MIT Sloan School of Management

Working Paper 4262-02
September 2002

Reporting Conservatism, Loss Reversals, and Earnings-based Valuation

Peter R. Joos, George A. Plesko

Reporting Conservatism, Loss Reversals, and Earnings-based Valuation*

Peter Joos and George A. Plesko

Draft 1: January 15, 2002
This version: September 1, 2002

Abstract

We study the determinants of losses and their increased frequency over time to understand their implications for the use of financial statements in valuation. We find the properties of losses change between 1971-2000 both in terms of the cash flow and accruals components. Departing from prior research, we explicitly model the estimated likelihood of loss reversal. We find firms estimated to be least likely to reverse have unusually large negative cash flows *and* accruals, comprised of relatively large amounts of *R&D* expenditures and Special Items. We also find the market assesses both the effect of reporting conservatism and the attractiveness of abandoning the investment in the firm when it prices losses. We interpret this as evidence that the probability of loss reversal summarizes financial information useful to investors and serves as a proxy for the earning power of assets when the firm reports a loss.
.

JEL classification: M41; D21;
Keywords: earnings; losses; conservatism; cash flows; accruals

Contact information:
Sloan School of Management
Massachusetts Institute of Technology
E52-325, 50 Memorial Drive
Cambridge, MA 02142-1347
Joos: 617-253-9459, pjoos@mit.edu
Plesko: 617-253-2668, gplesko@mit.edu (corresponding author)

* We thank SP Kothari, Joe Weber, Peter Wysocki and the participants of the accounting workshop at the Massachusetts Institute of Technology and the EAA 2002 Meeting in Copenhagen for helpful comments on an earlier draft.

Reporting Conservatism, Loss Reversals, and Earnings-based Valuation[*]

Abstract

We study the determinants of losses and their increased frequency over time to understand their implications for the use of financial statements in valuation. We find the properties of losses change between 1971-2000 both in terms of the cash flow and accruals components. Departing from prior research, we explicitly model the estimated likelihood of loss reversal. We find firms estimated to be least likely to reverse have unusually large negative cash flows *and* accruals, comprised of relatively large amounts of *R&D* expenditures and Special Items. We also find the market assesses both the effect of reporting conservatism and the attractiveness of abandoning the investment in the firm when it prices losses. We interpret this as evidence that the probability of loss reversal summarizes financial information useful to investors and serves as a proxy for the earning power of assets when the firm reports a loss.

I. Introduction

The number of firms reporting negative earnings (i.e., loss firms) has markedly increased over the last three decades. In the 1990s loss observations constitute about 35% of the US firm-years covered by the Standard & Poor Compustat database whereas they represent only about 15% of observations in the 1970s. Paradoxically, the increase in the frequency of accounting losses occurs as the US stock market rises to historically high levels. The divergence between these trends raises the questions of what drives the increase in the occurrence of loss observations and how investors value them. The questions are important since academics and other users of financial statements reserve a prominent role for accounting earnings in different decision contexts (see Watts and Zimmerman 1986). Focusing on firm valuation in particular, Modigliani and Miller (1966) discuss in their seminal paper how accounting earnings are a proxy for the expected and unobservable earning power of the firm's assets. However, they also note that negative earnings (i.e., losses) complicate the use of earnings-based valuation models since a loss impairs the ability of accounting earnings to be a proxy for a firm's assets' unobservable earnings power in valuation models. Consequently, the increase in the frequency of losses poses a considerable challenge for users of financial statements because of the need to consider other (accounting) proxies for the earning power of assets to value the firm.

We study the determinants of losses and their increased frequency over time to understand their implications for the use of financial statements in valuation. As our starting point, we focus on the relation between increased reporting conservatism in the US, the decline in cross-sectional firm profitability, and increased frequency of losses observed by Givoly and Hayn (2000). An increase in reporting conservatism implies a change in the structural relation between earnings, accruals, and cash flows (Givoly and Hayn 2000, p. 289). Consequently we hypothesize that if more losses occur as a result of increased reporting conservatism the implications of a current loss for the valuation of the firm change. We differentiate our research design from earlier studies (e.g., Basu 1997, Givoly and Hayn 2000) by adopting a broader notion of reporting conservatism. Although previous authors do not provide a unique definition of reporting conservatism, they typically relate the concept to the measurement of accruals. In contrast, we also consider the impact of structural changes in the nature of business operations, such as an increase in the investments in intangibles and R&D expenditures in particular, on the properties of losses and their implications for valuation. Whereas R&D investment does not generate negative accruals, its accounting treatment is conservative. The increase in the relative level of R&D investments during recent decades (see for example Amir and Lev 1996; Lev and Zarowin 1999) therefore potentially influences the occurrence of losses, their properties, and their implications for valuation.

We carry out two analyses to evaluate how increased conservatism affects the frequency and properties of losses. First, we investigate whether the characteristics of loss firms change over time consistent with increased reporting conservatism. Second, we study whether the probability of a firm's return to profitability (i.e., loss reversal) changes over time consistent with the effect of increased reporting conservatism. We focus on loss reversals because a loss places the firm in a temporary position: the firm's return to profitability is the maintained hypothesis of financial reporting, embodied in the going concern assumption. Similarly, loss reversal forms the basis of the abandonment option view of loss valuation: shareholders have the option to redeploy or liquidate the assets of the firm when the firm continues to incur losses (Hayn 1995;

Berger et al. 1996; Wysocki 2001). We assume the length of time the firm needs to reverse a loss and the actions the firm takes to reverse relate to three generic categories of variables that capture the business environment and operations of the firm: 1) variables that describe the loss history of the firm; 2) variables that measure the financial profile of the firm; 3) variables that capture the dividend paying behavior of the firm. We predict increased reporting conservatism will affect the ability of particular variables to predict loss reversals.

We test our predictions in a sample of loss observations from 1971 to 2000. We evaluate the effects of increased reporting conservatism on the properties of losses by splitting our sample in time: a first subsample covering 1971 through 1990 and a second covering the years 1991 through 2000. We find the properties of losses change between the sample periods in terms of the cash flow and accruals components of losses. When we estimate our model of loss reversal probability we find the pattern of results is consistent with increased reporting conservatism having an effect on the properties of losses and loss reversals. The loss history variables show on the one hand that first-time losses are more likely to reverse during the later period (1991–2000) than during the earlier period (1971–1990), indicating that losses have become more transitory over time. On the other hand, we find firms with multiple losses have become less likely to return to profitability in the later period: accounting loss sequences appear to persist in recent years potentially as a result of the greater use of conservative accounting methods. Focusing on the other financial statement variables in the reversal model, we find corroborating evidence of an increasing influence of long-term accruals on losses and their reversal.

In further analysis, we find the earnings of firms with the lowest probability of loss reversal have unusually large negative cash flows *and* accruals, establishing that accruals differences across loss firms do not solely determine our estimated likelihood of loss reversal. We also find firms with the lowest probability of loss reversal record larger amounts of *R&D* expenditures and Special Items than other firms, a pattern that becomes more pronounced during the 1991-2000 period. We argue that *R&D* and Special Items capture changes in business operations that are reported conservatively, leading to more negative cash flows and/or accruals.

Next we investigate whether market participants change their interpretation of losses for firm valuation consistent with changes in their properties. We estimate earnings response coefficients (ERC) for loss observations in the full sample and find no relation between losses and stock returns in the early sample period, consistent with losses being a poor proxy of the earning power of assets. In contrast, in the later period we find a significant negative relation between losses and returns. In further analysis, we establish that firms with the *lowest* probability of loss reversal drive the result in the full sample and that firms with a higher probability of loss reversal still exhibit no relation between returns and losses. When we redefine earnings to exclude *R&D* and Special Items we find the negative earnings response coefficient for observations with the lowest reversal probabilities disappears. Also, the redefined earnings of firms with higher probabilities of loss reversal exhibit a positive and statistically significant relation with returns, especially in recent years. Taken together, our evidence suggests not only that investors acknowledge the existence of conservative components when they price losses, but also that investors price losses consistent with the probability of loss reversal serving as a proxy for the earning power of assets.

Our study extends the literature on the effects of reporting conservatism on the use and implications of financial statements. Focusing on losses in particular, we show the properties and implications of losses for valuation change consistent with effects of increased reporting conservatism. As a central part of our analysis we model and estimate the process of loss reversal. Whereas previous research identifies variables that help to predict bankruptcy (e.g., Altman 1968), surprisingly little is known about what variables help to predict loss reversal of firms. We believe the practical relevance of the prediction of loss reversal has become more important given the increased frequency of losses for a large cross-section of firms. We show the loss histories of the firm along with contemporaneous financial information help to predict the firm's return to profitability in the near future. We also document that the role and importance of the variables in our empirical model change over the sample period consistent with increased reporting conservatism over the sample period.

We contribute to the valuation literature by showing how the probability of loss reversal relates to the pricing of losses: in addition to taking into account particular conservative components of losses the market values earnings of loss firms differently depending upon the expected probability of loss reversal. Our finding contributes to a better understanding of the role of the abandonment option in valuation (see also Hayn 1995). Given two otherwise identical firms, differences in the probability of reversal indicate differences in the earning power of assets of the firm and the attractiveness of abandonment and therefore affect how investors price losses.

In the next section we describe our sample and document the significance of loss firms in the economy and the aggregate patterns of loss duration. In Section III we investigate the properties of loss observations in our sample and describe and estimate our model of loss reversals. In Section IV we evaluate whether investors' valuation of earnings is consistent with the changing properties of losses. In the final section we summarize our results.

II. The Prevalence and Duration of Losses

We obtain a sample of loss firms from *Compustat*'s Industrial and Research Annual Data Bases for the period 1971-2000. Consistent with Hayn (1995) we define our earnings variable as income (loss) before extra-ordinary items and discontinued operations or *IB* (annual *Compustat* data item #18). Our initial sample contains 217,085 firm-year observations. Table 1 presents descriptive statistics on the prevalence of losses in our sample. We report statistics for both our main earnings variable of interest, *IB*, and for bottom-line earnings or net income *NI* (annual *Compustat* data item #172). Panel A shows the sample contains 29.63% loss observations. Similar to Table 1 in Hayn (1995) we find the number of loss observations increases over time, an pattern that continues to 2000 in our extended sample. We summarize the yearly loss-frequencies per decade and find that in the 1970s about 15% of earnings observations are losses. This percentage increases in the 1990s to about 36% (for both *IB* and *NI*).

In Panel B of Table 1, we document the distribution of the number of years with losses based on a sample of firms with at least 7 years of observations. This criterion allows us to study loss history over a longer window for a subset of firms in a later analysis.[1] Focusing on *IB*, panel B shows 27.21% of the firms in our sample never incur a loss over the period studied. In contrast, about 10% of firms incur more than 10 losses over this 30-year period. Similar to panel B, panel C shows the distribution of the number of years with losses, but now based on a sample of 885 firms with 30 years of observations (i.e., the complete sample period). We find about one-third of firms never incur a loss during the sample period. However, more than 7% of this sample has more than 10 losses over the entire period. The results in panels B and C are similar for *NI*.

The results in panels B and C of Table 1 show losses can persist for a considerable time, motivating us to explore the determinants of the losses and the market's valuation of information other than earnings in the case of losses. As a first step, we explore in Table 2 how a firm's return to profitability varies as a function of the recent loss history of the firm. In panel A, we document how reversal one year into the future varies as a function of the length of the past sequence of losses. We find that of firms experiencing their first loss (i.e., the sequence is 1 year long) 45.47% are profitable in the next year. The percentage changes drastically as a function of the past history of losses. Of firms suffering two consecutive losses, only 34.76% reverse to a profit the next year. The reversal probability monotonically decreases to 27.55% for firms with 5 sequential losses. Panel B documents how reversal over the following five years varies as a function of the past sequence of losses. This analysis reduces the number of observations as it imposes substantial restrictions on our dataset, requiring 10 consecutive observations for each loss firm (the current year observation, 4 past observations and 5 future observations). We find that for 6,983 firm-year observations where the current loss is the first in a (potential) sequence, 46.79% of observations are profitable again one year into the future, and 11.6 percent do not reverse within 5 years. For the companies that do not reverse in the next year, the conditional probability of reversing in subsequent years declines monotonically, from 36.77% after two losses to 31.88% after 5 years. In each column of the table, we find a pattern similar to the rows.

[1] To mitigate possible effects of survivorship bias we code a firm as non-reversing if it is dropped from the

The relative magnitude of the reversal percentages, however, varies considerably as a function of the length of the loss sequence of the firm across the columns of the table. For example, in the last column, comprised of 621 firms where the current loss is the fifth in the sequence, less than a third reverse the following year and about a quarter of the observations do not reverse at all over the 5-year horizon.

Taken together, the descriptive evidence in Table 2 suggests loss reversals follow a distinct pattern conditional on the number of losses already experienced. Interestingly, the longer the loss sequence of the firm, the lower the probability the current loss will reverse in the future, presenting particular challenges for fundamental analysis and/or valuation of the firm. In the next section we examine the characteristics of loss observations.

III. Properties of losses

We observe earlier the increased incidence of losses over the last three decades at a time when the US stock market rises to historically high levels. In this section we examine whether the characteristics of losses have changed over the sample period as the divergence between the trends in accounting earnings and market valuations suggests. We link our investigation to the accounting literature that studies increased reporting conservatism over the past decades (e.g., Givoly and Hayn 2000). In particular, we start by examining if the cash flow and accrual components of the loss observations in our sample change over time. Next, we develop an empirical model of loss reversals. The focus on loss reversal is a central feature of our analysis because previous research argues shareholders do not expect losses to persist since they have the

---

Compustat Annual File due to bankruptcy or liquidation but still appears in the Research File.

option to redeploy or liquidate (abandon) the assets of the firm (see Hayn, 1995; Berger et al. 1996; Wysocki 2001). A current loss therefore complicates the evaluation of the firm's future to the extent there exists uncertainty about its potential reversal. We model loss reversal to assess how investors use financial information to value loss firms when the loss impairs the ability of earnings to serve as a proxy for the earning power of assets. Finally, we explore the properties of losses as a function of the estimated probability of loss reversal.

As a first exploration of the relation between reporting conservatism and the properties of losses, we document the cash flow and accrual components of the loss observations in our sample in Table 3. As a reminder, we evaluate the effects of increased reporting conservatism on the properties of losses by splitting our sample into two subsamples: a first subsample covering 1971 through 1990 and a second covering 1991 through 2000. We define *CFO_SALES* as cash flow from operations scaled by sales (annual *Compustat* data item # 12). Consistent with previous literature (Hayn 1995), we measure cash flow from operations as net income (annual *Compustat* data item # 172) – accruals, where we measure accruals as (ΔCurrent Assets (data item #4) - ΔCash (data item #1) - ΔCurrent Liabilities (data item #5) + ΔDebt in Current Liabilities (data item #34) + Depreciation and Amortizations (data item #14). *ACC_SALES* is accruals (as defined before) scaled by sales (annual *Compustat* data item # 12). Panel A of Table 3 shows that in the full sample the means and medians of the cash flow and accrual components of losses are negative. We further observe a marked difference between the means of the variables across the subperiods: both the means and medians of the cash flow and the accrual component become significantly more negative (significant at the 5% level for cash flows and the 10% level for accruals), consistent with increased conservatism.

In panel B we use perfect foresight to distinguish between loss observations that return to profitability the following year and those that do not. We observe the means and medians of both cash flow and accrual components of non-reversing firms are more negative than their counterparts in the reversal subsample, suggesting firms that do not return to profitability suffer larger losses on average. We also document the deterioration of the cash flow and accrual components presented in panel A primarily occurs in the non-reversing sample. In the non-reversing sample, the means and medians of both loss components are significantly more negative in the later subperiod. In the reversal subsample, the differences between the means and medians across time periods are still negative but no longer statistically significant. The pattern of results therefore confirms that the characteristics of losses change over time. Interestingly, the change is more pronounced for the cash flow component than for the accruals component of the losses. Also, as panel B shows, the changing characteristics of losses relate to a firm's return to profitability the following year.

Next, we estimate models of loss reversal to assess if the characteristics of losses change over our sample period. Our descriptive results in Tables 1 and 2 show losses can persist for a number of years, i.e., reversals do not always take place in the immediate future. The eventual reversal, however, and the ability to maintain operations until that eventual reversal are a necessary condition for long-term profitability. We assume the length of time the firm needs to reverse the loss, and the actions the firm takes to reverse its position are related to the business environment and operations of the firm. We develop and employ an empirical model based on factors that capture aspects of the business environment and operations of the firm to estimate the likelihood of the firm's return to profitability one year in the future.

We focus on loss reversal one year into the future because the results in panel B of Table 2 show that regardless of the number of losses the firm has experienced, the unconditional probability of reversal is always highest in the next year. We model the year ahead reversal of losses by estimating the following model:

$$y_{t+1} = \boldsymbol{X_t} b + e_{t+1} \tag{1}$$

where y_{t+1} is an indicator variable equal to one if the firm becomes profitable in the subsequent period, and zero otherwise, $\boldsymbol{X_t}$ represents the information variables of the model, and $\boldsymbol{e}_{t+1}$ is an error term. If a variable predicts an increased likelihood of loss reversal then the sign of its coefficient will be positive.

In the absence of a formal theory of loss reversals, we consider several different types of information variables in our model. The first set of variables capture the firm's past loss history. We include these variables in the model since the results in panels B and C of Table 2 suggest loss reversal is related to the sequence of past losses. We measure both the incidence and the relative magnitude of past losses. Specifically, we consider the following variables: *FIRSTLOSS* is an indicator equal to one if this year's loss is the first in a sequence (i.e., the firm was profitable the previous year) and zero otherwise; *NUMLOSS* is an indicator variable equal to one if the firm incurred more than two losses in the past five years and zero otherwise; and finally, *MAGNLOSS3* is an indicator variable equal to one if the sum of the current loss and the past three earnings numbers is negative and zero otherwise.

Based on the patterns observed in Table 2, we expect the coefficient on *FIRSTLOSS* will be positive: if the current loss is the first in a sequence, the probability of loss reversal is higher relative to other loss firms. Similarly, we expect the coefficient on *NUMLOSS* to be negative:

the more losses the firm has incurred, the smaller the probability the loss will reverse in the next period. *MAGNLOSS3* captures whether the current loss is large relative to the cumulative earnings of the past three years. We predict a negative coefficient on *MAGNLOSS3* since *MAGNLOSS3* is one if the current loss is larger than the cumulative amount of income of the past three years. This would indicate the firm has relatively greater difficulty sustaining profitability.

To capture other financial information beyond loss history we select a second set of variables to capture demographics and past profitability of the firm. First, we include *SIZE*, measured as the log of current market value (annual *Compustat* data item # 199 * annual *Compustat* data item # 25). We expect this coefficient to be positive, consistent with large firms being financially stronger than small firms and therefore able to return to profitability more easily. The second variable, return-on-assets (*ROA*) is measured as income before extra-ordinary items (annual *Compustat* data item # 18) scaled by lagged total assets (annual *Compustat* data item # 6). Since all firms in our sample will have negative ROA in the current year, we predict a positive sign for ROA as firms with less negative ROAs will be more likely to return to profitability. The next variable, *NEGCEQ*, is an indicator variable equal to one if the firm has negative equity (annual *Compustat* data item # 60) and zero otherwise. *NEGCEQ* captures cumulative profitability. We interpret the occurrence of negative equity as an indication that the profitability problems of the firm are substantial, and predict a negative coefficient on this variable. We also include recent growth in sales, *SALESGROWTH*, measured as the percentage growth in sales (annual *Compustat* data item # 12) during the current year. Although we expect sales growth to signal a pending return to profitability, the effect of sales growth on the probability of loss reversal is weakened if high sales growth identifies young firms in the sample that have not yet achieved profitability. Relatively young firms can remain unprofitable for a number of years during the early stages of their life and therefore sales growth will not be a good predictor of loss reversals.[2]

We expect long-term accruals will also influence losses and loss reversal. For example, if a firm has been active in takeovers accounted for as purchases the earnings number is likely influenced by goodwill amortization. We therefore include a profitability measure in the model unaffected by these accruals, namely *EBITDA*. We measure our variable *EBITDA_SALES* as operating income before depreciation (annual *Compustat* data item # 13), scaled by sales (annual *Compustat* data item # 12). The predictive power of *EBITDA_SALES* for loss reversals depends on whether the current loss is caused by real operational problems or by accounting choices. We predict that higher (or less negative) values of *EBITDA_SALES* will be associated with a higher probability of loss reversal.[3]

Finally, we include two variables that capture the dividend paying behavior of the firm. Following Healy and Palepu (1988), who show management signals profitability changes through dividend changes, we consider that management potentially signals upcoming loss reversals similarly. We include *DIVDUM*, an indicator variable equal to one if the firm is paying dividends (annual *Compustat* data item # 21) and zero otherwise. We predict that if a firm continues to pay dividends while incurring losses it signals the loss sequence is expected to be relatively brief. As a result we predict a positive coefficient on *DIVDUM*. We also include

[2] Notice that we require each observation in the sample to have a history of five years of data. As a result, our sample does not include recent IPOs.

DIVSTOP, an indicator variable equal to one if a firm stopped paying dividends in the current year and zero otherwise. We predict that if a firm stops paying dividends this year because its financial situation is deteriorating rapidly the coefficient on this variable will be negative.

We estimate equation (1) annually to investigate whether the nature of losses and the loss reversal process changed over our sample period. To document the change we average the results over the two subperiods earlier defined. Before presenting the results of the model estimation, we discuss descriptive statistics for the variables included in the logistic regression (1) in Table 4. Panel A presents descriptive results for the six indicator variables defined earlier, conditional on whether the loss reverses or not. Focusing on the three loss variables, the results are consistent with our expectations. We observe that in the full sample the occurrence of a first loss is significantly associated with loss reversal: when the current loss is the first in a sequence (i.e., *FIRSTLOSS* is 1) 45.57% percent of firms experience loss reversal as opposed to 26.17% when the current loss occurs after a previous loss. Focusing on *NUMLOSS*, we see the probability of loss reversal is significantly smaller (23.55% vs. 42.51%) if the firm has experienced more than two losses in the last five years, i.e., *NUMLOSS* is 1. Finally, if the sum of the past three years of earnings is not larger than the current loss (i.e., *MAGNLOSS3* is 1) the probability of reversal is also smaller than if the sum is larger (27.68% vs. 50.38%). We also observe that the divergence between the percentages of reversals and no reversals widens in the later subperiod, suggesting the process of loss reversal as a function of the past history of losses changes.

[3] We also estimated our model with both a cash flow and an accruals variable include in lieu of *EBITDA*. The results remain qualitatively unchanged.

The panel further documents that negative equity (i.e., *NEGCEQ* is *1*) is statistically related to the probability of loss reversal. Current loss firms with negative equity become profitable in only 22.43% of the cases, compared to 35.32% for positive equity firms. The percentage of reversals conditional on negative equity declines in the later subperiod, consistent with a prolonged lack of profitability being more cosmetic in nature in this period. The dividend variable *DIVDUM* also relates significantly to the probability of loss reversal. The probability of loss reversal in the full sample for a current loss firm that pays dividends is 53.49% compared to 29.94% for firms that do not pay dividends. The results for the subperiod samples show this divergence widens in the later subperiod. Finally, all results for the *DIVSTOP* variable are insignificant.

Panel B provides descriptive statistics for the continuous variables defined earlier in the full sample and the two subperiod samples and shows the distributions of the variables differ across the two subperiods. In particular, the average size of loss firms increases over the sample period. Average *ROA* is negative by default and decreases in the later period. Similarly, *EBITDA_SALES*, also negative on average, decreases sharply over time. In contrast, *SALESGROWTH* is higher in the later period. All differences between means and medians of the two subperiod samples are significant at the 5% (with the exception of the differences between the mean and median of *SALESGROWTH*).

Panel C provides descriptive statistics for the continuous variables conditional on whether the firm becomes profitable the following year. We find reversing firms to be larger with higher (i.e., less negative) *ROA*s, *SALESGROWTH,* and *EBITDA_SALES* than firms that do not reverse. Unreported analyses show all mean and median differences between the reversal and no reversal samples are significant, with the exception of those of *SALESGROWTH*. Finally, we also find the pattern of panel A reflected in the reversal and no reversal subsamples. Similar to the results in panel B of Table 3, the time period changes are more pronounced in the no reversal sample, suggesting again that the characteristics of loss firms change over time related to their chances of becoming profitable the next year.

Table 5 presents the results of the logistic regression (1). The table reports the coefficients and associated *t*-statistics computed for the entire sample, and separately for each of the two subperiods following the procedure in Fama-MacBeth (1973). Since Table 3 demonstrates a shift in the nature of losses occurring between the two subperiods we focus our discussion of the results primarily on the two subperiod models and report the results for the full sample as a benchmark. In addition to the average coefficient estimates, we also present the estimated average marginal effects of each variable in the model. We measure the marginal effect as the change in the estimated probability of reversal given a local change in the value of the independent variable, evaluated at the sample mean for all variables (with indicator variables set equal to zero). The marginal effect of an indicator variable measures the effect on the probability of reversal caused by a change in the variable from 0 to 1.

Examining the results for 1971 – 1990 we find two of the three loss history variables are highly significant. Firms experiencing their first loss (*FIRSTLOSS*) are estimated to have a 4.1 percent higher probability of reversal than other firms. Also, firms with a current loss greater than the sum of the past three years income (*MAGNLOSS3*) are estimated to be 9.7 percent less likely to reverse. The effect of *NUMLOSS* on the probability of reversal in this period is less pronounced. While the coefficient estimate is negative for firms that experienced more than two losses in the past five years, it is not statistically significant.

The coefficients on *SIZE*, *EBITDA_SALES* and *DIVDUM* are positive and statistically significant, as expected. *EBITDA_SALES* also displays a large marginal effect on the probability of loss reversal (10.4%). In contrast, firms with negative equity (*NEGCEQ*) are less likely to reverse to profitability. The coefficient on *NEGCEQ* is statistically significant, with these firms estimated to be 4.3 percent less likely to reverse than similar positive equity firms. Finally, the coefficients on *DIVSTOP*, *ROA* and *SALESGROWTH* are not statistically significant.

For the 1991-2000 sample the model's fit increases measured by either the percentage of firms correctly classified or the pseudo-R^2. Apart from the insignificant coefficients on *SALESGROWTH*, none of the coefficient estimates changes in sign. Some, however, change in magnitude and significance. The coefficient on *FIRSTLOSS* increases (from 0.194 to 0.366) with a slight increase in the marginal effect from 4.1 percent to 5.0 percent. Further, the coefficient on *NUMLOSS* is now statistically significant with an estimated marginal effect of 7.6 percent, more than tenfold the point estimate for the first period. Firms with large losses (*MAGNLOSS3*) are still estimated to be less likely to reverse (i.e., the coefficient is still negative and significant), however the effect of large loses on the marginal effect decreases from 9.7 percent to 4.6 percent. The coefficients on and the marginal effects of *SIZE* and *SALESGROWTH* remain essentially the same over the periods. We observe a change in importance in the model of *ROA* in the second subperiod: the coefficient increases from 0.371 to 0.689, is significant, and the marginal effect on the probability of reversal increases to 12.3%. In contrast, the influence of both *NEGCEQ* and *EBITDA_SALES* on the probability of reversal decreases, with the marginal effect on the probability of reversal of *EBITDA_SALES* decreasing from 10.4% to 1.4%. Finally, while *DIVSTOP* remains insignificant the effect of *DIVDUM* on the probability of reversal increases: the coefficient increases from 0.182 to 0.487 and the marginal effect doubles to 8.1% from 4.0%.

In sum, the results of the logistic regression model in Table 5 confirm that the properties of losses and loss reversals change over time. In particular, the results for the loss history variables suggest that losses not only become more prevalent in the 1990s, the change in influence of *NUMLOSS* across the subperiods also indicates the probability of reversal given a series of losses falls dramatically: firms are able to remain unprofitable for longer periods without reversing back to profitability. The increased influence of the *FIRSTLOSS* variable combined with the decreased influence of the magnitude of the current loss further suggest that more 'big bath' type losses occur in the second subperiod from which firms more easily return to profitability. The most important change in the financial profile variables relates to *EBITDA_SALES*: an improvement in *EBITDA_SALES* contributes considerably less to the probability of reversal in the second subperiod, a result consistent with an increasing influence of long-term accruals on losses and their reversal.

We argue before that our probability model of loss reversal summarizes financial information investors can use to assess the earnings power of assets of the firm in the case of losses. We next explore in more detail if firm characteristics vary as a function of the estimated probabilities of reversal consistent with this argument. We focus specifically on characteristics of losses related to reporting conservatism since we find evidence in our earlier analysis that increased reporting conservatism potentially influences the properties of losses. Table 6 contains the results of the analysis with observations sorted into quartiles based on their estimated probability of reversal (observations with the lowest estimated probability are in quartile 1). First we document in panel A that the mean (median) probability of reversal decreases between subperiods from 0.36 (0.34) for 1971-1990 to 0.33 (0.30) for 1991-2000; a pattern we observe across subperiods in the first three quartiles but not in the fourth.

In panel B we provide details on the cash flow (*CFO_SALES*) and accruals (*ACC_SALES*) components of losses by quartile for each of the periods. We find that regardless of the period, cash flows are lowest (i.e., most negative) for firms with the lowest reversal probability and monotonically increase with the probability of reversal. Notice how the largest change between the two periods occurs in quartile 1 where mean cash flows fall from -3.18 to –16.54. Overall, with the exception of quartile 3, mean and median *CFO_SALES* are lower in the later period than in the earlier. Accruals follow a similar pattern. Overall, mean and median accruals stay constant or decline across subperiods with the largest decrease between the subperiods taking place in quartile 1. These patterns extend the evidence on the patterns of cash flows and accruals described in Table 3. Panel B in Table 6 shows the losses of firms least likely to return to profitability in the following year drive the statistically significant differences in mean cash flows and accruals observed over the two periods in Table 3. Consistent with Table 3, we find the declines in cash flow between subperiods to be much larger than the declines in accruals, contradicting that reporting conservatism with respect to accruals alone is responsible for the changing nature of losses in recent years (see also Givoly and Hayn 2000).

To explore further what distinguishes firms as a function of their estimated probability of loss reversal we study the influence of two particular accounting items on the characteristics of losses in more detail, namely *R&D* expense and Special Items. We focus on *R&D* since we adopt a broader definition of reporting conservatism than in related research by including the effects of structural changes in the nature of business operations. Recent research finds investments in intangibles, and in R&D in particular, has increased significantly over the past decades and has influenced the properties of reported accounting measures (e.g., Amir and Lev 1996, Collins et al. 1997, Lev and Zarowin 1999). Although R&D investment does not generate negative accruals, the immediate expensing of *R&D* investments is conservative and potentially influences the occurrence and properties of losses. In addition, we examine the specific influence of Special Items on the properties of losses since Special Items should only have a temporary effect on earnings, and reduce the short-term ability of earnings to measure performance (Dechow 1994). Recent research on reporting conservatism and losses also focuses on Special Items since negative Special Items related to restructurings and write-offs typically lower reported earnings through negative accruals (Givoly and Hayn 2000, p. 305). Particularly relevant for our focus on loss reversals are the findings in Carter (2000) and Burgstahler et al. (2002) which conclude that negative Special Items represent "inter-period transfers" that lead to increased earnings in subsequent periods. Carter (2000) in particular shows that the post-restructuring performance of firms is greater than the upward bias caused by the accelerated recognition of Special Item restructuring expenses. In other words, the presence of Special Items could have a particular impact on the properties of losses and their subsequent reversal.

We examine the *R&D* and Special Items components of losses in panel C of Table 6. We scale both components by sales to allow cross-sectional comparisons. We find that *R&D* as a percentage of sales increases in the second subperiod in all but quartile 3. The most pronounced increase occurs in quartile 1, where mean *R&D* expenditures go from 0.43 percent of sales to 2.68 percent, an increase of more than 500 percent. Notice also that quartile 2 firms report a mean increase of R&D of 300 percent between the two periods. The panel further shows that across all quartiles Special Items become more negative during 1991 – 2000 than 1971 – 1990. Again the average effect is most pronounced in quartile 1, where mean Special Item charges increase from 0.13 to 0.81 percent of sales. The change in quartile 1 is less pronounced in terms of median Special Items; the medians change only in quartiles 3 and 4 going from zero to –0.01 and –0.02, respectively. Our finding that firms with the lowest reversal probability report more negative Special Items on average contrasts with the evidence in Burgstahler et al. (2002) that negative Special Items relate to positive earnings changes. However, positive earnings changes are a necessary but not a sufficient condition for loss firms to become profitable; our research design therefore examines a stricter criterion.

Summarizing, we conclude based on the evidence in Tables 3 through 6 that the characteristics of losses change significantly over the past 30 years, consistent with claims of increased reporting conservatism. Losses become more prevalent in the 1990s and firms are able to remain unprofitable for longer periods without reversing back to profitability. We also document the reporting conservatism relates to accruals *and* cash flows: we observe a steep increase in the *R&D* investment as a percentage of sales in recent years for loss firms, particularly for those observations that obtain a low estimated probability of a return to profitability in the following year.

IV. The valuation of losses: earnings response coefficients

After showing how the characteristics of loss firms change over the last three decades, we now turn to the question of whether investors price losses differently over time as a result of the change. Earlier research on the valuation of loss firms considers the role of the abandonment option for the value-implications of losses. For example, Hayn (1995) explains how investors' consideration of the abandonment option explains the lower earnings response coefficients (ERCs) in large sample studies in the presence of losses. Burgstahler and Dichev (1997), Collins et al. (1997) and Collins et al. (1999) also study firm valuation in the presence of losses and use book value as a proxy for the abandonment value of the firm. We extend the investigation of the valuation of losses starting from our earlier evidence that losses, coupled with other information, allow for explicit estimates of the need to abandon or liquidate an investment. We interpret the prediction of loss reversal as one particular way to structure financial information to assess the likelihood of abandoning an investment in the firm. Otherwise put, we assume the loss reversal probability provides information about the earning power of assets when the firm faces a loss.

We carry out two analyses. First, we explore whether the market prices earnings consistent with the prediction of loss reversal. To do this, we investigate if ERCs of loss firms vary as a function of the probability of reversal. We estimate ERCs based on the following regression (see also Hayn 1995):

$$Ret_t \; = \; a \; + \; b \; IB_t \; + \; e_t \qquad (2)$$

where Ret_t is the return over the 12-month period commencing with the fourth month of fiscal year t, IB_t is the earnings per share variable in year t (annual *Compustat* data item #18 scaled by annual *Compustat* data item #25) scaled by P_{t-1} or share price (annual *Compustat* data item #199) at the end of year $t\text{-}1$, e_t is the error term. Consistent with our annual estimation of the loss reversal model, we estimate equation (2) in each year of the sample period and assess the significance of the ERCs using the Fama-Macbeth procedure (1973). We estimate equation (2) in the full sample and in subsamples based on the quartiles of the annual distribution of the probability of reversal distribution to document the variation of the ERCs as a function of the likelihood of loss reversal. To assess if investors change the valuation of losses over time, we also distinguish between the earlier defined subperiods in our research design.

Second, in light of the evidence in the previous section we also ask whether investors change the valuation of losses as a function of the change in the characteristics of the losses over time. Based on the results in panel C of Table 6, we redefine earnings to exclude the R&D and Special Items components and estimate ERCs based on the following regression:

$$Ret_t = a + b\ IBWO_t + e_t \qquad (3)$$

where $IBWO_t$ is earnings per share (annual *Compustat* data item #18 scaled by annual *Compustat* data item #25) in year t before *R&D* (annual *Compustat* data item #46) and Special Items (annual *Compustat* data item #17) scaled by P_{t-1} or share price (annual *Compustat* data item #199) at the end of year $t\text{-}1$; Ret_t is as previously defined and e_t is an error term. By comparing the results of equation (2) and (3), we can assess if investors explicitly consider the changing nature of losses in valuation.

Before turning to the results of the estimation of equations (2) and (3), we briefly discuss the variables of interest in the analysis in Table 7. Panels A and B provide descriptive statistics for returns (*Ret*) and earnings (*IB*), the dependent and independent variables in equation (2). Both panels show a marked difference in the distribution of these variables between the two subperiods in our sample. Panel A reports that while the mean return for loss firms during 1971-1990 was –0.05, with a median of –0.18, the mean return during 1991-2000 was *positive*, 0.12, while the median return increases to –0.11. The mean return of loss firms increases in all four quartiles between the two periods, with only quartile 4 (those firms estimated as most likely to reverse) having a negative mean return during 1991-2000. Note also the means and medians of the full sample and the first two quartiles are significantly different across both subperiods. Panel B shows that regardless of the subperiod, mean and median net income increase monotonically with the estimated probability of reversal. With the exception of quartile 3, mean and medians increase in the full sample and in the separate quartiles across the two subperiods. Again, all differences between means and medians are significant in the entire sample and in the first two quartiles.

Panel C contains descriptive statistics on the redefined earnings variable $IBWO_t$ or earnings per share excluding *R&D* and Special Items. Removing the effects of *R&D* and Special Items increases the mean earnings per share from –0.25 reported in panel B to -0.15 for 1971-1990, and from –0.22 in panel B to –0.09 in 1991-2000, with almost no effect on the standard deviations. The median value of *IBWO* is also larger in both periods than the median of *IB*. Panel C also shows that, regardless of the time period, the pattern of *IBWO* across the four quartiles remains the same, with higher probability of reversal firms having higher mean *IBWO*. Finally, all means and medians increase in the second subperiod. Unreported analysis shows that removing *R&D* and Special Items from income reduces the number of firms with losses in the sample by 1,444 (25.0%) for the 1971–1990 period and by 2,507 (32.3%) for the 1991–2000 period, consistent with these two components of losses becoming more important in the second subperiod.

The descriptive evidence in Table 7 suggests the relation between returns and losses (defined as *IB* or *IBWO*) changes over the sample period in the full sample and in the quartile subsamples. Whereas the probability of reversal appears positively correlated with both earnings variables in both subperiods, the table shows firms with *lower* probabilities of reversal exhibit *higher* returns in the later subperiod but not in the earlier subperiod. Table 8 shows how the change affects the ERCs in the different samples. Panel A of Table 8 shows the result of the estimation of equation (2). We observe that in 1971-1990 the estimated ERC in the full sample is 0.03 and statistically insignificant, similar to the statistically insignificant 0.01 ERC reported by Hayn (1995, Table 4) for loss firms. The lack of statistical significance carries through to each quartile in this subperiod. In contrast, when we estimate equation (2) in the 1991 – 1999 subperiod, the ERC is -0.17 and statistically significant, implying that larger losses yield higher returns. In analyzing the quartile regressions we find the result is driven entirely by the observations in quartile 1: the ERC in quartile 1 is also –0.17 and statistically significant while none of the other quartiles' estimates are statistically significant. Panel C of Table 8 shows the differences between ERCs are statistically significant across the two subperiods in the full sample and in quartile 1. In contrast, the differences across the two periods are not statistically different in quartiles 2 to 4.

Taken at face value, the results in panel A seem inconsistent with investors pricing losses as if they assess the probability of loss reversal or as if they consider the abandonment option when valuing the firm. Instead, it appears the market rewards the firms with the poorest prospects of loss reversal in the later subperiod. Given our evidence in Table 6 on the importance of the *R&D* and Special Items components of the losses with the lowest probability of reversals, we explore this anomalous result by focusing on how investors price *IBWO* in panel B of Table 8. We find the ERC on *IBWO* is 0.03 and not statistically significant in the full sample in both subperiods. Given the negative and statistically significant *IB*-based ERC for 1991-2000, the result suggests that the presence of *R&D* and Special Items drives our finding of a statistically significant negative ERC for loss firms in the second subperiod. The estimated results in quartile 1 bear this out. Again in contrast to the negative and statistically significant coefficient reported in panel A, we now find a statistically insignificant ERC in both periods (-0.00 and 0.03). In other words, the anomalous result of the *negative* statistically significant ERCs for loss firms disappears when we redefine earnings to exclude *R&D* and Special Items, consistent with investors paying particular attention to these components when valuing loss firms.[4]

The results across the remaining three quartiles in panel C of Table 8 further show investors, in addition to taking into account *R&D* and Special Items, consider the probability of loss reversal in pricing losses in the 1991-2000 period. The ERCs monotonically increase across all four quartiles and become statistically significant in quartiles 3 and 4. The value relevance of *IBWO*, i.e., the components of losses unrelated to *R&D* and Special Items, therefore varies as a function of the probability of reversal. The result is consistent with the probability of reversal summarizing financial information useful to investors to value a loss firm and serving as a proxy

---

[4]We separately tested the effect on ERCs on the 4,070 loss firms with positive earnings before *R&D* and Special Items. For these firms, the ERC on *IB* is negative and statistically significant (-0.27 with a t-statistic of 3.57) but the ERC on *IBWO* is positive (0.49 with a t-statistic of 2.46). While this might be attributed as a mechanical result, in

for the earning power of assets when the ability of earnings to do so is impaired. Notice that the result is stronger in the second subperiod where the logistic regression model of loss reversals obtains a better fit, and the estimated probability of reversal is less noisy.

V. Concluding Remarks and Future Research

Observing the growth in the number of publicly traded firms reporting accounting losses, we study the determinants of losses and their increased frequency over time to understand their implications for the use of financial statements in valuation. We focus on the relation between reporting conservatism and the frequency of losses and hypothesize that if more losses occur because of increased reporting conservatism the implications of a current loss for the valuation of the firm change. Different from previous research we adopt a broader notion of reporting conservatism that includes structural changes in the nature of business operations and consider the impact of the increase in R&D expenditures and Special Items over time on the properties of losses and their implications for valuation.

We find the properties of losses change between 1971-2000 both in terms of the cash flow and accruals components. Next, we model the probability of a firm's return to profitability (i.e., loss reversal) as a function of three generic categories of variables that capture the business environment and operations of the firm: 1) variables that describe the loss history of the firm; 2) variables that measure the financial profile of the firm; 3) variables that capture the dividend paying behavior of the firm. We predict and find increased reporting conservatism affects the ability of the included variables to predict loss reversals. In particular, we find first-time losses

that all explanatory variables switch sign, the explanatory power of the equation also increases, from an R^2 of 0.001

have become more transitory in recent years, consistent with an increased frequency of 'big bath' situations. In contrast, we find a firm with multiple losses becomes less likely to return to profitability in the near future, indicating increased persistence of loss sequences in recent years. Both effects are consistent with greater use of conservative accounting methods over time. The change in importance of the other financial statement variables in the reversal model confirms an increasing influence of long-term accruals on losses and their reversal.

When ranked by their estimated likelihood of loss reversal we find firms with the lowest probability have unusually large negative cash flows *and* accruals. In subsequent analysis, we document the cash flow and accrual components of the firms with the lowest reversal probability contain relatively large amounts of *R&D* expenditures and Special Items, especially in recent years. We interpret the pattern of loss components to illustrate how structural changes in the nature of business operations affect the properties of losses.

We next explore the valuation implications of losses and estimate earnings response coefficients (ERC) for loss observations. We find no relation between losses and stock returns in the period 1971-1990, consistent with losses being a poor proxy of the earning power of assets. In contrast, in the period 1991-2000 we find a significantly negative relation between losses and returns. We establish that firms with the *lowest* probability of loss reversal drive the result and that firms with a higher probability of loss reversal still exhibit no relation between returns and losses. When we redefine earnings to exclude *R&D* and Special Items we find the negative earnings response coefficient for observations with the lowest reversal probabilities disappears. The redefined earnings of firms with higher probabilities of loss reversal also exhibit a positive

---

to 0.016, suggesting that *IBWO* is more informative to the market in valuing these firms.

and statistically significant relation with returns especially in the later period. The result suggests the probability of reversal summarizes financial information useful to investors to value a loss firm: it serves as a proxy for the earning power of assets when the ability of earnings to do so is impaired. The market therefore assesses the effect of reporting conservatism *and* the attractiveness of abandoning the investment in the firm when it prices losses.

We see immediate possibilities for future research on the pricing of loss firms. First, our results, while robust, are based on an arguably simple model of the loss reversal process. Future research could examine additional explanatory variables of loss reversals or consider explicitly modeling the duration of loss sequences. Second, while we focus on two earnings components to explain the anomalous result of negative ERCs for certain loss firms, additional research can study the role other earnings attributes play in the valuation of loss firms.

References

Altman, E. (1968) "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy" *Journal of Finance* 22: 589-610

Amir, E., and B. Lev (1996) "Value-relevance of nonfinancial information: The wireless communications industry." *Journal of Accounting and Economics* 22: 3-30.

Basu, S. (1997) "The conservatism principle and the asymmetric timeliness of earnings." *Journal of Accounting and Economics* 24: 3-37.

Berger, P.G., E. Ofek, and I. Swary. (1996) "Investor valuation of the abandonment option." *Journal of Financial Economics* 42: 257-287.

Burgstahler, D., and I. Dichev. (1997) "Earnings, adaptation, and firm value." *The Accounting Review*, April: 187-215.

Burgstahler, D., J. Jiambalvo, and T. Shevlin. (2002) "Do stock prices fully reflect the implications of special items for future earnings? *Journal of Accounting Research*, 40: 585 – 612.

Carter, Mary Ellen. (2000) "Operating Performance Following Corporate Restructurings," working paper, Columbia University.

Collins, D.W., Maydew, E.L. and Weiss, I.S., (1997). Changes in the value relevance of earnings and book values over the past forty years. Journal of Accounting and Economics 24: 39-67.

Collins, D. W., M. Pincus, and H. Xie. (1999) "Equity valuation and negative earnings: The role of book value of equity." *The Accounting Review*, April: 29-61.

Dechow, P. M., (1994) "Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals." *Journal of Accounting and Economics*, 18: 3-42.

Fama, E., and J. MacBeth. (1973) "Risk, return, and equilibrium: empirical tests." *Journal of Political Economy*, 81: 607-636.

Francis, J., J.D. Hanna, and L. Vincent (1996), "Causes and Effects of Discretionary Asset Write-offs", *Journal of Accounting Research* 34 Supplement: 117-134.

Givoly, D. and C. Hayn, (2000) "The changing time-series properties of earnings, cash flows, and accruals: Has financial reporting become more conservative?" *Journal of Accounting and Economics* 29: 287 – 320.

Hayn, C. (1995) "The information content of losses." *Journal of Accounting and Economics* 20: 125-153.

P. Healy, P. and K Palepu, (1988) "Earnings information conveyed by dividend initiations and omissions," *Journal of Financial Economics* 21: 149-175.

Lev, B., and P. Zarowin. (1999) "The boundaries of financial reporting and how to extend them." *Journal of Accounting Research* 37 (Autumn): 353-385.

Modigliani F., and M.H. Miller. (1966) "Some estimates of the cost of capital to the electric utility industry, 1954-57." *The American Economic Review* LVI, 3: 333-391.

Palepu, K., (1986) "Predicting takeover targets: A methodological and empirical analysis," *Journal of Accounting and Economics* 8: 3-35.

Wysocki, P.D. (2001) "Real options and the informativeness of segment disclosures." Working Paper, MIT.

Table 1
Frequency of Losses

Panel A: Total Sample (all firm-years available)[a]

	IB		*NI*	
	No. Firm-years	% of Loss Firm-years	No. Firm-years	% of Loss Firm-years
All firms	217,085	29.63	217,085	29.74
1971-1980	54,875	15.14	54,875	15.62
1981-1990	70,665	32.72	70,665	32.51
1991-2000	91,545	35.92	91,545	36.07

Panel B: Distribution of the number of years with losses (based on a subsample of firms with at least 7 years of data)

	IB		*NI*	
	No. Firms	% of Firms	No. Firms	% of Firms
	11,435	100.00	11,435	100.00
Number of losses				
0	3,112	27.21	2,851	24.93
1	1,396	12.21	1,446	12.65
2	1,102	9.64	1,197	10.47
3	934	8.18	980	8.57
4	855	7.48	868	7.59
5	715	6.25	791	6.92
6	647	5.66	668	5.84
7	653	5.71	662	5.79
8	522	4.56	532	4.65
9	377	3.30	377	3.30
10	291	2.54	275	2.40
10 < and < 20	806	7.05	769	6.73
20 or more	25	0.22	20	0.17

Panel C: Distribution of the number of years with losses (based on a subsample of firms with 30 years of data)

	IB		*NI*	
	No. Firms	% of Firms	No. Firms	% of Firms
	885	100.00	885	100.00
Number of losses				
0	297	33.56	263	29.72
1	159	17.97	155	17.51
2	89	10.06	92	10.40
3	62	7.01	75	8.47
4	49	5.54	51	5.76
5	36	4.07	47	5.31
6	35	3.95	34	3.84
7	31	3.50	33	3.73
8	22	2.49	25	2.82
9	15	1.69	15	1.69
10	22	2.49	19	2.15
10 < and < 20	61	6.89	68	7.68
20 or more	7	0.79	8	0.90

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. *IB* is defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18). *NI* is net income (annual *Compustat* data item #172).

Table 2
Loss Reversals as a Function of the Loss History of the Firm[a]

Panel A: Relation between length of loss sequence and reversal one year into the future

Loss Sequence	*Obs.*	*Reversal (%)*
1 year	10,234	45.47
2 years	5,055	34.76
3 years	2,968	31.17
4 years	1,787	27.98
5 years	1,118	27.55

Panel B: Loss reversal in the current loss sample as a function of the string of past losses

Future	*Loss Sequence (number of years)*				
Reversal	*1*	*2*	*3*	*4*	*5*
Obs.	6,983	3,356	1,882	1,096	621
1 year	46.79	36.77	33.63	32.66	31.88
2 years	19.32	21.31	20.94	21.35	17.71
3 years	11.28	13.02	13.71	12.04	12.08
4 years	6.60	8.34	7.86	7.57	7.73
5 years	4.41	4.95	5.42	4.93	5.48
>5 years	11.60	15.61	18.44	21.44	25.12

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18).

Loss sequence refers to an uninterrupted sequence of annual losses. *Reversal* indicates that the loss firm becomes profitable.

Table 3
Properties of Losses: Descriptive Statistics[a]

Panel A: Cash Flow and Accrual Components[b]

	Sample	*Obs.*	*Mean*	*Std. Dev.*	*Median*
CFO_SALES	Full Sample	17,765	-3.87	88.73	-0.03
	1971-1990	8,129	-0.92	27.03	-0.01
	1991-2000	9,636	***-6.34***	117.84	***-0.05***
ACC_SALES	Full Sample	17,765	-0.48	30.28	-0.08
	1971-1990	8,129	-0.08	20.09	-0.07
	1991-2000	9,636	*-0.80*	36.74	*-0.08*

Panel B: Cash Flow and Accrual Components: Perfect Reversal Foresight[b]

		No Reversal				*Reversal*			
	Sample	*Obs.*	*Mean*	*Std. Dev.*	*Median*	*Obs.*	*Mean*	*Std. Dev.*	*Median*
CFO_SALES	Full Sample	11,840	-5.69	108.52	-0.05	5,925	-0.21	7.24	0.01
	1971-1990	5,227	-1.40	33.64	-0.02	2,902	-0.06	2.65	0.01
	1991-2000	6,613	***-9.08***	142.01	***-0.10***	3,023	-0.36	9.79	0.00
ACC_SALES	Full Sample	11,840	-0.56	36.66	-0.09	5,925	-0.29	7.94	-0.07
	1971-1990	5,227	-0.03	24.94	-0.08	2,902	-0.19	2.90	-0.06
	1991-2000	6,613	*-0.99*	43.75	*-0.09*	3,023	-0.38	10.74	-0.06

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18). *CFO_SALES* is cash flow from operations scaled by sales (annual *Compustat* data item # 12). We measure cash flow from operations as net income (annual *Compustat* data item # 172) – accruals, where we measure accruals as (ΔCurrent Assets (data item #4) - ΔCash (data item #1) - ΔCurrent Liabilities (data item #5) + ΔDebt in Current Liabilities (data item #34) + Depreciation and Amortizations (data item #14). *ACC_SALES* is accruals (as defined before) scaled by sales (annual *Compustat* data item # 12).

[b] Italicized (and bold) means and medians indicate that the difference between the subperiod means or medians is significant at the 10% (5%) level.

Table 4

Logit Model of Loss Reversal: Descriptive Statistics[a]

Panel A: Indicator Variables in the Loss Reversal Model

		Full Sample			*1971-1990*			*1991-2000*		
	Value	*Obs.*	*Reversal (%)*	c^2	*Obs.*	*Reversal (%)*	c^2	*Obs.*	*Reversal (%)*	c^2
FIRSTLOSS	0	11,962	26.17	.0001	5,098	29.34	.0001	6,864	23.82	.0001
	1	7,171	45.57		3,692	43.74		3,479	47.51	
NUMLOSS	0	9,987	42.51	.0001	5,441	40.21	.0001	4,546	45.25	.0001
	1	9,146	23.55		3,349	27.56		5,797	21.24	
MAGNLOSS3	0	4,861	50.38	.0001	2,668	48.35	.0001	2,193	52.85	.0001
	1	14,272	27.68		6,122	29.75		8,150	26.12	
NEGCEQ	0	16,346	35.32	.0001	7,582	37.10	.0001	8,764	33.79	.0001
	1	2,787	22.43		1,208	24.67		1,579	20.71	
DIVDUM	0	16,286	29.94	.0001	7,116	31.97	.0001	9,170	28.36	.0001
	1	2,847	53.49		1,674	49.94		1,173	58.57	
DIVSTOP	0	18,290	33.34	.1547	8,207	35.36	.8114	10,083	31.70	.2074
	1	843	35.71		583	35.85		260	35.38	

Panel B: Continuous Variables in the Loss Reversal Model[b]

	Sample	*Obs.*	*Mean*	*Std. Dev.*	*Median*
SIZE	Full Sample	19,133	2.97	2.07	2.83
	1971-1990	8,790	2.44	1.87	2.33
	1991-2000	10,343	***3.41***	2.13	***3.33***
ROA	Full Sample	19,133	-0.29	2.23	-0.09
	1971-1990	8,790	-0.19	1.01	-0.07
	1991-2000	10,343	***-0.38***	2.89	***-0.11***
SALESGROWTH	Full Sample	19,133	0.00	2.02	-0.02
	1971-1990	8,790	-0.01	1.54	-0.04
	1991-2000	10,343	0.01	2.35	*-0.01*
EBITDA_SALES	Full Sample	19,133	-2.70	54.63	-0.00
	1971-1990	8,790	-0.60	7.40	0.01
	1991-2000	10,343	***-4.48***	73.95	***-0.01***

Panel C: Continuous Variables in the Loss Reversal Model: Perfect Reversal Foresight[b]

		No Reversal				*Reversal*			
	Sample	*Obs.*	*Mean*	*Std. Dev.*	*Median*	*Obs.*	*Mean*	*Std. Dev.*	*Median*
SIZE	Full Sample	12,734	2.79	1.97	2.72	6,399	3.31	2.22	3.09
	1971-1990	5,679	2.28	1.79	2.19	3,111	2.74	1.98	2.56
	1991-2000	7,055	***3.20***	2.01	***3.19***	3,288	***3.85***	2.29	***3.66***
ROA	Full Sample	12,734	-0.36	2.06	-0.12	6,399	-0.17	2.53	-0.05
	1971-1990	5,679	-0.22	0.92	-0.09	3,111	-0.14	1.17	-0.04
	1991-2000	7,055	***-0.46***	2.64	***-0.16***	3,288	-0.21	3.35	-0.05
SALESGROWTH	Full Sample	12,734	-0.01	2.30	-0.04	6,399	0.02	1.27	-0.01
	1971-1990	5,679	-0.02	1.69	-0.06	3,111	-0.01	1.22	-0.01
	1991-2000	7,055	-0.00	2.70	***-0.02***	3,288	*0.05*	1.32	-0.01
EBITDA_SALES	Full Sample	12,734	-3.89	66.46	-0.03	6,399	-0.33	11.22	0.03
	1971-1990	5,679	-0.84	8.86	-0.01	3,111	-0.15	3.35	0.02
	1991-2000	7,055	***-6.34***	88.86	***-0.07***	3,288	-0.49	15.31	0.03

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18). *SIZE* is log of current market value (annual *Compustat* data item # 199 * annual *Compustat* data item # 25). *ROA* or return-on-assets is income before extra-ordinary items (annual *Compustat* data item # 18) scaled by lagged total assets (annual *Compustat* data item # 6). *SALESGROWTH* is percentual growth in sales (annual *Compustat* data item # 12) over the current year. *EBITDA_SALES* is operating income before depreciation (annual *Compustat* data item # 13), scaled by sales (annual *Compustat* data item # 12). *FIRSTLOSS* is an indicator variable equal to one if this year's loss is the first in a sequence (i.e., the firm was profitable last year) and zero otherwise; *NUMLOSS* is an indicator variable equal to one if the firm incurred more than two losses in the past five years and zero otherwise; *MAGNLOSS3* is an indicator variable equal to one if the sum of the current loss and the past three earnings numbers is negative and zero otherwise. *NEGCEQ* is an indicator variable equal to one if the firm has negative equity (annual *Compustat* data item # 60) and zero otherwise. *DIVDUM* is an indicator variable equal to one if the firm is paying dividends (annual *Compustat* data item # 21) and zero otherwise. *DIVSTOP* is an indicator variable equal to one if the firm stopped paying dividends in the current year and zero otherwise.

[b] Italicized (and bold) means and medians indicate that the difference between the subperiod means or medians is significant at the 10% (5%) level.

Table 5
Logit Models of Loss Reversal[a]

	Predicted Sign	*Full Sample* Avg. Coefficient (*t*-statistic)	Marginal Effect[b]	*1971-1990* Avg. Coefficient (*t*-statistic)	Marginal Effect[b]	*1991-2000* Avg. Coefficient (*t*-statistic)	Marginal Effect[b]
Intercept		-0.449 (-4.340)		-0.426 (-2.870)		-0.486 (-3.685)	
FIRSTLOSS	+	0.259 (3.899)	0.044	0.194 (2.454)	0.041	0.366 (3.189)	0.050
NUMLOSS	-	-0.188 (-2.955)	-0.033	-0.027 (-0.409)	-0.007	-0.454 (-7.592)	-0.076
MAGNLOSS3	-	-0.361 (-5.741)	-0.078	-0.421 (-4.653)	-0.097	-0.261 (-3.908)	-0.046
SIZE	+	0.058 (3.355)	0.011	0.064 (2.578)	0.014	0.048 (2.185)	0.007
ROA	+	0.491 (2.163)	0.095	0.371 (1.095)	0.078	0.689 (3.036)	0.123

NEGCEQ	-	-0.191 (-2.671)	-0.033	-0.219 (-2.157)	-0.043	-0.143 (-1.551)	-0.016
SALESGROWTH	?	0.023 (0.558)	0.008	0.045 (0.695)	0.012	-0.015 (-1.089)	0.000
EBITDA_SALES	+	0.376 (2.918)	0.070	0.447 (2.297)	0.104	0.257 (2.187)	0.014
DIVDUM	+	0.297 (3.897)	0.056	0.182 (1.919)	0.040	0.487 (4.682)	0.081
DIVSTOP	?	-0.125 (-1.784)	-0.022	-0.130 (-1.569)	-0.030	-0.114 (-0.873)	-0.008
Observations		811		598		1165	
Pseudo-R^2		8.2%		6.4%		11.3%	
Percent Concordant[c]		68.4		66.0		72.5	

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18). The table presents the results of the annual estimation of logistic regressions where *loss reversal* is the dependent variable, i.e., a variable that takes the value of one when the firm becomes profitable one-year into the future, and zero otherwise. For the other variable definitions, see the notes to Table 3. The table shows the average coefficient over the estimation period and associated the *t*-statistic derived using the Fama-Macbeth (1973) procedure.

[b] *Marginal Effect* is the change in the estimated probability of reversal given a change in the value of the independent variable, evaluated at the sample mean for all variables with dummy variables set equal to zero. The marginal effect of a dummy variable is from a change in the variable from 0 to 1.

[c] *Percent Concordant* indicates the within-sample percentage of observations correctly classified by the model. *Pseudo R^2* measures the increase in log likelihood of a model containing all variables relative to a model containing only the intercept. Both statistics are averaged over the number of years in the estimation period.

Table 6
Earnings Component Analysis by Quartile of the Probability of Reversal[a]

Panel A: Descriptive Statistics Prob (Reversal)[b]

Sample	Period	No. Obs.	Mean	Std.	Median
Full	1971-1990	6,364	0.36	0.14	0.34
	1991-2000	8,035	***0.33***	0.17	***0.30***
Quartile 1	1971-1990	1,597	0.22	0.08	0.22
	1991-2000	2,011	***0.14***	0.07	***0.16***
Quartile 2	1971-1990	1,589	0.30	0.07	0.29
	1991-2000	2,009	***0.25***	0.06	***0.25***
Quartile 3	1971-1990	1,594	0.39	0.08	0.38
	1991-2000	2,010	***0.37***	0.08	***0.37***
Quartile 4	1971-1990	1,584	0.52	0.09	0.51
	1991-2000	2,005	***0.55***	0.10	***0.55***

Panel B: Cash Flows and Accruals [b]

Sample	Period	*CFO_SALES* No. Obs.	*CFO_SALES* Mean	*CFO_SALES* Std.	*CFO_SALES* Median	*ACC_SALES* No. Obs.	*ACC_SALES* Mean	*ACC_SALES* Std.	*ACC_SALES* Median
Quartile 1	1971-1990	1,490	-3.18	58.92	-0.05	1,490	0.52	43.87	-0.12
	1991-2000	1,927	***-16.54***	180.03	***-0.71***	1,927	*-1.38*	32.34	*-0.15*
Quartile 2	1971-1990	1,467	-0.13	2.27	-0.01	1,467	-0.11	1.10	-0.07
	1991-2000	1,889	***-1.11***	32.73	***-0.06***	1,889	*-0.24*	2.57	-0.07
Quartile 3	1971-1990	1,493	-0.08	2.31	0.00	1,493	-0.23	3.03	-0.06
	1991-2000	1,861	-0.06	0.89	***-0.01***	1,861	-0.12	0.34	*-0.07*
Quartile 4	1971-1990	1,461	0.07	1.95	0.02	1,461	-0.11	1.61	-0.06
	1991-2000	1,830	0.01	0.22	0.02	1,830	-0.09	0.19	-0.06

Panel C: R&D and Special Items[b]

Sample	Period	RD_SALES No. Obs.	RD_SALES Mean	RD_SALES Std.	RD_SALES Median	SPI_SALES No. Obs.	SPI_SALES Mean	SPI_SALES Std.	SPI_SALES Median
Quartile 1	1971-1990	1,460	0.43	5.03	0.00	1,483	-0.13	2.44	0.00
	1991-2000	1,942	***2.68***	13.54	***0.10***	1,881	***-0.81***	12.33	0.00
Quartile 2	1971-1990	1,454	0.06	0.22	0.00	1,476	-0.03	0.31	0.00
	1991-2000	1,934	***0.24***	1.13	0.00	1,876	*-0.07*	0.74	0.00
Quartile 3	1971-1990	1,445	0.07	0.48	0.00	1,479	-0.04	0.43	0.00
	1991-2000	1,951	0.06	0.16	0.00	1,877	-0.05	0.15	***-0.01***
Quartile 4	1971-1990	1,426	0.02	0.28	0.00	1,473	-0.03	0.34	0.00
	1991-2000	1,932	***0.04***	0.08	0.00	1,873	***-0.06***	0.17	***-0.02***

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18).
The panels show descriptive statistics for four variables in subsamples based on the quartiles of *Prob(Reversal)*. The *Prob(Reversal)* is the predicted probability from annual logistic regressions reported in Table 4.
CFO_SALES is cash flow from operations scaled by sales (annual *Compustat* data item # 12). We measure cash flow from operations as net income (annual *Compustat* data item # 172) – accruals, where we measure accruals as (ΔCurrent Assets (data item #4) - ΔCash (data item #1) - ΔCurrent Liabilities (data item #5) + ΔDebt in Current Liabilities (data item #34) + Depreciation and Amortizations (data item #14). *ACC_SALES* is accruals (as defined before) scaled by sales (annual *Compustat* data item # 12). *RD_SALES* is *R&D* expenditures (annual *Compustat* data item # 46) scaled by sales (annual *Compustat* data item # 12). *SPI_SALES* is Special Items (annual *Compustat* data item # 17) scaled by sales (annual *Compustat* data item # 12).
[b] Italicized (and bold) means and medians indicate that the difference between the subperiod means or medians is significant at the 10% (5%) level.

Table 7
ERC Analysis: Descriptive Statistics[a]

Panel A: Descriptive Statistics Return (Ret)[b]

Sample	Period	No. Obs.	Mean	Std.	Median
Full	1971-1990	6,364	-0.05	0.59	-0.18
	1991-2000	8,035	***0.12***	0.82	***-0.11***
Quartile 1	1971-1990	1,597	-0.11	0.63	-0.25
	1991-2000	2,011	***0.21***	0.97	***-0.10***
Quartile 2	1971-1990	1,589	-0.02	0.63	-0.17
	1991-2000	2,009	***0.22***	0.89	***-0.04***
Quartile 3	1971-1990	1,594	-0.02	0.59	-0.15
	1991-2000	2,010	***0.03***	0.72	-0.13
Quartile 4	1971-1990	1,584	-0.06	0.47	-0.13
	1991-2000	2,005	*-0.02*	0.59	-0.13

Panel B: Descriptive Statistics Net Income (IB)[b]

Sample	Period	No. Obs.	Mean	Std.	Median
Full	1971-1990	6,364	-0.25	0.31	-0.13
	1991-2000	8,035	***-0.22***	0.28	***-0.11***
Quartile 1	1971-1990	1,597	-0.41	0.39	-0.28
	1991-2000	2,011	***-0.34***	0.34	***-0.20***
Quartile 2	1971-1990	1,589	-0.27	0.31	-0.15
	1991-2000	2,009	***-0.24***	0.29	***-0.13***
Quartile 3	1971-1990	1,594	-0.20	0.26	-0.11
	1991-2000	2,010	-0.21	0.24	***-0.13***
Quartile 4	1971-1990	1,584	-0.11	0.14	-0.06
	1991-2000	2,005	*-0.10*	0.15	***-0.05***

Panel C: Descriptive Statistics Adjusted Net Income (IBWO)[b]

Sample	Period	No. Obs.	Mean	Std.	Median
Full	1971-1990	5,785	-0.15	0.30	-0.06
	1991-2000	7,759	***-0.09***	0.27	***-0.04***
Quartile 1	1971-1990	1,460	-0.32	0.38	-0.19
	1991-2000	1,942	***-0.20***	0.31	***-0.10***
Quartile 2	1971-1990	1,454	-0.18	0.29	-0.09
	1991-2000	1,934	***-0.12***	0.30	***-0.06***
Quartile 3	1971-1990	1,445	-0.09	0.24	-0.05
	1991-2000	1,951	***-0.07***	0.23	***-0.03***
Quartile 4	1971-1990	1,426	-0.01	0.16	-0.01
	1991-2000	1,932	***0.02***	0.16	***0.02***

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18). The panels show descriptive statistics for three variables in the full sample and in subsamples based on the quartiles of *Prob(Reversal)*. The *Prob(Reversal)* is the predicted probability from annual logistic regressions reported in Table 4. Ret_t is the return over the 12-month period commencing with the fourth month of fiscal year *t*; IB_t is the earnings per share variable in year *t* (annual *Compustat* data item #18) scaled by P_{t-1} or share price (annual *Compustat* data item #199) at the end of year *t-1*. *IBWO* is the earnings per share variable (annual *Compustat* data item #18) in year *t* before *R&D* (annual *Compustat* data item #46) and Special Items (annual *Compustat* data item #17) scaled by P_{t-1} or share price (annual *Compustat* data item #199) at the end of year *t-1*.

[b] Italicized (and bold) means and medians indicate that the difference between the subperiod means or medians is significant at the 10% (5%) level.

Table 8
ERC Analysis: Annual Estimation[a]

Panel A: ERC Results: $Ret_t = a + b\ IB_t + e_t$ [b]

Sample	Period	No. Obs.	Intercept		*IB*		Adj. R^2
			a	*t*-stat.	*b*	*t*-stat	
Full	1971-1990	423	-0.03	-0.72	0.03	0.65	0.01
	1991-2000	891	0.08	1.22	-0.17	-3.68	0.01
Quartile 1	1971-1990	105	-0.08	-1.39	0.03	0.48	0.03
	1991-2000	222	0.17	1.37	-0.17	-2.30	0.01
Quartile 2	1971-1990	104	0.00	0.02	-0.00	-0.05	0.02
	1991-2000	222	0.23	2.62	0.00	0.01	0.01
Quartile 3	1971-1990	105	-0.04	-0.80	0.00	0.04	0.03
	1991-2000	222	0.05	0.61	-0.03	-0.20	0.01
Quartile 4	1971-1990	104	-0.02	-0.34	0.16	1.36	0.01
	1991-2000	221	0.00	0.06	0.21	1.61	0.01

Panel B: ERC Results: $Ret_t = a + b\ IBWO_t + e_t$ [c]

Sample	Period	No. Obs.	Intercept		*IBWO*		Adj. R^2
			a	*t*-stat.	*b*	*t*-stat	
Full	1971-1990	384	-0.03	-0.67	0.03	0.52	0.01
	1991-2000	861	0.12	1.74	0.03	0.29	0.00
Quartile 1	1971-1990	96	-0.09	-1.53	-0.00	-0.01	0.03
	1991-2000	214	0.23	1.82	0.03	0.20	0.01
Quartile 2	1971-1990	95	0.01	0.22	0.01	0.18	0.03
	1991-2000	213	0.24	2.69	0.09	0.54	0.01
Quartile 3	1971-1990	95	-0.03	-0.80	-0.06	-0.63	0.02
	1991-2000	215	0.07	1.02	0.25	1.77	0.02
Quartile 4	1971-1990	95	-0.03	-0.67	0.18	1.79	0.03
	1991-2000	213	-0.0	-0.65	0.73	4.50	0.04

Panel C: t-test for ERC differences across subperiods[d]

	IB Coefficient		*IBWO Coefficient*	
Sample	*t-test*	*p*-value	*t-test*	*p*-value
Full	3.03	0.01	0.06	0.96
Quartile 1	2.09	0.05	-0.21	0.84
Quartile 2	-0.04	0.97	-0.45	0.65
Quartile 3	0.17	0.87	-1.87	0.08
Quartile 4	-0.24	0.82	-3.02	0.01

[a] The data is collected from *Compustat*'s Industrial and Research Annual Data Bases and covers the period 1971-2000. Losses are based on *IB*, defined as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18).

[b] Panel A of the table shows the results of the following annual regressions in the full sample and in subsamples based on the quartiles of *Prob(Reversal)*: $Ret_t = a + b\ IB_t + e_t$; where Ret_t is the return over the 12-month period commencing with the fourth month of fiscal year t; IB_t is the earnings per share variable in year t (annual *Compustat* data item #18) scaled by P_{t-1} or share price (annual *Compustat* data item #199) at the end of year $t-1$, e_t is the error term. The *Prob(Reversal)* is the predicted probability from the annual logistic regressions reported in Table 4. The panel reports the average coefficient over the estimation period and associated the *t*-statistic derived using the Fama-Macbeth (1973) procedure. Adj. R^2 and No. Obs. are averaged over the estimation period.

[c] Panel B of the table shows the results of the following annual regressions in the full sample and in subsamples based on the quartiles of *Prob(Reversal)*: $Ret_t = a + b\ IBWO_t + e_t$; where Ret_t is the return over the 12-month period commencing with the fourth month of fiscal year t; $IBWO_t$ is as defined in panel A. The panel reports the average coefficient over the estimation period and associated the *t*-statistic derived using the Fama-Macbeth (1973) procedure. Adj. R^2 and No. Obs. are averaged over the estimation period.

[d] Panel C shows the results of *t*-tests of the difference between the average coefficient on *IB* and *IBWO* across the two subperiods.