The results in Table 3 suggest that the earnings of the persistent loss group are indeed persistent. Hence, the forecast earnings ($FEARN_t$) of the persistent loss group not only provide relevant information about these firms' earnings in the next quarter, but also are informative about their performance in the longer horizon.

[Insert Table 3 here]

5.4 Investors' expectations of loss persistence and the association between forecast earnings and future stock returns

5.4.1 Investors' expectations of loss persistence

To test Hypothesis 1(a), I use the framework developed by Mishkin (1983). The econometric specification of the Mishkin test comprises one "forecast equation" and one "pricing equation":

Forecast equation: $$EARN_{t+1} = \alpha_0 + \alpha_1 EARN_t + \delta_{t+1} \qquad (4)$$

Pricing equation: $$BHAR_{t+1} = \beta(EARN_{t+1} - \alpha_0 - \alpha_1^* EARN_t) + \mu_{t+1} \qquad (5)$$

where $BHAR_{t+1}$ is the buy-hold size-adjusted return over the period starting two trading days after the earnings announcement date of quarter t and ending one trading day after the earnings announcement date of quarter t+1.[18] The null hypothesis of market efficiency imposes the constraint: $\alpha_1=\alpha_1^*$. Alternatively, if investors underestimate loss persistence, then the coefficient on $EARN_t$ in the pricing equation will be smaller than the one in the forecast equation, i.e., $\alpha_1>\alpha_1^*$. In addition, if investors treat the losses as transitory, then α_1^* will be insignificantly different from zero.

Table 4 Panel A reports the Mishkin test results for the 12,438 observations with predicted persistent losses. The coefficient on $EARN_t$ in the forecast equation, α_1, is 0.409 (t=42.38), consistent with the high loss persistence in this portfolio. The corresponding coefficient in the pricing equation, α_1^*, is 0.020 (t=0.16), which is significantly lower than α_1. The statistical insignificance of α_1^* suggests that investors treat predicted persistent losses as if they are transitory. The likelihood test for market efficiency is 11.14 (marginal significance level=0.001), and the null hypothesis of $\alpha_1=\alpha_1^*$ is strongly rejected. Panel B reports the Mishkin test results for the 12,454 observations with predicted transitory losses. α_1 is 0.007 (t=0.69) and α_1^* is 0.034 (t=0.49). Both α_1 and α_1^* are statistically insignificant, which is consistent with the transitory nature of the losses in this portfolio. The likelihood test for market efficiency is 0.15 (marginal significance level=0.700), and the null hypothesis of $\alpha_1=\alpha_1^*$ is not rejected. The results in Table 4 suggest that investors do not fully distinguish the differences in loss persistence identified by the model, and instead appear to assume that all losses are transitory. Specifically, the expectations embedded in the stock prices of firms with predicted persistent losses

[18] Results are similar using abnormal returns over the four-trading-day window starting two trading days prior to the earnings announcement date of quarter t+1. Results are also robust to the inclusion of the additional explanatory variables identified by Kraft et al. (2007) and additional lags of earnings.

underestimate the persistence of these losses. In contrast, the expectations embedded in the stock prices of firms with predicted transitory losses correctly reflect the transitory nature of these losses. Overall, the results in Table 4 support the prediction of H1(a).

[Insert Table 4 here]

5.4.2 The association between forecast earnings and future stock returns

Table 5 Panel A presents equal-weighted portfolio size-adjusted returns over the 90-day window ($BHAR90_{t+1}$), 180-day window ($BHAR180_{t+1}$), and one-year window ($BHAR365_{t+1}$) starting two trading days after the earnings announcement date of quarter t.[19] The mean size-adjusted returns of the predicted persistent loss portfolio are significantly negative in all return windows. For example, the mean portfolio return is -3.10% (t=-2.82) over the 90-day period and -12.0% (t=-5.15) over the one-year period. Portfolio returns increase monotonically in forecast earnings, with the predicted transitory loss portfolio having a mean return of -0.9% (t=-2.55) over the 90-day period and -1.5% (t=-1.81) over the one-year period. The abnormal return to a hedge portfolio that takes a long position in firms with predicted transitory losses and a short position in firms with predicted persistent losses is 10.4% (t=4.15) over the one-year period.[20] Table 5 Panel B reports $BHAR365_{t+1}$ of the persistent and transitory loss groups by calendar quarters. The mean size-adjusted returns of the persistent loss group are significantly negative in all calendar quarters, ranging from -10.6% to -14.6%. The small variations in the abnormal returns suggest that the results are not driven by loss firms in a particular quarter.

[Insert Table 5 here]

[19] The results using valued-weighted portfolio returns (weighted by each firm's market value of equity at the end of quarter t) are similar. The results are also similar if the return windows start one month or 45 calendar days after the end of quarter t.

[20] Although firms in the new economy industries are more likely to report losses than firms in the traditional industries as Figure 1 shows, the results are similar in these two subsamples. Untabulated results show that over the one-year window, the hedge return based on $FEARN_t$ is 12.3% in the traditional economy subsample, and 13.2% in the new economy subsample.

Figure 4 provides evidence on the stability of the abnormal returns to the trading strategy. It plots the hedge portfolio return over the one-year window ($BHAR365_{t+1}$) for the entire sample period from 1984 to 2006. Figure 4 shows that the strategy is consistently profitable and yields positive returns in 20 of the 23 years in the sample. In summary, the results in Table 5 and Figure 4 are consistent with the prediction of H1(b). The persistent loss group experiences significantly negative abnormal returns over the following four quarters, while the future abnormal returns of the transitory loss group are close to zero.

[Insert Figure 4 here]

5.5 *The cluster of the abnormal returns around future earnings announcement dates*

Hypothesis 2 predicts that the abnormal returns associated with forecast earnings will be clustered around future earnings announcement dates. The quarterly announcement period is defined as the four-trading-day window starting two trading days prior to the earnings announcement date. Total announcement period over the one-year measurement window of $BHAR365_{t+1}$ includes four subsequent quarterly announcement periods, or 16 trading days.

Table 6 presents size-adjusted returns over the announcement and non-announcement periods. Total return is $BHAR365_{t+1}$ from Table 5 Panel A. The positive association between forecast earnings and future stock returns is evident in both the announcement and non-announcement periods. In the announcement period, the mean return is -2.7% (t=-9.50) for firms with predicted persistent losses and 1.1% (t=5.38) for firms with predicted transitory losses. The hedge return in the announcement period is 3.8% (t=10.39). Hence, 37% of the total hedge return (10.4%) is realized in the announcement period, which accounts for only 6% of the total trading days in a year. In the non-announcement period, the mean return is -9.4% (t=-4.20) for firms with predicted persistent losses and -2.6% (t=-3.25) for firms with predicted transitory losses. The hedge return in the non-announcement period is 6.8% (t=2.85).

[Insert Table 6 here]

Figure 5 plots the hedge return in the announcement period for the entire sample from 1984 to 2006. The figure shows that the hedge returns in the announcement period are consistently positive for all of the 23 years in the sample period. In addition, the strategy becomes more profitable as the proportion of loss firms increases over time. Overall, the results in Table 6 and Figure 5 are consistent with the prediction of H2. The abnormal returns predicted by the forecast earnings are clustered around future earnings announcement dates, suggesting that the abnormal returns are due to systematic valuation errors rather than risk compensation.

[Insert Figure 5 here]

5.6 *The effects of analyst coverage on the overvaluation of firms with predicted persistent losses*

I use the first available mean forecast for quarter t+1 (I/B/E/S FPI=6) after the earnings announcement of quarter t as the consensus analyst forecast ($FEPS_t$). Analyst coverage ($NUMEST_t$) is the number of analysts that provide forecasts for the firm's EPS of quarter t+1. The first column in Table 7 Panel A shows that approximately half of the loss observations in the sample have analyst coverage, with the transitory loss group having the most coverage (61%) and the persistent loss group having the least coverage (46%). The next three columns in Table 7 Panel A report $BHAR365_{t+1}$ for firms in each tercile of $NUMEST_t$. Observations in each $FEARN_t$ portfolio are sorted into terciles based on $NUMEST_t$ by quarter. The mean size-adjusted returns for the predicted persistent loss portfolio are -8.9% (t=-2.30) when the firms' analyst coverage is in the bottom tercile and -5.9% (t=-1.67) when their analyst coverage is in the top tercile.

Consistent with the findings in prior studies (e.g., Lang and Lundholm, 1996), the results suggest that larger analyst coverage is associated with better information environment. The last column in Table 7 Panel A reports portfolio returns for loss firms with no analyst following. Compared to firms with analyst coverage, firms without analyst coverage have lower future returns in each level of $FEARN_t$. In particular, the mean size-adjusted return of the predicted persistent loss portfolio is -17.1% (t=-7.62) for firms without analyst coverage. It appears that investors may benefit from the information provided by analyst forecasts and that the overvaluation of firms with predicted persistent losses is less severe when these firms are followed by analysts.

[Insert Table 7 here]

To investigate whether analyst forecasts reflect more accurate expectations of loss persistence, I estimate the following two equations:

Fundamental regression: $$EPS_{t+1} = \alpha_0 + \alpha_1 EPS_t + \tau_{t+1} \quad (6)$$

Analyst forecast regression: $$FEPS_t = \alpha_0^* + \alpha_1^* EPS_t + \omega_t \quad (7)$$

where α_1^* represents analysts' expectations of loss persistence. If analysts correctly anticipate loss persistence, then α_1^* will be equal to α_1, the true loss persistence. Alternatively, if analysts underestimate loss persistence, then α_1^* will be smaller than α_1.

Table 7 Panel B reports regression results of equations (6) and (7) using quintile rankings of the actual and forecast pro forma EPS for firms in the predicted persistent and transitory loss portfolios. The sample in this test is restricted to firms with negative pro forma EPS in quarter t. The results show that α_1^* is smaller than the corresponding α_1 and the likelihood tests reject the null hypothesis of $\alpha_1^*=\alpha_1$ in both the persistent and transitory loss groups. This suggests that analysts underestimate loss persistence in both portfolios. However, α_1^* in the predicted persistent loss portfolio is significantly larger than the one in the predicted transitory loss portfolio (0.726 vs. -0.052). This is in sharp contrast to the Mishkin test results in Table 4, which show that α_1^* is similar in both portfolios. This evidence indicates that analyst forecasts, albeit optimistic, largely capture the differences in loss persistence. Accordingly, investors' expectations of loss persistence are more accurate when these firms are followed by analysts.[21]

5.7 Robustness tests

5.7.1 Abnormal returns based on $FEARN_t$ after controlling for other return predictors

The results in Table 5 suggest that forecast earnings are associated with future stock returns. In this section, I examine whether the predictive power of forecast earnings is correlated and subsumed by other commonly known return predictors. These predictors include book-to-market ratio (BTM_t) (Fama and French, 1992), accruals (ACC_t) (e.g., Sloan, 1996; Richardson et al., 2005), price momentum (MOM_t) (e.g., Jegadeesh and Titman, 1993; Chan et al., 1996; Lee and Swaminathan, 2000), return volatility (VOL_t) (Ang et al., 2006), standardized unexpected earnings (SUE_t) (e.g., Bernard and Thomas, 1990; Ball and Bartov, 1996; Rangan and Sloan, 1998; Narayanamoorthy, 2006), earnings-to-price ratio (ETP_t) (e.g., Basu, 1977; Basu, 1983; Lakonishok et al., 1994), and level of earnings ($EARN_t$) (Balakrishnan et al., 2010). I use a regression framework to simultaneously control for the effects of all these return predictors:

$$\begin{aligned} BHAR365_{t+1} = \gamma_0 + \gamma_1 FEARN_t + \gamma_2 EARN_t + \gamma_3 ETP_t + \gamma_4 SUE_t + \gamma_5 BTM_t \\ + \gamma_6 ACC_t + \gamma_7 MOM_t + \gamma_8 VOL_t + \eta_{t+1} \end{aligned} \tag{8}$$

I transform all independent variables into quintile rankings and then scale the rankings so that they have a range of one and a mean of zero. The regression coefficients can be interpreted as hedge portfolio returns (Bernard and Thomas, 1990). Untabulated results show that

[21] I redo the Mishkin test for loss firms with analyst coverage and the results (untabulated) show that investors' optimistic bias about loss persistence is less severe in this subsample than in the full sample. The evidence suggests that investors benefit from analyst forecasts. However, it is possible that analysts choose to follow loss firms that are easier to forecast, or they may change coverage due to other exogenous reasons.

$BHAR365_{t+1}$ is positively correlated with $FEARN_t$ (Pearson=0.066). $FEARN_t$ has strong correlations with $EARN_t$ (Pearson=0.791), BTM_t (Pearson=0.313) and VOL_t (Pearson=-0.388).

Table 8 reports the ordinary least squares regression results of equation (8). The t-statistics are adjusted for two-way cluster-robust standard errors (clustered by firm and quarter), which are robust to both time-series and cross-sectional correlations (Petersen, 2008). Model 1 reports regression results of $BHAR365_{t+1}$ on $FEARN_t$ alone. The coefficient estimate on $FEARN_t$ is 0.104 (t=2.72), identical to the hedge return reported in Table 5 Panel A. Model 2 reports regression results of $BHAR365_{t+1}$ on $EARN_t$, which has the highest correlation with $FEARN_t$. The hedge portfolio return on $EARN_t$ is 8.7%. The trading strategy based on $FEARN_t$ generates 20% higher hedge return than the naïve classification of Balakrishnan et al. (2010).[22] These results corroborate the findings in Table 2 Panel C, which show that the model developed in this paper has better forecast accuracy and more accurately differentiates loss persistence than the naïve classification in Balakrishnan et al.

[Insert Table 8 here]

Model 3 reports regression results of $BHAR365_{t+1}$ on $FEARN_t$ and other predictors excluding $EARN_t$. The hedge return on $FEARN_t$ drops slightly to 8.4% (t=2.83) due to the correlations between $FEARN_t$ and other return predictors. The trading strategies based on SUE_t, BTM_t, and ACC_t yield highly significant hedge returns of 8.1%, 7.4% and 6.7%, respectively. The trading strategy based on VOL_t yields a weakly significant hedge return of 4.7%. After controlling for other factors, hedge returns based on ETP_t and MOM_t are statistically insignificant. Model 4 replaces $FEARN_t$ in Model 3 with $EARN_t$. The coefficient on $EARN_t$ is

[22] Balakrishnan et al. (2010) partition the sample into deciles based on earnings (scaled by total assets). As a result, loss firms are concentrated in the lowest two earnings deciles. So it is not directly evident from their results how much hedge returns their investment strategy can generate within loss firms.

0.052 and statistically insignificant (t=1.59). This suggests that the predictive power of current earnings is subsumed by other well-known return predictors.[23] The results of Model 3 and Model 4 show that although $FEARN_t$ and $EARN_t$ are highly correlated, $FEARN_t$ contains additional information about loss firms' future prospects due to the other variables included in equation (2). This is consistent with the results in Section 5.3, which show that the earnings forecast model developed in this paper has better forecast accuracy than the naïve random walk model. Moreover, it appears that this additional information contained in $FEARN_t$ has minimal correlation with the information contained in other return predictors.

Finally, Model 5 includes $FEARN_t$ and $EARN_t$ in the same regression. Because of the positive correlation between $FEARN_t$ and $EARN_t$, the hedge return on $FEARN_t$ drops slightly to 7.4% (t=2.98) while the coefficient on $EARN_t$ drops to 0.033 (t=0.87).[24] Given the strong correlation between $FEARN_t$ and $EARN_t$, the regression results may suffer the multicollinearity problem. To address this concern, I adopt the two-pass portfolio construction approach in Dechow and Dichev (2002) to examine the incremental predictive power of one variable while holding the other variable constant.[25] Untabulated results show that $FEARN_t$ still strongly predicts future returns when $EARN_t$ is held constant across portfolios. Over the one-year window,

[23] This finding suggests that the levels of losses alone cannot provide sufficient information about loss persistence. However, it does not conflict with the results of Balakrishnan et al. (2010). Their investment strategy is to take a long position in extreme profit firms and a short position in extreme loss firms. As Figure 2 shows, losses firms behave very differently in earnings persistence than profit firms, the majority of their sample.

[24] Fama (1998) shows that using buy-hold return over long horizon can lead to spurious inference of abnormal return. Following his suggestion, I use calendar time instead of event time to construct portfolios and examine monthly average abnormal returns. I regress future 12 monthly size-adjusted returns on $FEARN_t$ and control variables. The return cumulation period starts on the first day of the second month after the earnings announcement date, e.g., April 1 for all firms announcing in February. Untabulated results show that the monthly hedge returns based on $FEARN_t$ are all positive and are statistically significant at 5% level in 7 out of the 12 months. The average monthly hedge return is 0.64%, which is equivalent to 7.7% per annum. This number is very close to the 7.4% reported in Table 8 (Model 5). In addition, the statistically significant hedge returns are concentrated around future earnings announcement dates, which is consistent with the findings in Table 6. I thank an anonymous reviewer for this comment.

[25] For details of the two-pass portfolio construction, see Dechow and Dichev (2002, p. 51).

the hedge return based on $FEARN_t$ is 4.9% (t=2.84). In contrast, $EARN_t$ can no longer predict future returns when $FEARN_t$ is held constant across portfolios.

5.7.2 The overvaluation of predicted persistent losses in firms with positive short interest

Firms with predicted persistent losses are generally small. In addition, the negative abnormal returns of the persistent loss group are larger in magnitude in firms with smaller analyst coverage. Thus, a possible alternative explanation is that short sales constraints drive the results. To assess this alternative explanation, I examine the firms with positive short interest ratio (SIR_t), as these firms are less likely subject to short sales constraints. SIR_t is obtained from Bloomberg and is defined as the number of shares sold short divided by the monthly average trading volume in the last month of quarter t. Due to data availability, the sample in this test starts from the first quarter of 1991 and includes 30,669 firm-quarter observations with positive SIR_t. The first two columns of Table 9 show that the observations are evenly distributed across $FEARN_t$ portfolios and that the mean SIR_t is slightly higher for firms with predicted persistent losses. The next four columns in Table 9 report $BHAR365_{t+1}$ for firms in each quartile formed on SIR_t. The mean size-adjusted return of the persistent loss group is -11.1% (t=-2.66) for observations in the top quartile of SIR_t and -4.3% (t=-0.83) for observations in the bottom quartile of SIR_t. The evidence does not support short sales constraints explanation, which predicts that the results should be stronger in firms with lower short interest ratio.

[Insert Table 9 here]

5.7.3 The predictability of forecast earnings for future returns in the absence of special items

As shown in Table 2, special items are important predictors of loss firms' future earnings. To mitigate the concern that the predictive power of $FEARN_t$ is driven by investors' failure to price the implications of special items for future earnings (e.g., Bartov et al., 1998; Burgstahler et al., 2002; Dechow and Ge, 2006), I examine the association between $FEARN_t$ and future returns in a subsample of loss observations with zero special items.[26] Over the one-year window, the hedge return based on $FEARN_t$ is 9.9% (t=3.89) (untabulated), which compares well to the full sample results reported in Table 5 Panel A. This indicates that the predictability of forecast earnings for stock returns is not driven by the effects of special items.

5.7.4 Excluding the extreme observations

Kraft et al. (2006) argue that when testing the *cause* of an accounting-related anomaly, researchers need to ensure that the proposed relation is not driven by a small number of observations. To examine whether the results are robust to the exclusion of influential observations, I implement the least trimmed squares procedure and drop 1% of total observations that are the most influential. Future abnormal returns of the loss firms in the remaining sample are still positively associated with forecast earnings. The hedge return is 19.9% (untabulated), even higher than the full sample results.

6. CONCLUSIONS AND DISCUSSIONS

As loss firms become prevalent in the U.S. economy, it is important to understand the characteristics of losses and how investors value them. This study examines investors' expectations of loss persistence. The results show that investors do not fully distinguish the differences in loss persistence, and instead appear to assume that all losses are transitory. Consequently, investors are surprised by future announcements of negative earnings for firms

[26] There are 43,217 loss observations with zero special items from 1983 to 2006. I exclude special items from the earnings forecast model and re-estimate forecast earnings for this group of firms. Untabulated results show that the magnitude and statistical significance of the coefficients of the remaining variables in the forecast model are similar to those reported in Table 2 Panel A. The resulting sample with non-missing forecast earnings includes 41,401 firm-quarter observations from 1984 to 2006.

with predicted persistent losses, and these firms experience significantly negative future abnormal returns.

Two behavioral heuristics documented by prior studies could potentially explain why loss firms' investors exhibit such an optimistic bias about loss persistence. The first behavioral heuristic is that investors tend to be overconfident, e.g., Odean (1998), Daniel et al. (1998, 2001). Investors of loss firms, especially those firms with predicted persistent losses, are more likely to display overconfidence bias than investors of profit firms. This is because negative earnings are less relevant to firms' future performance than positive earnings, and therefore investors often need to gather information through other channels to help them gauge the future prospects of loss firms, such as interviewing management, verifying rumors, and analyzing the demand of the company's products. This kind of information is not readily available and requires significant personal effort to obtain and analyze. Daniel et al. (1998) argue that an overconfident investor tends to overestimate the accuracy of his private signals, especially when this private information requires great personal involvement. As a result, loss firms' investors may overweight their private signals and underweight public signals like earnings, leading to stock prices' underreaction to loss persistence.

The second behavioral heuristic is the disposition effect introduced into the finance literature by Shefrin and Statman (1985). Disposition effect is the tendency of investors to sell assets whose price has increased, while keeping assets that have dropped in value. Frazzini (2006) argues that the presence of a large subset of investors who display disposition effect can hamper the transmission of information and induce underreaction to news. Due to this behavioral heuristic, investors are reluctant to sell the stocks of firms with predicted persistent losses whose value has dropped significantly. This induces a drift in these firms' stock returns.

This study raises additional issues for future research. For instance, I do not find evidence indicating that investors misunderstand the persistence of profits. This could be either due to the low power of the earnings forecast model for profit firms or because investors have a better sense of the persistence of profits. To investigate whether investors correctly anticipate the persistence of profits requires a better model that can capture the differences in profit persistence. It may also be worthwhile to examine the role of pro forma earnings and management forecasts. Bhattacharya et al. (2007) find that less sophisticated individual investors are more likely to trade on pro forma earnings. Because pro forma earnings are likely to portray a better future performance than GAAP earnings, the finding of Bhattacharya et al. (2007) may potentially explain why investors underestimate loss persistence.

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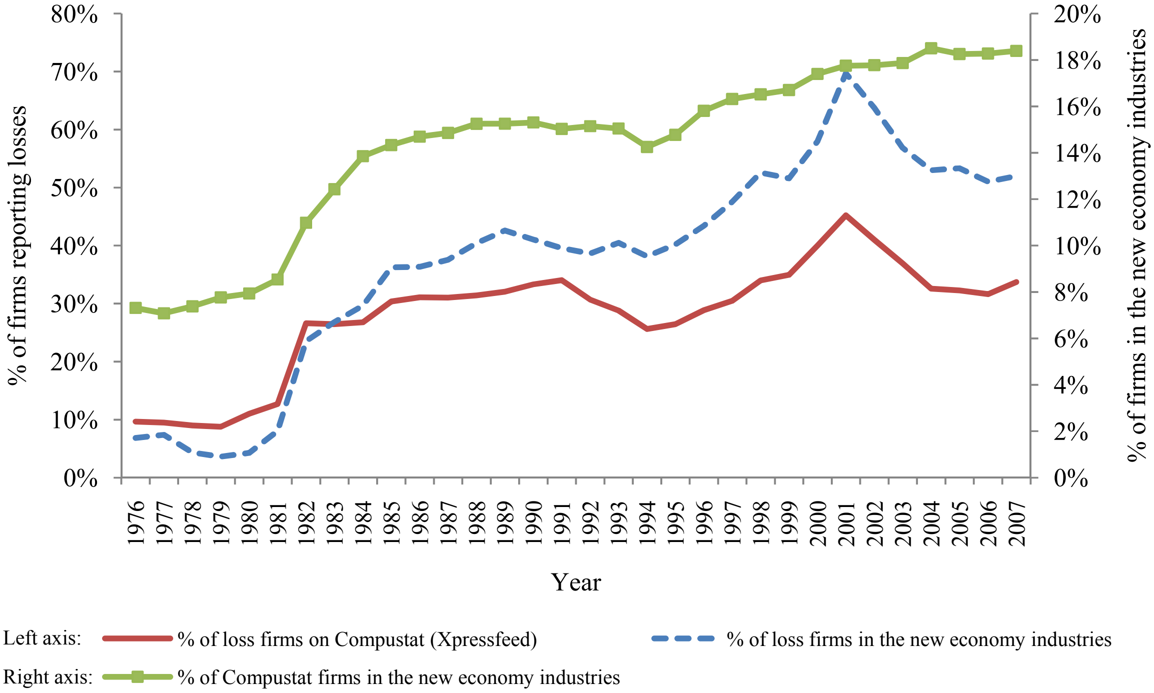
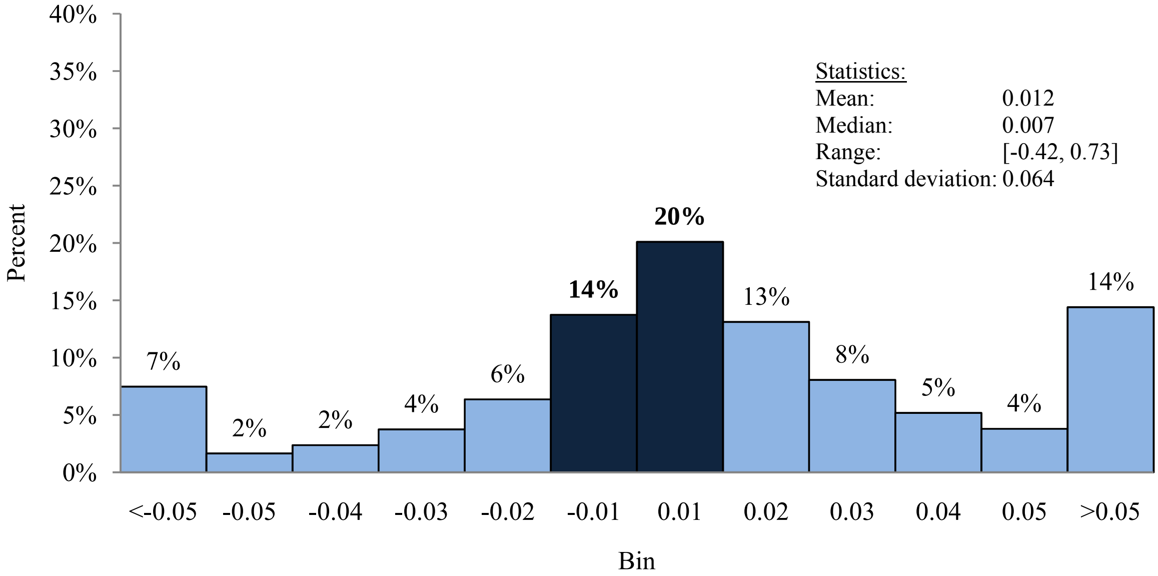
Figure 1: The proportion of loss firms during the period 1976-2007



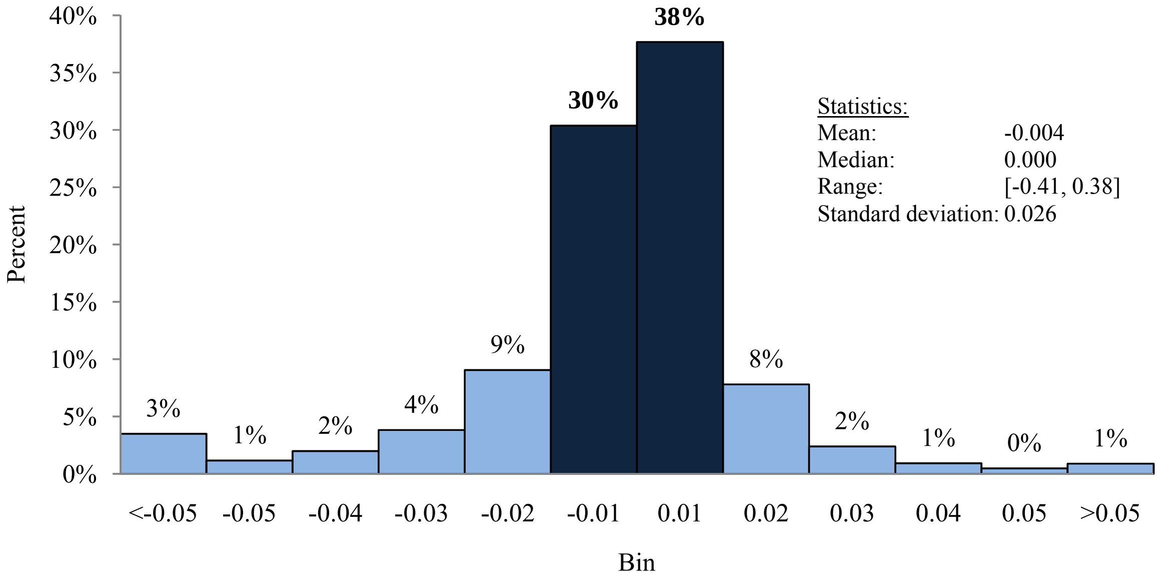
The figure plots the percentage of firms on Compustat (Xpressfeed) that report quarterly losses (*left axis*) during the period from 1976 to 2007. Loss is defined as negative income before extraordinary items (IBQ). Observations are aggregated by calendar year. The sample includes 767,549 firm-quarter observations, among which 222,377 are loss observations and 499,929 are profit observations. The figure also plots the percentage of Compustat firms in the new economy industries (*right axis*) and the percentage of loss firms in the new economy industries (*left axis*). New economy industries include pharmaceutical products, telecommunications, computers and electronic equipment. Industry classification is based on Fama and French (1997) 48 industry groups.

Figure 2: The distribution of changes in quarterly earnings for loss and profit firms

Panel A: The distribution of changes in earnings from quarter t to t+1 for firms reporting *<u>losses</u>* *in quarter t*



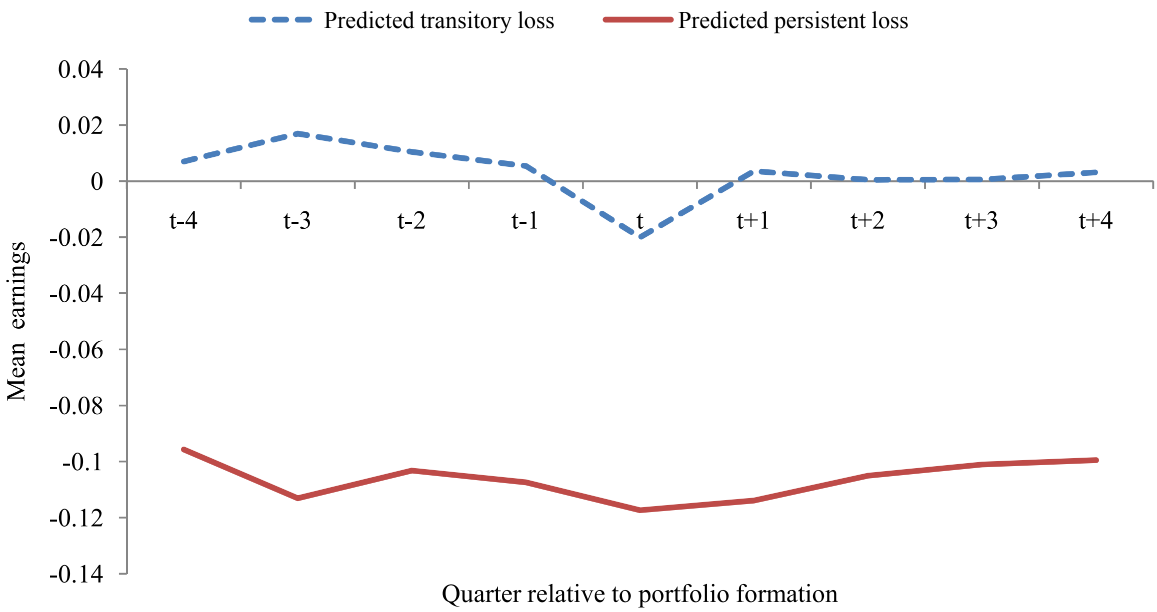
Panel B: The distribution of changes in earnings from quarter t to t+1 for firms reporting *<u>profits</u>* *in quarter t*



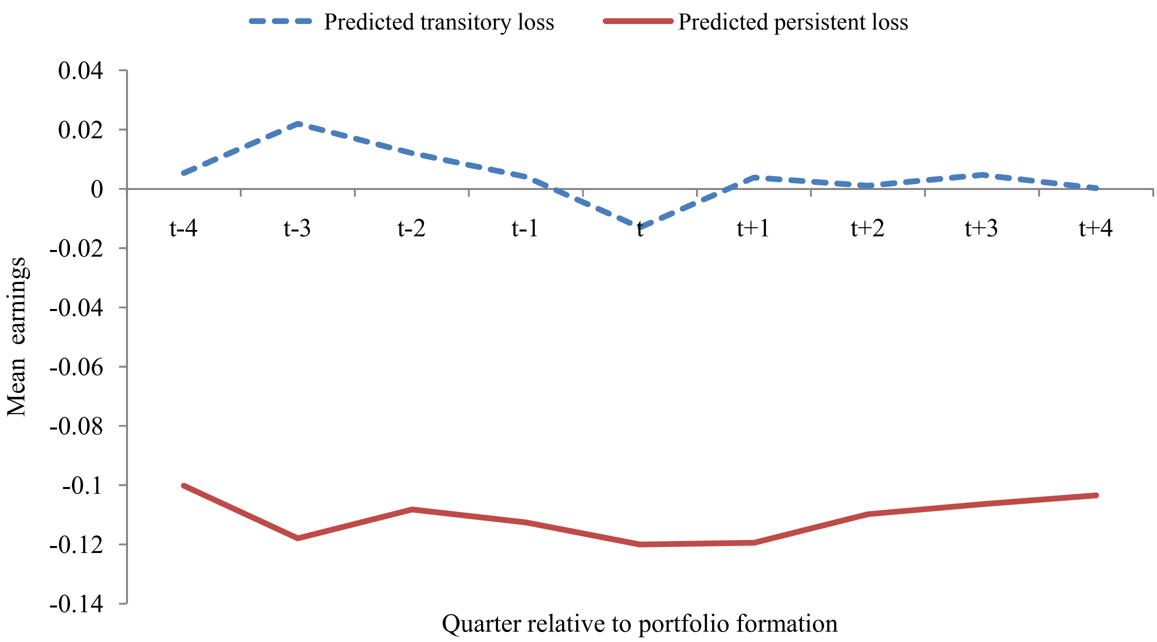
The figures plot the distribution of changes in income before extraordinary items (IBQ) from quarter t to quarter t+1, divided by total assets (ATQ) at the end of quarter t for firms reporting losses (Panel A) and profits (Panel B) in quarter t. The sample period is from 1983 to 2006. The loss sample includes 64,539 firm-quarter observations, while the profit sample includes 221,591 firm-quarter observations. Section 4 discusses the sample selection criteria. The highlighted two columns represent observations with earnings changes within 1% of total assets.

Figure 3: Time-series plots of the mean earnings of firms with predicted persistent and transitory losses

Panel A: Full sample

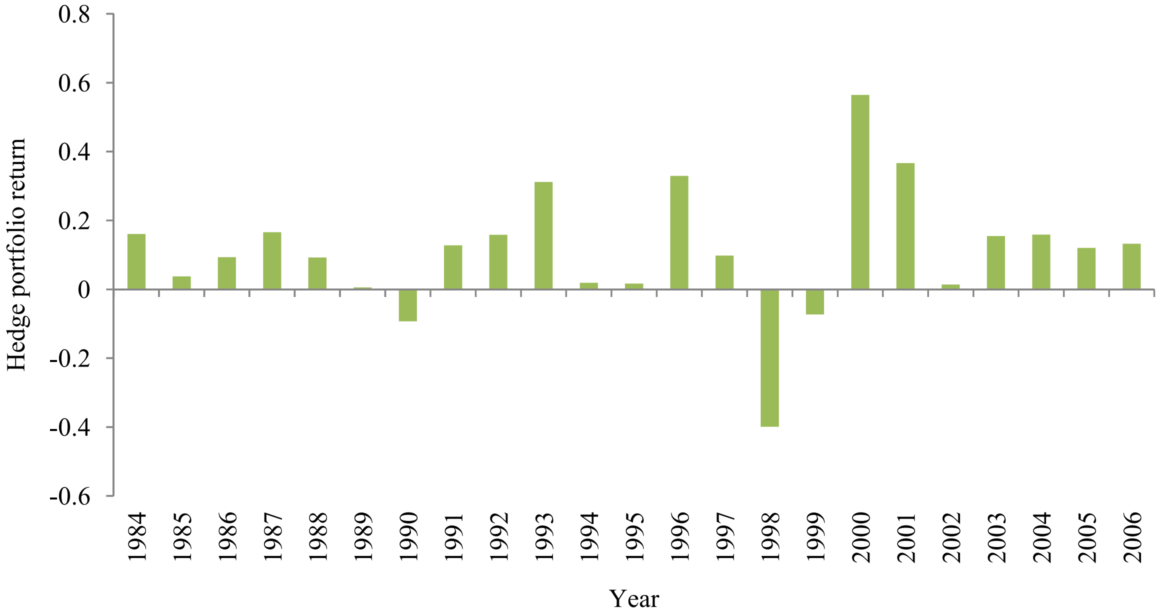


Panel B: Observations with no special items



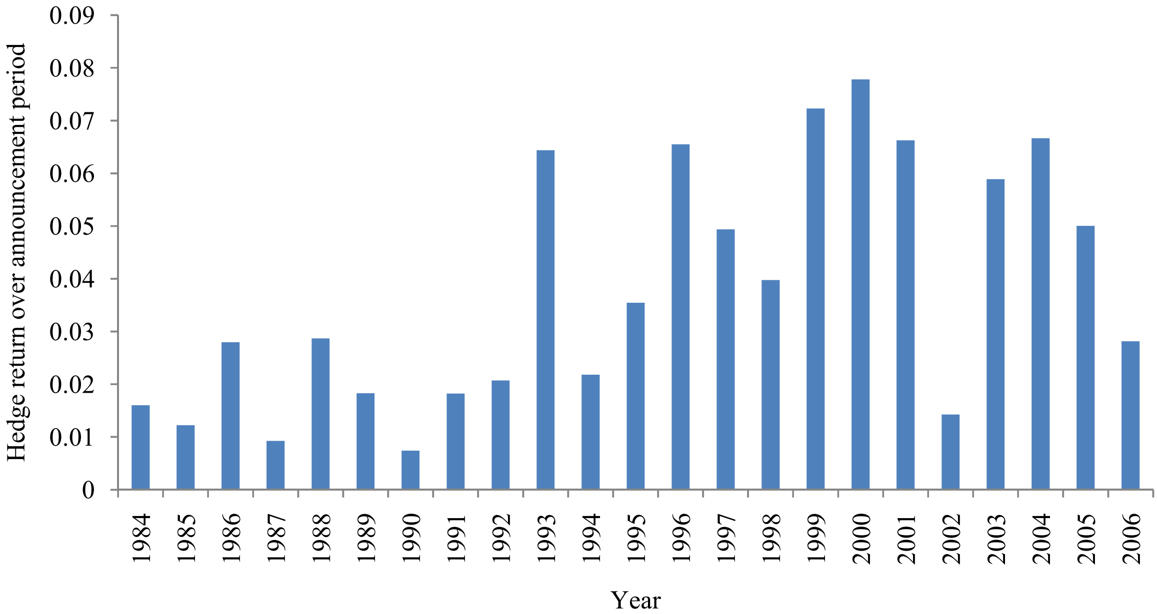
The figures plot the mean earnings of firms with predicted persistent and transitory losses. Quarter t represents the quarter in which forecast earnings are estimated. Earnings are income before extraordinary items (IBQ) divided by total assets (ATQ) at the begining of the quarter. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of forecast earnings ($FEARN_t$).

Figure 4: Hedge returns to the strategy that takes a long position in predicted transitory losses and a short position in predicted persistent losses



The figure plots the hedge portfolio returns measured over the one-year period starting two trading days after the earnings announcement date (RDQ) for the strategy that takes a long position in predicted transitory losses and a short position in predicted persistent losses for the sample period from 1984 to 2006. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of forecast earnings. Porfolio returns are calculated as the equal-weighted returns of the observations in each portfolio. Observations are reclassfied into different portfolios each quarter.

Figure 5: Hedge returns in the earnings announcement period to the strategy that takes a long position in predicted transitory losses and a short position in predicted persistent losses



The figure plots the hedge returns measured over the four future earnings announcement periods for the strategy that takes a long position in predicted transitory losses and a short position in predicted persistent losses for the sample period from 1984 to 2006. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of forecast earnings. Porfolio returns are calculated as the equal-weighted returns of the observations in each portfolio. Observations are reclassfied into different portfolios each quarter. The announcement period is defined as the four-trading-day period starting two trading days prior to the earnings announcement date (RDQ). Total announcement period over the one-year measurement window of $BHAR365_{t+1}$ includes four subsequent quarterly announcement periods, or 16 trading days.

Table 1: Descriptive statistics for the 64,539 firm-quarter loss observations for the period 1983- 2006

Panel A: Mean loss reversal and future earnings by the length of loss sequence

Length of loss sequence	No. of obs.	% of total	Mean $REVERSAL_{t+1}$ (Joos and Plesko 2005)	Mean $EARN_{t+1}$
1 quarter	23,256	36	0.525	-0.009
2 quarters	10,283	16	0.402	-0.018
3 quarters	5,785	9	0.343	-0.024
4 quarters	5,097	8	0.155	-0.059
5 quarters	3,899	6	0.160	-0.062
6 quarters	2,931	5	0.135	-0.064
7 quarters	2,244	3	0.134	-0.070
8 quarters	1,743	3	0.115	-0.072
9 quarters - 16 quarters	6,252	10	0.105	-0.077
17 quarters or more	3,049	5	0.051	-0.084
Total	64,539	100	0.332	-0.035

Panel B: Descriptive statistics of variables in the earnings forecast model

Variable	N	Mean	Median	Std Dev	25%	75%
$EARN_{t+1}$	64,539	-0.035	-0.011	0.073	-0.050	0.003
$EARN_t$	64,539	-0.048	-0.021	0.067	-0.059	-0.007
$EARN_{t-3}$	64,539	-0.025	-0.004	0.068	-0.038	0.010
$SIZE_t$	64,539	4.824	4.692	1.712	3.659	5.922
$SALESG_t$	64,539	0.032	-0.007	0.410	-0.140	0.114
$FIRSTLOSS_t$	64,539	0.360	0.000	0.480	0.000	1.000
$LOSS\_SEQ_t$	64,539	1.822	1.000	1.701	0.000	4.000
$DIVDUM_t$	64,539	0.153	0.000	0.360	0.000	0.000
SPI_t	64,539	-0.010	0.000	0.028	-0.003	0.000
SPI_{t-3}	64,539	-0.003	0.000	0.017	0.000	0.000
$Q3_t$	64,539	0.230	0.000	0.421	0.000	0.000
$Q4_t$	64,539	0.284	0.000	0.451	0.000	1.000

Loss is defined as negative income before extraordinary items (IBQ). $REVERSAL_{t+1}$ is an indicator variable that is equal to one if the loss firm becomes profitable in the quarter t+1, and zero otherwise. $EARN_t$ is income before extraordinary items (IBQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. Loss sequence in Panel A counts the number of sequential quarterly losses in the past and includes the loss in the current quarter. $SIZE_t$ is the logarithm of market value of equity (PRCCQ*CSHOQ) at the end of the quarter t. $SALESG_t$ is the percentage growth in sales (SALEQ) during quarter t. $FIRSTLOSS_t$ is an indicator variable that is equal to one if the loss in quarter t is the first loss in a sequence (i.e., the firm was profitable in quarter t-1), and zero otherwise. $LOSS\_SEQ_t$ is an ordinal variable that counts the number of sequential losses over the four quarters before the current loss. $DIVDUM_t$ is an indicator variable that is equal to one if the firm pays dividends (DVPSXQ) in quarter t, and zero otherwise. SPI_t is special items (SPIQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $Q3_t$ ($Q4_t$) is a dummy variable indicating the third (fourth) fiscal quarter.

Table 1: continued

Panel C: Pearson (above diagonal) / Spearman (below diagonal) correlations

Variable	$EARN_{t+1}$	$EARN_t$	$EARN_{t-3}$	$SIZE_t$	$SALESG_t$	$FIRSTLOSS_t$	LOSS_SEQ	$DIVDUM_t$	SPI_t	SPI_{t-3}	$Q3_t$	$Q4_t$
$EARN_{t+1}$	1.000	0.546	0.540	0.062	-0.096	0.272	-0.374	0.197	-0.063	0.077	-0.114	0.089
$EARN_t$	0.481	1.000	0.503	0.046	-0.113	0.228	-0.325	0.184	0.379	0.054	0.009	-0.083
$EARN_{t-3}$	0.534	0.403	1.000	0.011	-0.160	0.315	-0.511	0.195	-0.064	0.380	-0.073	0.052
$SIZE_t$	0.054	0.058	0.000	1.000	0.034	0.033	0.015	0.216	-0.140	-0.059	0.004	0.022
$SALESG_t$	-0.041	-0.044	-0.124	0.087	1.000	-0.219	0.224	-0.073	-0.028	-0.011	0.000	0.041
$FIRSTLOSS_t$	0.360	0.293	0.413	0.018	-0.268	1.000	-0.804	0.227	-0.134	0.049	-0.010	0.101
$LOSS\_SEQ_t$	-0.460	-0.388	-0.625	0.028	0.261	-0.868	1.000	-0.275	0.121	-0.090	0.032	-0.081
$DIVDUM_t$	0.263	0.254	0.245	0.198	-0.069	0.227	-0.273	1.000	-0.037	0.052	-0.014	0.053
SPI_t	-0.159	0.165	-0.147	-0.209	-0.060	-0.156	0.157	-0.084	1.000	0.051	0.008	-0.156
SPI_{t-3}	0.029	0.011	0.213	-0.119	-0.016	0.035	-0.070	0.028	0.123	1.000	-0.100	0.069
$Q3_t$	-0.100	0.004	-0.051	0.006	0.004	-0.010	0.028	-0.014	0.007	-0.086	1.000	-0.343
$Q4_t$	0.098	-0.090	0.038	0.016	0.068	0.101	-0.089	0.053	-0.161	0.055	-0.343	1.000

$EARN_t$ is income before extraordinary items (IBQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $SIZE_t$ is the logarithm of market value of equity (PRCCQ*CSHOQ) at the end of the quarter t. $SALESG_t$ is the percentage growth in sales (SALEQ) during quarter t. $FIRSTLOSS_t$ is an indicator variable that is equal to one if the loss in quarter t is the first loss in a sequence (i.e., the firm was profitable in quarter t-1), and zero otherwise. $LOSS\_SEQ_t$ is an ordinal variable that counts the number of sequential losses over the four quarters before the current loss. $DIVDUM_t$ is an indicator variable that is equal to one if the firm pays dividends (DVPSXQ) in quarter t, and zero otherwise. SPI_t is special items (SPIQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $Q3_t$ ($Q4_t$) is a dummy variable indicating the third (fourth) fiscal quarter.

Table 2: The earnings forecast model, descriptive statistics for portfolios formed on forecast earnings and forecast accuracy

Panel A: Fama-MacBeth regression results of the earnings forecast model

$$EARN_{t+1} = \alpha + \beta_1 EARN_t + \beta_2 EARN_{t-3} + \beta_3 SIZE_t + \beta_4 SALESG_t + \beta_5 FIRSTLOSS_t$$
$$+\beta_6 LOSS\_SEQ_t + \beta_7 DIVDUM_t + \beta_8 SPI_t + \beta_9 SPI_{t-3} + \beta_{10} Q3_t + \beta_{11} Q4_t + \varepsilon_{t+1}$$

		Fama-MacBeth regression (No. of regressions: 96)		
Variable	Predicted sign	Coefficient	t-statistic	p value
$EARN_t$	+	0.500	37.35	0.000
$EARN_{t-3}$	+	0.324	25.86	0.000
$SIZE_t$	+	0.001	3.00	0.004
$SALESG_t$	?	0.001	0.89	0.376
$FIRSTLOSS_t$	+	0.002	2.09	0.039
$LOSS\_SEQ_t$	-	-0.001	-3.66	0.000
$DIVDUM_t$	+	0.006	10.93	0.000
SPI_t	-	-0.604	-27.93	0.000
SPI_{t-3}	-	-0.344	-11.33	0.000
$Q3_t$	-	-0.014	-14.16	0.000
$Q4_t$	+	0.009	13.69	0.000
INTERCEPT		-0.011	-8.08	0.000
Adjusted R-square		45.5%		

$EARN_t$ is income before extraordinary items (IBQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $SIZE_t$ is the logarithm of market value of equity (PRCCQ*CSHOQ) at the end of the quarter t. $SALESG_t$ is the percentage growth in sales (SALEQ) during quarter t. $FIRSTLOSS_t$ is an indicator variable that is equal to one if the loss in quarter t is the first loss in a sequence (i.e., the firm was profitable in quarter t-1), and zero otherwise. $LOSS\_SEQ_t$ is an ordinal variable that counts the number of sequential losses over the four quarters before the current loss. $DIVDUM_t$ is an indicator variable that is equal to one if the firm pays dividends (DVPSXQ) in quarter t, and zero otherwise. SPI_t is special items (SPIQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $Q3_t$ ($Q4_t$) is a dummy variable indicating the third (fourth) fiscal quarter. The estimation period is from 1983 to 2006. There are 96 quarterly regressions. Reported coefficients, t-statistic and p values are derived using the Fama and MacBeth (1973) procedure.

Table 2: continued

Panel B: Descriptive statistics for portfolios formed on $FEARN_t$

Portfolio ranking on $FEARN_t$	No. of obs.	No. of firms	$FEARN_t$	$EARN_t$	$EARN_{t+1}$	$EARN_{t+4}$	$REVERSAL_{t+1}$ (Joos and Plesko 2005)	MVE_t ($ million)
Predicted persistent loss	**12,438**	**3,094**	**-0.113**	**-0.117**	**-0.114**	**-0.100**	**0.085**	**291**
2	12,491	4,038	-0.043	-0.046	-0.041	-0.039	0.169	448
3	12,496	4,422	-0.022	-0.022	-0.019	-0.020	0.290	708
4	12,491	4,749	-0.008	-0.015	-0.008	-0.012	0.440	890
Predicted transitory loss	12,454	5,023	0.011	-0.020	0.004	0.003	0.674	1,843
Transitory-Persistent			0.124***	0.097***	0.117***	0.103***	0.589***	1,552***

Panel C: Forecast errors for different earnings forecast models

Portfolio ranking on $FEARN_t$	Model 1 $FE_1=EARN_{t+1}-FEARN_t$		Model 2 $FE_2=EARN_{t+1}-EARN_t$		Model 3 $FE_3=EARN_{t+1}-EARN_{t-3}$		Model 4 $FE_4=EARN_{t+1}-0$	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Predicted persistent loss	**-0.001**	**0.084**	**0.003*****	**0.108**	**-0.001**	**0.109**	**-0.114*****	**0.102**
2	0.002***	0.058	0.005***	0.068	-0.010***	0.073	-0.041***	0.061
3	0.002***	0.046	0.003***	0.053	-0.014***	0.053	-0.019***	0.047
4	0.001	0.036	0.007***	0.042	-0.014***	0.042	-0.008***	0.037
Predicted transitory loss	-0.007***	0.032	0.024***	0.042	-0.013***	0.037	0.004***	0.032

$FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. $EARN_t$ is income before extraordinary items (IBQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $EARN_{t+1}$ and $EARN_{t+4}$ are earnings in quarter t+1 and t+4, respectively. $REVERSAL_{t+1}$ is an indicator variable that is equal to one if the loss firm becomes profitable in the quarter t+1, and zero otherwise. MVE_t is the market value of equity (PRCCQ*CSHOQ) at the end of the quarter t. Model 1 is the earnings forecast model in equation (2). Model 2 is the random walk model. Model 3 is the seasonal random walk model. Model 4 assume losses are transitory, i.e., the expected earnings for quarter t+1 are zero. Forecast errors (FE) are the differences between the actual earnings in quarter t+1 ($EARN_{t+1}$) and the expected earnings derived from each model. The reported numbers in Panel B are the mean of each variable. STD in Panel C is standard deviation of forecast errors. ***, **, * denote significance at 0.01, 0.05 and 0.10 level using a two-tailed t-test.

Table 3: The persistence of the predicted persistent losses

Panel A: Quintile classifications based on forecast earnings of quarter t+1 ($FEARN_t$) and forecast earnings of quarter t+4 ($FYOYEARN_t$)

Portfolio ranking on $FEARN_t$		Portfolio ranking on $FYOYEARN_t$: 1	2	3	4	5	Missing $FYOYEARN_t$
Predicted persistent loss	12,438 100%	**9,371** **75%**	1,496 12%	247 2%	85 1%	23 0%	1,216 10%
2	12,491 100%	1,774 14%	**6,658** **53%**	2,112 17%	701 6%	191 2%	1,055 8%
3	12,496 100%	155 1%	2,496 20%	**5,389** **43%**	2,723 22%	730 6%	1,003 8%
4	12,491 100%	63 1%	580 5%	2,829 23%	**5,370** **43%**	2,602 21%	1,047 8%
Predicted transitory loss	12,454 100%	23 0%	211 2%	863 7%	2,562 21%	**7,857** **63%**	938 8%

Panel B: Pearson correlations of future earnings

Portfolio ranking on $FEARN_t$	Corr ($EARN_{t+1}$, $EARN_{t+2}$)	Corr ($EARN_{t+1}$, $EARN_{t+3}$)	Corr ($EARN_{t+1}$, $EARN_{t+4}$)
Predicted persistent loss	**0.565*** **	**0.513*** **	**0.445*** **
2	0.351***	0.290***	0.236***
3	0.240***	0.193***	0.185***
4	0.262***	0.177***	0.157***
Predicted transitory loss	0.316***	0.210***	0.182***

$FEARN_t$ is the forecast earnings of quarter t+1 based on equation (2). $FYOYEARN_t$ is the forecast earnings of quarter t+4 based on equation (3). Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. Bolded cells in Panel A represent observations with identical rankings based on both $FEARN_t$ and $FYOYEARN_t$. $EARN_{t+1}$ is income before extraordinary items (IBQ) in quarter t+1 divided by total assets (ATQ) at the beginning of quarter t+1. ***, **, * denote significance at 0.01, 0.05 and 0.10 level.

Table 4: Mishkin (1983) tests of investors' expectations of loss persistence

$$EARN_{t+1} = \alpha_0 + \alpha_1 EARN_t + \delta_{t+1}$$
$$BHAR_{t+1} = \beta(EARN_{t+1} - \alpha_0 - \alpha_1^* EARN_t) + \mu_{t+1}$$

Panel A: Predicted persistent losses (N=12,438)

Forecast equation			*Pricing equation*		
Parameter	Coefficient	t-statistic	Parameter	Coefficient	t-statistic
α_1	0.409	42.38	α_1^*	0.020	0.16
			β	0.349	8.45

Test of investors' expectations of loss persistence:

Null hypothesis	Likelihood ratio statistic	Marginal significance level
$\alpha_1 = \alpha_1^*$	11.14	0.001

Panel B: Predicted transitory losses (N=12,454)

Forecast equation			*Pricing equation*		
Parameter	Coefficient	t-statistic	Parameter	Coefficient	t-statistic
α_1	0.007	0.69	α_1^*	0.034	0.49
			β	1.056	15.87

Test of investors' expectations of loss persistence:

Null hypothesis	Likelihood ratio statistic	Marginal significance level
$\alpha_1 = \alpha_1^*$	0.15	0.700

$FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. There are 12,438 firm-quarter observations in the portfolio of predicted persistent losses and 12,454 firm-quarter observations in the portfolio of predicted transitory losses. $EARN_t$ is income before extraordinary items (IBQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. $BHAR_{t+1}$ is buy-hold size-adjusted return over the period starting two trading days after earnings announcement date (RDQ) of quarter t and ending one trading day after earnings announcement date of quarter t+1. Buy-hold size-adjusted return is computed by measuring the buy-hold return in excess of the buy-hold return on the CRSP size-matched decile portfolio. The two equations are jointly estimated using iterative weighted non-linear least squares.

Table 5: Size-adjusted returns of portfolios formed on $FEARN_t$

Panel A: Size-adjusted portfolio returns over different measurement windows

Portfolio ranking	Equal-weighted size-adjusted returns		
on $FEARN_t$	$BHAR90_{t+1}$	$BHAR180_{t+1}$	$BHAR365_{t+1}$
Predicted persistent loss	**-0.031*** **	**-0.064*** **	**-0.120*** **
	(-2.82)	**(-4.15)**	**(-5.15)**
2	-0.031***	-0.052***	-0.073***
	(-3.78)	(-4.35)	(-3.45)
3	-0.028***	-0.048***	-0.060***
	(-5.75)	(-5.83)	(-5.18)
4	-0.017***	-0.039***	-0.042***
	(-4.40)	(-6.57)	(-4.93)
Predicted transitory loss	-0.009**	-0.020***	-0.015*
	(-2.55)	(-3.59)	(-1.81)
Transitory-Persistent	**0.022***	**0.044** **	**0.104*** **
	(1.77)	**(2.52)**	**(4.15)**

Panel B: Size-adjusted portfolio returns by calendar quarters

	Equal-weighted $BHAR365_{t+1}$			
	1st quarter	**2nd quarter**	**3rd quarter**	**4th quarter**
Predicted persistent loss	**-0.114** **	**-0.106** **	**-0.146*** **	**-0.112** **
	(-2.31)	**(-2.36)**	**(-3.64)**	**(-2.12)**
Predicted transitory loss	-0.011	-0.028	-0.019	-0.004
	(-0.64)	(-1.52)	(-1.05)	(-0.28)
Transitory-Persistent	**0.103** **	**0.078***	**0.127*** **	**0.108** **
	(2.13)	**(2.01)**	**(3.04)**	**(2.42)**

$FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. $BHAR90_{t+1}$, $BHAR180_{t+1}$, and $BHAR365_{t+1}$ are buy-hold size-adjusted returns over the 90-day, 180-day and one-year period starting two trading days after earnings announcement date (RDQ) of quarter t. Buy-hold size-adjusted return is computed by measuring the buy-hold return in excess of the buy-hold return on the CRSP size-matched decile portfolio. The time period is from the first quarter of 1984 to the fourth quarter of 2006 (92 quarters). Reported portfolio returns and t-statistic (in parentheses) are calculated over the time-series of cross-sectional mean returns on each portfolio (Fama-MacBeth procedure). ***, **, * denote significance at 0.01, 0.05 and 0.10 level using a two-tailed t-test.

Table 6: Announcement period and non-announcement period portfolio returns

	Equal-weighted size-adjusted returns		
Portfolio ranking on $FEARN_t$	Total period return ($BHAR365_{t+1}$)	Announcement period return	Non-announcement period return
Predicted persistent loss	**-0.120***** **(-5.15)**	**-0.027***** **(-9.50)**	**-0.094***** **(-4.20)**
2	-0.073*** (-3.45)	-0.004 (-1.26)	-0.070*** (-3.44)
3	-0.060*** (-5.18)	0.004* (1.89)	-0.065*** (-5.97)
4	-0.042*** (-4.93)	0.008*** (3.86)	-0.049*** (-5.94)
Predicted transitory loss	-0.015* (-1.81)	0.011*** (5.38)	-0.026*** (-3.25)
Transitory-Persistent	**0.104***** **(4.15)**	**0.038***** **(10.39)**	**0.068***** **(2.85)**

$FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. $BHAR365_{t+1}$ is buy-hold size-adjusted return over the one-year period starting two trading days after earnings announcement date (RDQ) of quarter t. The announcement period is defined as the four-trading-day period starting two trading days prior to the earnings announcement date. Total announcement period over the one-year measurement window of $BHAR365_{t+1}$ includes four subsequent quarterly announcement periods, or 16 trading days. Non-announcement period starts two trading days after the earnings announcement date of quarter t and ends three trading days prior to the earnings announcement date of quarter t+4, exclusive of the three intervening quarterly earnings announcement periods. The time period is from the first quarter of 1984 to the fourth quarter of 2006 (92 quarters). Reported portfolio returns and t-statistic (in parentheses) are calculated over the time-series of cross-sectional mean returns on each portfolio (Fama-MacBeth procedure). ***, **, * denote significance at 0.01, 0.05 and 0.10 level using a two-tailed t-test.

Table 7: The effects of analyst coverage on the overvaluation of firms with predicted persistent losses

Panel A: Equal-weighted portfolio returns ($BHAR365_{t+1}$) for loss firms with and without analyst coverage

Portfolio ranking on $FEARN_t$	% with analyst coverage	$NUMEST_t$ T1 N=11,474	$NUMEST_t$ T2 N=10,378	$NUMEST_t$ T3 N=10,536	No coverage N=29,982
Predicted persistent loss	**46%**	**-0.089****	**-0.061****	**-0.059***	**-0.171*****
		(-2.30)	**(-1.98)**	**(-1.67)**	**(-7.62)**
2	51%	-0.046*	-0.043	-0.017	-0.110***
		(-1.66)	(-1.40)	(-0.54)	(-5.67)
3	50%	-0.048**	-0.067***	-0.032	-0.083***
		(-2.41)	(-3.26)	(-1.16)	(-6.13)
4	52%	-0.059***	-0.063***	0.002	-0.064***
		(-3.90)	(-2.84)	(0.08)	(-4.37)
Predicted transitory loss	61%	-0.012	-0.006	-0.011	-0.035***
		(-0.77)	(-0.38)	(-0.66)	(-3.00)
Transitory-Persistent		**0.067***	**0.055**	**0.052**	**0.136*****
		(1.82)	**(1.61)**	**(1.46)**	**(4.82)**

A firm with analyst coverage means there are analyst forecasts for the firm's earnings of quarter t+1. $NUMEST_t$ is the number of analysts providing forecasts for the firm's earnings of quarter t+1. $FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. $BHAR365_{t+1}$ is buy-hold size-adjusted return over the one-year period starting two trading days after earnings announcement date (RDQ) of quarter t. Observations in each $FEARN_t$ portfolio are ranked into terciles based on $NUMEST_t$ by quarter. The time period is from the first quarter of 1984 to the fourth quarter of 2006 (92 quarters). Reported portfolio returns and t-statistic (in parentheses) are calculated over the time-series of cross-sectional mean returns on each portfolio (Fama-MacBeth procedure). ***, **, * denote significance at 0.01, 0.05 and 0.10 level using a two-tailed t-test.

Table 7: continued

Panel B: Analysts' expectations of loss persistence

$$EPS_{t+1} = \alpha_0 + \alpha_1 EPS_t + \tau_{t+1}$$
$$FEPS_t = \alpha_0^* + \alpha_1^* EPS_t + \omega_t$$

Predicted persistent loss with pro forma EPS_t<0 (N=5,399)

Fundamental regression			*Analyst forecast regression*		
Parameter	Coefficient	t-statistic	Parameter	Coefficient	t-statistic
α_1	0.743	81.96	α_1^*	0.726	77.71

Test of analysts' expectations of loss persistence:

Null hypothesis	Likelihood ratio statistic	Marginal significance level
$\alpha_1 = \alpha_1^*$	3.71	0.054

Predicted transitory loss with pro forma EPS_t<0 (N=3,453)

Fundamental regression			*Analyst forecast regression*		
Parameter	Coefficient	t-statistic	Parameter	Coefficient	t-statistic
α_1	0.012	0.71	α_1^*	-0.052	-3.05

Test of analysts' expectations of loss persistence:

Null hypothesis	Likelihood ratio statistic	Marginal significance level
$\alpha_1 = \alpha_1^*$	22.61	0.000

EPS_t is actual earnings per share of quarter t in I/B/E/S database. Consensus forecast of EPS for quarter t+1 ($FEPS_t$) is the first available mean forecast for quarter t+1 (I/B/E/S FPI=6) after the earnings announcement date of quarter t. The regressions use quintile rankings instead of the actual values of the variables.

Table 8: Abnormal returns based on $FEARN_t$ after controlling for other return predictors

$$BHAR365_{t+1} = \gamma_0 + \gamma_1 FEARN_t + \gamma_2 EARN_t + \gamma_3 ETP_t + \gamma_4 SUE_t + \gamma_5 BTM_t + \gamma_6 ACC_t + \gamma_7 MOM_t + \gamma_8 VOL_t + \eta_{t+1}$$

	Predicted	Equal-weighted $BHAR365_{t+1}$				
Variable	Sign	Model 1	Model 2	Model 3	Model 4	Model 5
INTERCEPT		-0.065***	-0.065***	-0.065***	-0.064***	-0.065***
		(-4.28)	(-4.29)	(-4.24)	(-4.24)	(-4.24)
$FEARN_t$	**+**	**0.104*** **		**0.084*** **		**0.074*** **
		(2.72)		**(2.83)**		**(2.98)**
Control variables						
$EARN_t$	+		0.087***		0.052	0.033
			(2.63)		(1.59)	(0.87)
ETP_t	+			-0.015	-0.027	-0.032
				(-0.89)	(-0.86)	(-1.03)
SUE_t	+			0.081***	0.060***	0.078***
				(4.02)	(2.75)	(3.57)
BTM_t	+			0.074***	0.070***	0.063***
				(3.00)	(2.82)	(2.63)
ACC_t	-			-0.067***	-0.069***	-0.067***
				(-5.64)	(-5.79)	(-5.69)
MOM_t	+			0.009	0.013	0.010
				(0.34)	(0.49)	(0.39)
VOL_t	-			-0.047*	-0.057**	-0.044
				(-1.67)	(-1.97)	(-1.62)
Firm clustering		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Quarter clustering		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adjusted R-square		0.2%	0.2%	0.6%	0.6%	0.6%

$BHAR365_{t+1}$ is buy-hold size-adjusted return over the one-year period starting two trading days after earnings announcement date (RDQ) of quarter t. $FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. $EARN_t$ is income before extraordinary items (IBQ) in quarter t divided by total assets (ATQ) at the beginning of quarter t. ETP_t is income before extraordinary items (IBQ) in quarter t divided by market value of equity (PRCCQ*CSHOQ) at the end of quarter t. BTM_t is book value of equity (CEQQ) divided by market value of equity (PRCCQ*CSHOQ) at the end of quarter t. ACC_t is ΔCurrent Assets-ΔCurrent Liabilities-Depreciation, or in terms of Xpressfeed quarterly data items: Δ(ACTQ-CHEQ)-Δ(LCTQ-DLCQ)-DPQ, divided by total assets (ATQ) at the beginning of quarter t, where Δ denotes change from quarter t-1 to t. SUE_t is the seasonal difference in income before extraordinary items (IBQ), i.e., quarter t minus quarter t-4, divided by market value of equity (PRCCQ*CSHOQ) at the beginning of quarter t. MOM_t is cumulative return over the 12-month period prior to the end of quarter t. VOL_t is return volatility over the 12-month period prior to the end of quarter t. All independent variables are sorted into quintiles each quarter. The quintile rankings are scaled to have a range of one and a mean of zero. The numbers in parentheses are t-statistic calculated using two-way cluster-robust standard errors. ***, **, * denote significance at 0.01, 0.05 and 0.10 level using a two-tailed t-test.

Table 9: The overvaluation of predicted persistent losses in firms with positive short interest

			Equal-weighted $BHAR365_{t+1}$			
Portfolio ranking on $FEARN_t$	N	Mean SIR_t	SIR_t Q1 N=7,642	SIR_t Q2 N= 7,677	SIR_t Q3 N=7,692	SIR_t Q4 N=7,658
Predicted persistent loss	**6,238**	**6.28%**	**-0.043**	**-0.047**	**-0.099*** **	**-0.111*** **
			(-0.83)	**(-0.91)**	**(-2.96)**	**(-2.66)**
2	6,237	5.66%	0.009	-0.006	-0.030	-0.077***
			(0.23)	(-0.17)	(-0.89)	(-2.67)
3	5,937	5.82%	-0.034*	0.009	-0.009	-0.063**
			(-1.66)	(0.28)	(-0.33)	(-2.49)
4	5,989	5.50%	-0.012	0.014	-0.021	-0.031
			(-0.57)	(0.53)	(-1.11)	(-1.59)
Predicted transitory loss	6,268	5.30%	-0.027	0.029	0.036	-0.002
			(-1.46)	(1.43)	(1.49)	(-0.01)
Transitory-Persistent			**0.016**	**0.076**	**0.135*** **	**0.109*** **
			(0.28)	**(1.57)**	**(3.48)**	**(2.72)**

SIR_t is the number of shares sold short divided by the monthly average trading volume in the last month of quarter t. SIR_t is collected from Bloomberg. $FEARN_t$ is computed using the average of quarterly estimated coefficients of equation (2) over quarter t-4 to t-1 and predicting variables measured in quarter t. Predicted persistent (transitory) losses are loss observations in the first (fifth) quintile of the quarterly distribution of $FEARN_t$. $BHAR365_{t+1}$ is buy-hold size-adjusted return over the one-year period starting two trading days after earnings announcement date (RDQ) of quarter t. Observations with positive SIR_t are sorted into quartiles based on SIR_t by quarter. The time period is from the first quarter of 1991 to the fourth quarter of 2006 (64 quarters). Reported portfolio returns and t-statistic (in parentheses) are calculated over the time-series of cross-sectional mean returns on each portfolio (Fama-MacBeth procedure). ***, **, * denote significance at 0.01, 0.05 and 0.10 level using a two-tailed t-test.