Valuing Loss Firms*

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Abstract

We hypothesize that when confronted with a loss, investors price earnings conditional on the likelihood of the firm's return to profitability. We argue such pricing is consistent with the abandonment option hypothesis as described by Hayn (1995) and show both the pricing of losses and their characteristics vary as a function of their expected reversal. We document a more pronounced stock price response to transitory losses (i.e., losses likely to reverse), consistent with investors assessing the likelihood of exercising the abandonment option to be smaller. However, we also find evidence consistent with investors pricing persistent losses (i.e., losses not likely to reverse) *negatively*, a result inconsistent with the abandonment option hypothesis.
Further analysis shows investors price the components of losses differently depending on the likelihood of reversal. Aggregate accruals explain the pricing of persistent losses while aggregate cash flows explain the pricing of transitory losses. The result for persistent losses relates to the presence of an increasingly larger R&D component: investors reward firms that make larger R&D outlays with larger returns. One consequence of the growing R&D component in persistent losses is that they have become a weaker indicator of the likelihood of exercising the abandonment option.

Keywords: earnings; losses; cash flows; accruals; valuation; persistence
Data Availability: Data are available from sources identified in the text.

I. Introduction

The frequency of firms reporting losses has markedly increased over the last three decades. Whereas only 15% of observations covered by the Standard & Poor Compustat database report a loss during the 1970s, by the 1990s loss observations constitute about 35% of the US firm-years observations. The increased frequency of firms reporting losses poses an important challenge for financial statement users who rely on accounting earnings in various decision contexts (Watts and Zimmerman 1986). In the context of valuation, Modigliani and Miller (1966) discuss in their seminal paper how accounting earnings are a proxy for the expected and unobservable earning power of firms' assets. They note that losses complicate the use of earnings-based valuation models since a loss reduces the ability of reported earnings to provide information about the earnings power of a firm's assets. Given the increase in the frequency of losses in the cross-section, the question of how investors price negative earnings has gained considerable relevance. In this study, we hypothesize that investors, when confronted with a loss, assess the probability of loss reversal, i.e., the firm's return to profitability, and price earnings conditional upon that probability.

We focus on loss reversals because a loss places the firm in a temporary position: a return to profitability is the maintained hypothesis of financial reporting, embodied in the going-concern assumption. In addition, the assumption that a loss is temporary is consistent with the abandonment option approach to loss valuation, studied by Hayn (1995). The abandonment option hypothesis suggests shareholders of loss firms will redeploy or liquidate the assets of the firm if losses are otherwise expected to continue (Hayn 1995, p. 126; Berger et al. 1996;

Wysocki 2001).[1] Hayn (1995, p. 127) argues that losses represent a case where current earnings signal future earnings will be sufficiently low so as to make the abandonment option attractive, leading investors to stop valuing the firm strictly on the basis of reported earnings and reducing the return-earnings correlation. Accordingly, Hayn (1995) predicts that the presence of loss observations in cross-sectional samples will dampen estimates of earnings response coefficients and earnings-returns correlations. She finds evidence supporting her prediction and similarly observes a more pronounced price response to a reported loss when the likelihood of exercising the abandonment option is relatively smaller.

Building on Hayn (1995), we propose a proxy for the likelihood of exercising the abandonment option based on an expectation of loss reversal. We show investors can use concurrent and past financial information of the firm to estimate the probability of loss reversal. We ensure that we use only contemporaneously available information to estimate the proxy to mimic the process investors use to assess the probability of loss reversal. To assess if the valuation of losses varies as a function of the estimated loss reversal probability, we focus on two groups of firms, defined by their likelihood of reversal: the persistent loss group consists of observations with the lowest estimated probabilities of loss reversal, and the transitory loss group of the observations with the highest estimated probabilities. We predict that, if the persistent loss group consists of observations with a high likelihood of exercising the abandonment option, then the earnings response coefficient [ERC] in this group will not be significantly different from zero; if the transitory loss group consists of observations with a low likelihood of exercising the

[1] As Watts (2003) describes, the abandonment option does not require the liquidation of the firm since management can opt to liquidate only the unprofitable investments within the firm, thereby leaving only those operations that are profitable. Given that liquidation of publicly-traded firms is a relatively rare event, this characterization is consistent with observed empirical patterns.

abandonment option, then the ERC in this group will be positive and significantly different from zero.

Using a sample of loss observations from 1971 and 2000, we find a parsimonious set of variables capturing the firm's profitability, loss history, and dividend policy is able to predict a return to profitability (i.e., loss reversal). As the change in frequency of losses over time potentially implies a change in their characteristics and reversal probabilities, we use successive seven-year panels spanning the sample period to estimate each loss firm's probability of reversal in the next year. The methodology allows the model's parameters to change over time if the nature of losses changes. We find, consistent with the overall increase in the number of loss firms in the population of firms, the average estimated probability of reversal declines over the sample period.

Focusing on valuation, we find the ERC in the transitory group is significantly positive, consistent with our prediction. By contrast, the ERC in the persistent group is both significant and *negative*, implying larger losses correspond to higher stock returns. Since an examination of the distributions of returns and losses shows they contain extreme observations (i.e., the means and medians of the distributions are very different), we re-estimate the ERCs using the ranks of the observations and find that, while the result in the transitory group remains unchanged, the ERC in the persistent group becomes insignificant, as predicted. When we study the change in ERC of the different groups of loss observations over time, we find the ERC in the transitory group remains unchanged over the sample period, but the ERC in the persistent group becomes more negative, consistent with the negative valuation of persistent losses being a recent phenomenon.

Overall, our results provide evidence consistent with a more pronounced stock price response to a loss when investors assess the loss to be transitory and the likelihood of exercising the abandonment option to be smaller. In the transitory group, stock returns and losses appear to reflect the same information, consistent with Hayn (1995). By contrast, the evidence that investors price persistent losses consistent with the abandonment option hypothesis appears mixed. Although the average ERC based on the rank regressions is insignificant, consistent with our prediction, we also find evidence suggesting a negative correlation exists between the information in persistent losses and returns, especially in recent years.

To explore the pattern of ERCs further we focus on differences between the components of persistent and transitory losses. Building on the findings in Givoly and Hayn (2000) and Skinner (2004) we consider two sets of loss components: 1) the cash flow and accruals components of losses; 2) the research and development (R&D) and Special Items (SPI) components of the losses. We find large differences between the relative magnitudes of the components in the two groups of losses: persistent losses contain large negative cash flow *and* negative accruals whereas transitory losses on average consist of *positive* cash flows and negative accruals. On average, persistent losses exhibit a larger R&D component (leading to larger negative cash flows) and a more *negative* SPI component than the transitory losses. The medians however show the majority of persistent losses has no SPI component, while the majority of the transitory losses no R&D component.

We further observe that investors price the components of losses differently as a function of the expected persistence of the losses. For persistent losses, investors price the aggregate accruals component, R&D and SPI components, but not the aggregate cash flow component. In particular, investors price the large R&D component of persistent losses *negatively*, consistent with them rewarding larger R&D outlays with higher returns. The negative coefficient on R&D

potentially explains why we fail to find a significant response coefficient for aggregate earnings or cash flows in the persistent loss group: the pricing of the R&D component of persistent losses appears to offset the pricing of the other components of persistent losses. Conversely, for transitory losses, investors price only the cash flow component and not the accruals, R&D, or (non-zero) SPI components. This evidence is consistent with investors identifying negative accruals, and in particular the SPI components of transitory loss firms, as being transitory and therefore not value-relevant (see also the evidence in Skinner 2004). Finally, the time-series evidence on the pricing of the components highlights the increasing value-relevance of the R&D component of persistent losses.

Summarizing, while we cannot explain all observed pricing patterns of the loss components, our evidence is consistent with three observations: 1) investors look beyond aggregate earnings and aggregate cash flows and accruals when valuing losses; 2) investors value certain components of losses differently over the sample period, consistent with the properties of losses changing over time; 3) the presence of a growing R&D component in persistent losses implies a low probability of loss reversal has become a weaker indicator of the likelihood of exercising the abandonment option.

Our research contributes to the valuation literature by establishing the existence of a relation between the *ex ante* loss persistence, serving as proxy for the likelihood of exercising the abandonment option, and investors' valuation of loss firms. Whereas previous research on the pricing of losses predominantly considers loss observations to be a homogenous group, we argue that loss characteristics vary along dimensions that are important for their value-relevance.

Our research also extends the literature on the (changing) properties of earnings. Specifically, we complement the findings in Givoly and Hayn (2000), who conclude the observed decline in profitability of US firms over time does not follow from a decline in cash flows but rather from a decline in accruals. We show that for loss firms the largest observed change over the last decades is the presence of an increasingly larger negative cash flow component in persistent losses, related to an increase over time in R&D outlays.

In short, our findings enhance the understanding of how investors use information beyond *aggregate* earnings to value the firm in the increasingly common case when the firm reports a loss. Investors' behavior is consistent with their considering the causes and nature of the loss to assess its long-term implications for firm value.

In the next section we describe our sample and document the prevalence and duration of losses. In Section III we describe the financial profile of loss observations and present our model of loss reversals, followed in Section IV by our tests of valuation as a function of loss persistence. In section V we study the changing properties and valuation over the sample period, and the role of earnings components in providing information to the market. The final section summarizes and concludes.

II. The Prevalence and Duration of Losses

We collect our sample of firm-year observations from *Compustat*'s Industrial and Research Annual Data Bases for the years 1971-2000. Consistent with Hayn (1995) we define earnings as income (loss) before extraordinary items and discontinued operations or IB (annual *Compustat* data item #18). Our initial sample contains 217,085 firm-year observations, of which 29.63% are loss observations.

As shown in Figure 1, the incidence of losses has increased over the past thirty years. Similar to Table 1 in Hayn (1995) and to patterns reported in Givoly and Hayn (2000) and Klein and Marquardt (2003), we find the number of loss observations, i.e., firms with negative amounts for IB, increases over time. From 1971 to 1980 loss observations represent less than 20% of the sample in each year. From 1981 to 1984 loss firms increase their share of the sample from 21.42 to 28.67%. From 1985 through 2000 loss firms constitute more than 30% of all observations, and more than 40% in 1998 and 2000.[2]

In Panel A of Table 1 we document the distribution of the number of years with losses based on a sample of firms with at least seven years of observations.[3] Panel A shows only 27.21% of the firms in our sample never incur a loss over the period studied. By contrast, about 10% of firms incur 10 or more losses over this 30-year period. Similar to panel A, panel B shows the distribution of the number of years with losses, based on a sample of 885 firms with observations for the entire 30 year sample period. We find about one-third of firms never incur a loss during the sample period, but, again, more than 10% of this sample has 10 or more losses over the entire period.

Panels A and B of Table 1 show losses are not only common but can persist for a considerable time. To preface our focus on loss reversals in the following section, we show in Table 2 how firms' return to profitability varies as a function of their recent loss history. In panel A, we document how the likelihood of reversal in the next year relates to the sequence of prior losses. Of firms experiencing a first loss during the sample (i.e., the loss sequence is 1 year) 45.47% are profitable the next year. However, the percentage of firms reversing decreases drastically and monotonically as a function of the past history of losses. With two consecutive

[2] We observe a similar pattern when we define a loss as a negative net income observation (*Compustat* data item #172).

[3] The seven-year criterion allows us to study loss history over a longer window for a subset of firms in a later analysis. To mitigate possible effects of survivorship bias we code a firm as non-reversing if it is dropped from the Compustat Annual File due to bankruptcy or liquidation but still appears in the Research File.

losses the probability of reversal decreases to 34.76%; for firms with 5 consecutive losses it is only 27.55%.

Panel B documents how the pattern of reversal over a five-year horizon varies as a function of the sequence of prior losses. The 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 for the 6,983 firm-year observations where the current loss is the first in a (potential) sequence, 46.79% of observations return to profitability the next year, and 11.60% do not reverse within 5 years. For losses that do not immediately reverse, the conditional probability of reversing in subsequent years declines monotonically, from 36.77% after two losses to 31.88% after 5 years. Each column of the table shows a pattern similar to the rows, i.e., the relative magnitude of the reversal percentages decline as a function of the length of the loss sequence of the firm. For example, in the last column, consisting 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 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 prior losses: the longer the loss sequence, the lower the *ex ante* probability the current loss will eventually reverse, presenting particular challenges for fundamental analysis and/or valuation of the firm.

III. Loss reversal model

The increased frequency of losses challenges investors to consider information other than aggregate accounting earnings when valuing loss firms since negative earnings are a poor measure of the earning power of the firm's assets. We hypothesize investors will price the earnings of a loss firm conditional on whether they expect the loss to reverse.

To test our prediction we carry out a two-step analysis. First, we estimate a proxy for investors' *ex ante* assessment of the persistence of the observed loss. Next, we use the estimated reversal probability to classify observations into a persistent or transitory sample and estimate earnings response coefficients in each sample.[4] As a starting point, we observe in Table 1 that losses can persist for a number of years, i.e., a reversal to profitability of a current loss does not necessarily take place in the immediate future. However, the results in panel B of Table 2 show that regardless of the number of losses a firm has experienced, the unconditional probability of reversal is always highest in the following year. In our research design, we therefore focus on loss reversal in the next year to estimate our proxy for investors' *ex ante* assessment of the persistence of an observed loss and therefore the likelihood of exercising the abandonment option. Specifically, we estimate a model of loss reversal based on factors related to the firm's business environment and operations as follows:

$$y_{t+1} = \boldsymbol{X_t}\boldsymbol{\beta} + \varepsilon_{t+1} \tag{1}$$

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 ε_{t+1} is an error term.

[4] Our approach is similar to Chambers (1996, p.9), who argues "investors estimate initial-loss persistence using information available at the time of the initial loss". However, his definition of persistence is different from ours, making the results non-comparable. While we define persistence in reference to the probability of loss reversal, Chambers defines persistence as "the ratio of ex-post observed present value of total loss-period negative earnings scaled by initial-year losses" (Chambers 1996, p. 11). Using his definition, losses reversing after a different number of years could exhibit similar persistence.

Our research design allows for the possibility that the nature and properties of loss observations have changed over our sample period. Not only does Figure 1 and the results in other studies (e.g., Hayn 1995, Klein and Marquardt 2003) show the frequency of loss observations increases substantially over the sample period, but several recent studies also illustrate the properties and valuation of earnings have changed in recent decades (e.g., Collins et al. 1997, Givoly and Hayn 2000). Since it is possible the changing nature of earnings over our sample period influences the increased occurrence and/or valuation of losses, we estimate equation (1) sequentially using rolling sample years. That is, we estimate equation (1) annually and compute predicted reversal probabilities using information from the current year and five-years prior to the year of estimation. For example, to estimate equation (1) in 1976, our earliest year of estimation (i.e., *t*=1976) we use data from 1976 when we observe the loss and from past years 1971 through 1975 to compute the information variables in the model. We use the observed reversal of the 1976 losses in 1977 to construct the independent variable in the model (i.e., $t+1$ = 1977). We repeat the estimation procedure using successive panels of data, each time dropping the oldest year and adding a new year, over the entire sample period. As such, the methodology yields time-varying parameters of equation (1) to obtain predictions of loss firm's probability of reversal.

In the absence of a structural model of loss reversals, we estimate our proxy for investors' *ex ante* assessment of loss persistence by including three broad categories of (accounting) variables in equation (1).[5] Our first set of variables measures the financial profile of the firm. In

[5] Our objective is to obtain a reasonable proxy for investors' *ex ante* assessment of the persistence of the current loss using accounting information. We evaluated different specifications of the model, incorporating other financial profile variables of the firm such as the variables in Piotroski (2000), Altman's Z-score (Altman 1968), or macro-economic variables as in Klein and Marquardt (2003). We find the current parsimonious set of variables performs

a first specification of the model, we measure profitability using return-on-assets (ROA) as income before extra-ordinary items (annual *Compustat* data item # 18) scaled by lagged total assets (annual *Compustat* data item # 6). We include both contemporaneous ROA and a past five-year average PAST_ROA. We predict positive signs on both ROA and PAST_ROA, consistent with higher profitability (i.e., less negative ROA or PAST_ROA) indicating a higher probability of a return to profitability.

In a second specification, we decompose ROA into its cash flow and accrual components. We define CFO as cash flow from operations scaled by lagged total assets. Consistent with previous literature (Hayn 1995), we measure cash flow from operations as net income (annual *Compustat* data item # 172) – accruals. We measure accruals or ACC 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), scaled by lagged total assets. We decompose earnings into cash flows and accruals for two reasons. First, Givoly and Hayn (2000) document the properties of cash flows and accruals have changed over the period we study. Specifically, they find an increase in the amount of negative non-operating accruals, rather than changes in cash flows, are responsible for the observed decline in profitability. Second, we expect long-term accruals will mechanically influence loss reversal. For example, for firms with acquisitions accounted for as purchases, goodwill amortization likely influences earnings downward for a number of years. By separating earnings into its cash flow and accruals components we are able to assess whether cash flows and accruals reflect different

qualitatively similarly to expanded sets of variables in the reversal model. Importantly, the different reversal model specifications had no qualitative impact on our later earnings response coefficient analysis.

information about future loss reversals.[6] As in the ROA-specification, we include contemporaneous and past CFO and ACC in the model, where we measure PAST_CFO and PAST_ACC as the average over the past five years. Consistent with our ROA-specification, we predict positive coefficients on all cash flow and accrual variables.

To complement the profitability variables, we include size and growth variables in the model. We include size since Hayn (1995) documents a strong link between the occurrence of losses and firm size. We expect a positive coefficient on SIZE, measured as the log of current market value (annual *Compustat* data item # 199 * annual *Compustat* data item # 25), consistent with large firms being financially stronger than small firms and therefore more easily able to return to profitability. We include a measure of growth to control for the possibility that current earnings do not fully capture the future prospects of growing firms (see Hayn 1995, p. 148). Our proxy for growth is 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 be positively associated with the likelihood of a return to profitability, the effect is weakened if high sales growth identifies relatively young firms in the sample that have not yet achieved profitability. Young firms can remain unprofitable for a number of years during the early stages of their life so that sales growth will not be a good predictor of loss reversals.[7]

Our second set of variables measures the incidence and frequency of past losses. We include two variables that characterize the past loss sequence to complement the (continuous)

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[6] In additional (unreported) analysis, we re-estimate equation (1) using EBITDA or operating income before depreciation (annual *Compustat* data item # 13), scaled by lagged assets, or Depreciation and Amortization (annual *Compustat* data item # 14) scaled by lagged total assets in the model. We find that, whereas EBITDA helps predict future loss reversal (i.e., its coefficient is positive and significant), the coefficient on Depreciation and Amortization is generally not significant in the models.

[7] We require each observation in the sample to have a history of five years of data before the current loss observation. As a result, our sample does not include recent IPOs.

ROA and CFO or ACC variables that measure the profitability of the firm in the recent past. FIRSTLOSS is an indicator variable equal to one if the current year's loss is the first in a sequence (i.e., the firm was profitable the prior year) and zero otherwise. Based on the patterns in Table 2, we expect the coefficient on FIRSTLOSS to be positive: if the current loss is the first in a sequence the probability of loss reversal is higher relative to other loss firms. We also include a variable to capture the number of losses in the sequence over the past five years: LOSS_SEQ is a count of the number of sequential losses over the past five years before the current loss. Based again on the descriptive evidence in Table 2, we expect a negative coefficient on LOSS_SEQ as the longer a firm has been incurring losses the less likely it is to return to profitability in the next year.

Finally, since prior research relates dividend policy to a firm's future earnings, a third category of explanatory variables measures the dividend paying behavior of the firm. Healy and Palepu (1988) show management signals profitability changes through dividend changes. With respect to underperforming firms, DeAngelo and DeAngelo (1990) show dividend changes relate to persistent losses while DeAngelo et al. (1992) show information about dividend reductions increases the ability of current earnings to predict future earnings. Recently, Skinner (2004) relates management's dividend signals to the persistence of losses. We therefore include two indicator variables to capture the dividend behavior of the firm. First, we define DIVDUM to be equal to one if the firm is paying dividends (annual *Compustat* data item # 21) and zero otherwise. We predict a positive coefficient on DIVDUM, consistent with firms continuing to pay dividends while incurring losses signaling their expectation the loss sequence will be brief.[8] Second, we include DIVSTOP, an indicator variable equal to one if a firm stops paying dividends in the current year and zero otherwise. Based on the results of Healy and Palepu (1986) and DeAngelo et al. (1992), we predict the coefficient on DIVSTOP will be negative.

Table 3 presents descriptive statistics for the variables included in the logistic regression. Panel A shows a first loss is significantly associated with loss reversal: when the current loss is the first in a sequence (i.e., FIRSTLOSS = 1) 44.65% of losses reverse compared to 25.19% when the current loss occurs after a previous loss (the χ^2-statistic for the difference in the reversals is also highly significant). Panel A further shows DIVDUM significantly relates to the probability of loss reversal (p-value of χ^2-statistic is 0.001). Consistent with our expectation, the probability of loss reversal for a firm paying dividends is 53.72% compared to 28.70% for firms not paying dividends. We also find a relatively small number of sample firms eliminate their dividends in the same year as the loss (776 out of 18,274 or 4.24%), with no statistically significant difference in the probability of reversal between them and other loss firms.[9]

Panel B provides descriptive statistics for the continuous and ordinal variables used in the model. We present statistics for the full sample of observations and for two samples based on the *ex post* observed loss reversal. In general the pattern of the variables suggests that, consistent with expectations, firms with reversing losses experience better (less negative) profitability, are larger, and have shorter loss sequences than firms whose losses do not reverse the next year. The

[8] Joos and Plesko (2004) investigate the dividend signaling hypothesis in a sample of loss firms and find that dividend increases by loss firms with negative cash flows constitute a strong signal of future performance improvements.
[9] The percentage is less than the 15 percent DeAngelo et al. (1992) report; however, they condition their sample on identifying dividend paying firms first, a restriction we do not impose.

exceptions are median ACC and mean SALESGROWTH for which we find no difference between our persistent and transitory loss samples.

Table 4 reports the results and analysis of equation (1) computed using the Fama-MacBeth procedure (1973).[10] Panel A of the Table reports two specifications of equation (1). In the first column (Specification I), we include ROA and PAST_ROA as profitability variables; in the second (II), we decompose ROA into its cash flow and accrual components. We observe for specification I that all variables, except PAST_ROA and SALESGROWTH, have significant coefficients in the predicted direction. Firms with relatively higher current profitability, firms reporting a first loss or having a shorter loss sequence, larger firms, dividend paying firms, and firms that do not stop paying dividends, all exhibit a higher probability of loss reversal. In unreported analysis, we find that PAST_ROA becomes highly significant when we exclude the loss history variables. In other words, the (binary) FIRSTLOSS and (ordinal) LOSS_SEQ variables appear to capture the information contained in the (continuous) PAST_ROA variable.

The results for specification II are very similar to those for specification I. The key difference is that both contemporaneous CFO and ACC have significantly positive coefficients; also the coefficient on SALESGROWTH is now also significant. As in specification I, the coefficients for the variables capturing past performance are not significant when loss history variables are included. Panel A also shows that the within-sample performance of both specifications is very similar, although the sample sizes are different: the average *p*-value of the likelihood ratio statistic of the models is 0.001 and both models produce the same percentage of concordant pair classifications.

[10] Note that in Table 3 we present the descriptive statistics for the sample pooled over time. In Table 4 we present averages of coefficients based on annual estimations of the models. The reported sample size in the panel A of Table 4 therefore represents an *average* sample size.

Using the annual estimated coefficients from Table 4, we compute predicted probabilities of loss reversal from each specification. Specifically, we average the annual equation (1) coefficients over consecutive five-year panels to compute predicted reversal probabilities. We follow this methodology to mimic the process we assume investors use to assess *ex ante* loss reversal probabilities, and assume investors consider a number of years of information to assess the predicted probabilities in any given year. As an example, we average the annual coefficients of 1976 through 1980 to obtain predicted reversal probabilities for losses occurring in 1981. Using this methodology, we ensure that we use only information available at the time of the analysis to estimate the reversal probabilities. That is, we use information about the reversal of losses occurring in 1976 through 1980 to obtain *ex ante* estimates of the probability of reversal of losses occurring in 1981. As before, we repeat this procedure using successive panels of data, each time dropping the oldest year and adding a new year, until we reach the end of the sample period.

Using the annual quartiles of the distribution of the predicted reversal probabilities, we classify the loss observations into samples of persistent and transitory losses. We define persistent (transitory) losses as those with probabilities in the first (fourth) quartile of the distribution: persistent losses are those least likely to reverse and transitory losses are those most likely to reverse.[11] Table 5 presents descriptive information on the predicted reversal probabilities of the models reported in Table 4 for the samples of persistent and transitory losses. Panel A shows that the models provide a sharp contrast between persistent and transitory losses:

[11] In contrast to Chambers (1996) who relies on perfect foresight of both the number and magnitude of incurred losses to construct his measure of persistence for first-time losses, our *ex ante* estimates use contemporaneously available information.

persistent losses have an estimated reversal probability of about 15%, while transitory losses exhibit a reversal probability of slightly more than 50%, regardless of specification.[12]

Panel B presents evidence on the time-series trend of the average annual reversal probability over the sample period. The panel reports the coefficients and *t*-statistics of regressions of average annual reversal probabilities on year-indicator variables. We find that, whereas the average predicted reversal probability decreases in the persistent loss sample over the sample period, the average reversal probability remains unchanged in the transitory group. In unreported analysis, we examine the time-series properties of the coefficients in the model and observe that most coefficients in specifications I and II remain unchanged over the sample period. The only significant changes are an increase in the coefficient on DIVDUM and a decrease in the coefficient on SALESGROWTH. That is, the signaling value of dividend payments for loss firms increases over the sample period (see also Joos and Plesko 2004 and Skinner 2004). By contrast, the effect of an increase in sales growth on the predicted probability of reversal decreases over the sample period.

In panel C, we evaluate the *out-of-sample* classification accuracy of the specifications. We verify the classification accuracy of the predicted reversal probabilities using the *ex post* sample proportion of reversals as a benchmark. For example, to verify the accuracy of the predicted probabilities of losses occurring in 1981, we use the proportion of 1981 losses that actually reverse in 1982 as the benchmark for the predicted reversal probabilities to classify losses into a reversal and non-reversal group. Specification I of the model correctly classifies

[12] We carry out all analyses in the full sample of loss observations as well and find the results in the full sample reflect an average of the results in the persistent and transitory sample. For example, in the full sample the mean (median) predicted reversal probability is 0.337 (0.337) using specification I and 0.344 (0.338) using specification II.

on average 83% (median=83%) of observations in the persistent sample, and 51% (median=52%) in the transitory sample. The results for specification II are similar, albeit lower. Given the similar performance of both specifications of equation (1), we report results based on specification I in the remainder of the paper, since it is the more parsimonious model of the two and allows us to work with larger sample sizes.[13]

Overall, Table 5 shows the reversal models allow us to define two groups of loss observations that exhibit distinct patterns of reversal probabilities over the sample period. We see in particular that persistent losses become more persistent over time. This pattern, together with the observed increase in loss frequency shown in Figure 1 and Table 1 suggest the nature of losses changes over our sample period.

IV. The Valuation of Losses: Earnings Response Coefficients

The results of the previous section show that a parsimonious model can assess the persistence of a firm's loss. In this section we test whether investors price losses as a function of their expected persistence. Our pricing analysis extends the work of Hayn (1995) who considers the role of the abandonment option for the value-implications of losses. In her analysis, Hayn (1995) uses two proxies for the future prospects of the firm (bond ratings and a liquidation value) to test how the option affects valuations and concludes the market reaction to a loss is greater when abandonment is less likely. Our model of loss reversal captures a particular way for

[13] We re-estimated all the analyses using the coefficients from specification II of equation (1) and found the results to be qualitatively similar.

investors to structure financial information to assess the persistence of a loss, or alternatively the likelihood of abandoning their investment in the firm.[14]

To explore the pricing of losses, we estimate ERCs in the persistent and transitory loss samples using the following regression (see also Hayn 1995):

$$RET_t = \alpha + \beta IB_t + \varepsilon_t \tag{2}$$

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-1*, ε_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). As a reminder, we predict that, if the persistent loss group consists of observations with a high likelihood of exercising the abandonment option, then the ERC in this group will be insignificantly different from zero; if the transitory loss group consists of observations with a low likelihood of exercising the abandonment option, then the ERC in this group will be positive and significantly different from zero.

Table 6 presents the results of the ERC analysis. Panel A shows all means and medians of IB are negative (by construction), and both mean and median IB are more negative in the persistent loss sample than in the transitory loss sample. Means are also more negative than their corresponding medians in both samples, suggesting the presence of influential observations in each group. Panel A also shows returns (RET) follow a pattern different from IB across the

[14] A number of other studies, such as 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.

samples: surprisingly mean annual returns are *positive* in the persistent loss sample (0.193), but negative in the transitory sample (-0.050). However, median returns of persistent loss firms are more negative than median returns of transitory losses (-0.196 versus -0.162), consistent with extreme observations influencing the return distributions.

Panel B reports the results of the Fama-Macbeth estimations of the ERCs. We estimate equation (2) using both the raw IB and RET data and the ranks of observations to avoid the potential influence of the extreme IB and RET observations in the sample. Focusing on the raw data results, we find a *negative* and statistically significant ERC in the persistent sample; by contrast, the ERC in the transitory sample is positive and significant (at the 10% level), as predicted. These findings are consistent with the patterns of the means of IB and RET in panel A: *on average* earnings and returns have opposite signs in the persistent sample but the same sign in the transitory sample. The intercepts in the different samples reflect the sign of average returns in each sample, but are never significant.

The results of the rank regressions show that extreme observations influence the pattern of ERCs. In the persistent sample the rank ERC is insignificant, suggesting that while investors price losses (i.e., median returns are negative) they impose no additional penalty on the magnitude of reported persistent losses. The result is consistent with our prediction that if persistent losses signal that exercising of the abandonment option is likely, investors will not price earnings. In the transitory sample, the result becomes stronger when we use ranks: the ERC is positive and highly significant, consistent with earnings and returns reflecting the same information about the performance of the firm (i.e., the larger the loss, the more negative the return).

In Panel C we test the annual ERCs for a time-series trend over the sample period. We report the results using the rank data since panel B reveals extreme observations (for returns especially) influence the estimations.[15] Panel C shows that only the ERCs in the persistent sample decrease over time; in the transitory sample annual ERCs exhibit no change over the sample period. We verify (in untabulated analysis) that the annual ERC in the persistent sample becomes negative and statistically different from zero (-0.096, *t*-stat=-2.723) during the last 10 years of the sample period (i.e., the 1990s).[16] In other words, during the 1990s, earnings and returns started to reflect the performance of persistent loss firms differently, a pattern we do not observe in the transitory loss subsample.

Summarizing, the ERC results show market returns reflect the information in transitory losses. The result is consistent with our prediction and corroborates Hayn's (1995) argument for finding a more pronounced pricing effect of a loss when investors are least likely to consider the abandonment option, or in our case, when we estimate the loss to be transitory. By contrast, we find evidence consistent with the market not responding to the magnitude of persistent losses, as predicted, or even responding negatively to them in the latter part of the sample period. Finally, the time-series evidence shows the market response to persistent, but not to transitory losses has changed over the sample period. While the non-response to persistent losses is consistent with our prediction, the negative response in the latter part of the sample period warrants further investigation.

[15] When we use the ERCs based on the raw data, we obtain qualitatively similar results.
[16] We find a similar result when we estimate ERCs using the raw data instead of the ranks.

V. Earnings Response Coefficients: Additional Analyses

To better understand the pattern of ERCs as a function of the *ex ante* reversal probability of current losses, we carry out additional analyses of the characteristics and pricing of the different types of losses. Following Givoly and Hayn (2000) who find large negative accruals but not cash flows drive the decline in firm profitability in recent years, we focus first on a decomposition of the losses into cash flows and accruals. In other words, we extend Givoly and Hayn's research by relating the cash flow and accruals composition of losses to investors' differential pricing of persistent and transitory losses.

In panel A of Table 7 we provide descriptive statistics for the CFO and ACC components of losses as a function of the *ex ante* loss reversal probability.[17] The panel shows a correspondence between the type of loss and its relative magnitude of cash flow and accruals components. Persistent losses exhibit significantly more negative average and median values for both components relative to transitory losses. Also, in the persistent sample *both* CFO and ACC are negative, with the magnitude of the negative CFO component being larger. By contrast, in the transitory loss sample mean and median CFO are positive, and only the mean and median accruals component is negative.

The result that persistent losses contain a relatively larger negative CFO component is not surprising given Sloan's (1996) finding that the cash flow component of earnings is more persistent than the accruals component. However, Sloan's result does not explain why we find a non-significant or even a negative ERC in the latter part of sample period for persistent losses.

[17] As a reminder, we classify observations into the persistent and transitory samples based on the *ex ante* loss reversal probability from a model that uses information in aggregate ROA (i.e., specification I in Table 4), and not its components CFO and ACC. This eliminates the possibility that the results could follow mechanically from our initial classification method.

To address the issue, we study two specific components of earnings highlighted by previous research, namely R&D expenditures and Special Items. We focus on investments in intangibles, and on R&D in particular, since recent research finds the magnitude of R&D expenditures increases significantly over the past decades, influencing the properties of reported accounting measures (e.g., Amir and Lev 1996, Collins et al. 1997, Lev and Zarowin 1999). As US GAAP requires managers to expense R&D outlays when they occur, R&D potentially drives the negative cash flow components of persistent losses in Panel A.

Other recent studies prompt us to examine the influence of Special Items. Givoly and Hayn (2000, p. 305) discuss how Special Items related to restructurings and write-offs typically lower reported earnings through negative accruals. Skinner (2004) singles out the presence of Special Items in losses as a signal of their persistence: he argues Special Items reflect managers' accounting discretion more than other components of losses and therefore are more likely to generate transitory losses. Similarly, earlier work by Dechow (1994) shows Special Items have only a temporary effect on earnings and reduce the short-term ability of earnings to measure performance. Carter (2000) and Burgstahler et al. (2002) both conclude negative Special Items represent 'inter-period transfers' that lead to increased earnings in subsequent periods, with Carter (2000) showing the post-restructuring performance of firms being greater than the upward bias caused by the accelerated recognition of Special Item restructuring expenses.

Panel A of Table 7 provides descriptive statistics on the R&D and Special Items components of losses. We define R&D and Special Items (SPI) as annual *Compustat* data item #46 and data item #17, respectively, scaled by lagged total assets (annual *Compustat* data item #

6).[18] Note that we code our R&D variable to be negative such that R&D reflects cash outlays. We find significant differences in the relative magnitude of R&D and SPI between the samples: persistent loss observations have more R&D outlays, consistent with their cash flows on average being more negative; persistent loss observations also have more negative average SPI, potentially explaining their relatively larger negative accruals. The pattern of medians across samples further shows more than half of persistent losses contain an R&D component and that more than half of the transitory losses contain a *negative* SPI component. Relative to persistent losses, transitory losses therefore *more often* contain a negative SPI component, albeit a smaller one on average.

Panel B shows the change in annual medians of the components of losses over the sample period. In the persistent loss sample, the cash flow and R&D components become more negative over the period while the accruals component exhibits a small increase; the relative magnitude of the SPI component remains unchanged. By contrast, in the transitory loss sample, *only* the SPI component changes, i.e., it becomes more negative over the sample period, consistent with evidence in Skinner (2004). Note that we cannot estimate the time-series test for the R&D component in the transitory loss sample since its median is zero in every sample year.

Summarizing, the results in Table 7 highlight the different characteristics of persistent and transitory losses; in addition, the table indicates the properties of persistent and transitory losses have changed over time. Overall, the evidence shows a relatively larger negative CFO and R&D component for persistent losses and the more frequent presence of SPIs in transitory losses. We next study the valuation implications of the different and changing properties of persistent and transitory losses by estimating two rank-regressions:

[18] We repeat the analysis with R&D and Special Items scaled by sales and find qualitatively similar results.

$$RET_t = \alpha + \beta CFO_t + \gamma ACC_t + \varepsilon_t \qquad (3)$$

$$RET_t = \alpha + \beta OTHIB_t + \gamma R\&D_t + \delta SPI_t + \varepsilon_t \qquad (4)$$

To remain consistent with the specification of IB in equation (2) we measure CFO, ACC, R&D, and SPI per share and scale the per share variables by lagged price per share in equations (3) and (4). We define OTHIB as (IB-R&D-SPI) such that OTHIB captures components of earnings other than R&D or SPI. As before, we estimate equations (3) and (4) using the Fama-Macbeth (1973) methodology.

The results in Panel A of Table 8 are consistent with investors pricing CFO and ACC differently conditional on whether the loss is estimated to be persistent or transitory.[19] We find investors price only the accruals component of persistent losses suggesting market returns reflect the information in the negative accruals component of persistent losses, but not the information in cash flows, despite our earlier evidence of a large presence of negative cash flows in persistent losses. We elaborate on this result below when we focus on the pricing of R&D and SPI. In contrast to what we find for persistent losses, we observe investors price only the cash flow component of transitory losses. This result is consistent with investors identifying the negative accruals to be transitory and therefore not pricing them. Panel A further shows the response coefficients of CFO decrease in both samples over time, whereas the market's pricing of the accruals component of losses does not change.

Panel B presents evidence on the pricing of the R&D and SPI components of losses. The panel shows that in the persistent loss sample the coefficients on OTHIB and SPI are positive and significant (for OTHIB at the 10% level). In addition, investors also appear to price the

[19] Untabulated analysis shows the differences between the coefficients on CFO and ACC are highly significant in the persistent loss sample (*t*-statistics of 3.275).

R&D component of persistent losses *negatively*. The panel further shows the response coefficients on OTHIB and R&D decrease over time in the persistent sample. In other words, over time investors value the OTHIB component of persistent losses *less* (i.e., the positive coefficient on OTHIB becomes smaller) and value the R&D component of persistent losses more (i.e., the negative coefficient on R&D become more negative) over time.[20] Different from the results for persistent losses, the results for transitory losses show positive and significant coefficients on OTHIB and SPI, but the coefficient on R&D is statistically indistinguishable from zero. In addition, the time-series evidence indicates the response coefficients for the transitory loss components do not change over the sample period.

Focusing on R&D, the results indicate investors price the R&D component of persistent and transitory losses differently. Given our coding of the R&D variable, the negative response coefficient on R&D for persistent losses is consistent with larger R&D investments corresponding to larger positive returns. Since we find in panel A of Table 8 that the response coefficient of *aggregate* CFO in the persistent loss sample is zero, the result in panel B implies that investors look beyond aggregate cash flows and aggregate earnings when pricing *ex ante* persistent losses. The finding of a increasingly negative coefficient on the R&D component of persistent losses potentially explains the negative ERC in panel B of Table 6 for the persistent loss sample or, as discussed, in the rank regressions for the 1990s. As the R&D component of persistent losses becomes larger, it influences the pricing of persistent losses more heavily, leading to negative ERCs in this sample of loss observations. The presence of a growing R&D

[20] We find (in untabulated analysis) that the decrease in the negative response coefficient on R&D is most pronounced during the 1990s (average coefficient = -0.110, *t*-statistic=-2.333) when we also observed the largest decrease in response coefficient on ERC.

component in persistent losses and its pricing also imply persistent losses become a weaker indicator of the likelihood of exercising the abandonment option.

The insignificant coefficient on R&D in the transitory loss sample contrasts with the result in the persistent loss sample. One interpretation of this difference follows from the characteristics and importance of R&D for firm value differing across loss groups. Specifically, the increasing R&D investments represent one of the key assets of persistent loss firms (see panel A in Table 7: mean (median) of 18% (5%) of firm assets). We conjecture the other components of the loss do not reflect the implications of this key asset for firm value. Therefore, the R&D component *per se* carries important information incremental to the other components of the loss and investors price persistent losses as if they are able to separately assess the effect on firm value of R&D investments. By contrast, for transitory losses, the results are consistent with other components of the loss reflecting the effect of (relatively small) R&D outlays on firm value. R&D investments reveal no information to investors *incremental* to the information in the other components of losses, potentially because investors are unable to separate out the effects on firm value of the R&D investments. Our aggregate R&D data, however, do not allow us to provide conclusive evidence on why investors price the R&D component of persistent and transitory losses differently, a question we leave for future research to address.

Focusing on the SPI component, investors pricing SPI positively in both samples appears at odds with findings in Burgstahler et al. (2002) that (negative) Special Items are predominantly transitory and that the market accordingly does not price them. In addition, since SPI predominantly consist of accruals, the positive coefficient on SPI in the transitory sample is at odds with our finding in panel A of Table 8 that investors do not price the accruals component in the transitory loss sample. One potential explanation for the result is that our analysis does not evaluate the pricing of SPI or R&D conditional on the firm reporting non-zero SPI and R&D as previous research has done (e.g., Burgstahler et al. 2002). The zero medians for SPI and R&D in the persistent and transitory loss samples, respectively, in panel A of Table 7 indicate a large number of observations report zero SPI or R&D.[21] To evaluate the pricing of SPI and R&D conditional on the firm reporting non-zero amounts, we carry out additional analyses in samples limited to firms with non-zero SPI and R&D components.[22]

Using only firms with non-zero R&D or SPI components, we find (in untabulated analyses) that the results in the persistent loss sample remain qualitatively unchanged. By contrast, in the transitory loss sample, *only* the coefficient on OTHIB remains significantly different from zero. That is, in contrast to the results in panel B, we find investors do *not* price the SPI component of transitory losses in this sample of firms. Assuming the SPI component of transitory losses represents transitory accruals, the market's non-response to negative SPI is consistent with the findings in Burgstahler et al. (2002) and in panel A of Table 7 that investors do not value the accruals in the transitory loss sample. The results again support our previous conclusion that investors look beyond aggregate earnings when they price (transitory) losses. However, the focus on non-zero SPI observations alone does not help to explain why investors value the SPI component in the persistent loss sample. We conjecture that a different composition of SPI potentially causes the difference between both samples (e.g., restructuring expenses versus other components of special items) and leave the study of this issue for future research.

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[21] Untabulated analysis shows 49.02% (36.79%) of persistent loss observations have a zero SPI (R&D) component; the corresponding numbers are 35.71% (60.51%) for the transitory loss sample.

[22] In unreported analysis, we verify all earlier descriptive evidence in this smaller sample with only non-zero R&D and SPI observations. We confirm that all observed patterns remain qualitatively unchanged. For example, we still observe a large discrepancy between mean and median return and earnings in the samples. Also the relative magnitude of the components in the different samples remains qualitatively unaltered in this smaller sample.

Summarizing, we observe (changing) differences in the characteristics of persistent and transitory losses. We also observe investors pricing the components of persistent and transitory losses differently. While our decomposition analysis is unable to fully explain all observed pricing differences, the results suggest future research using a refinement of our decomposition analysis could potentially reveal more precisely how the market prices expected persistent and transitory losses. At the very least, our evidence is consistent with three generic observations: 1) investors look beyond aggregate earnings and aggregate cash flows and accruals when valuing loss observations; 2) investors value certain loss components differently over the sample period, consistent with the properties of losses changing over time; 3) the presence of a growing R&D component in persistent losses implies persistent losses become a weaker indicator of the likelihood of exercising the abandonment option.

VI. Concluding Remarks

Building on Hayn (1995) we hypothesize that investors value a loss differently as a function of the expected likelihood of exercising the abandonment option. We predict that, 1) if investors believe the occurrence of the loss implies a high likelihood of exercising the abandonment option its earnings response coefficient will be insignificantly different from zero, and 2) if they believe the loss implies a low likelihood of exercising the abandonment option, then its earnings response coefficient will be positive and significantly different from zero. We develop a proxy for the likelihood of exercising the abandonment option based on a model of loss reversal, with the probability of reversal inversely related to the likelihood of exercising the abandonment option. We show a parsimonious model of one year-ahead loss reversal using information on the financial profile of the firm, its loss sequence, and its dividend policy is useful in predicting the firm's return to profitability. Using the estimated probabilities of loss reversal to define samples of persistent (i.e., losses with a low reversal probability) and transitory (i.e., with a high reversal probability) losses, we show the pricing of different types of losses varies as a function of their expected probability of reversal. Specifically, the results show market returns reflect the information in transitory losses, consistent with our prediction. By contrast, we find mixed evidence on the pricing of persistent losses. While some results point to the market not responding to the magnitude of persistent losses as predicted, other results are consistent with the market responding negatively, especially in the latter part of the sample period.

We further explore the pricing patterns by analyzing the components of persistent and transitory losses. We find large differences between the relative magnitude of cash and accruals, and R&D and Special Items components of persistent and transitory losses. In addition, we observe investors price these components differently as a function of the expected persistence of the losses. Focusing specifically on the components of persistent losses, we observe an increasingly large R&D component in persistent losses potentially explains their negative valuation: investors price the R&D component of persistent losses negatively, as if rewarding firms that make larger R&D outlays with larger returns. Additionally, the presence of a growing R&D component in persistent losses implies persistent losses become a weaker indicator of the likelihood of exercising the abandonment option.

Our findings emphasize the role of financial statement analysis to assess the exact nature of losses to establish their valuation effects. While the decomposition analysis in the study allows us to explain certain differences in valuation between persistent and transitory losses, we are unable to fully interpret all observed pricing differences. Future research can focus on refinements of our decomposition analysis to evaluate more precisely how the market prices persistent and transitory losses, especially since our results are consistent with investors looking beyond aggregate earnings and aggregate cash flows and accruals when valuing loss observations.

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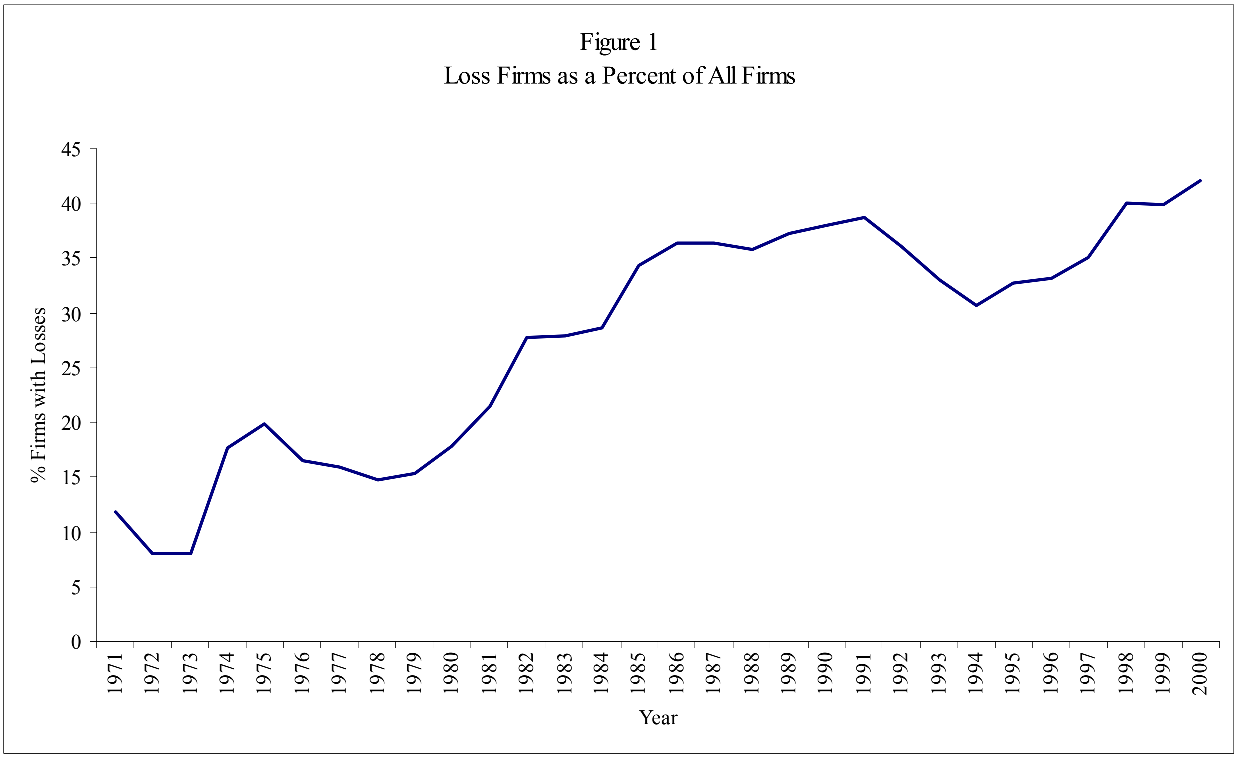

Figure 1 is based on data collected from *Compustat*'s Industrial and Research Annual Data Bases and cover the period 1971-2000. The figure represents the percentage of each year's observations in the sample reporting negative income (losses) where we define negative income as income (loss) before extra-ordinary items and discontinued operations (annual *Compustat* data item #18).

Table 1: Frequency of Losses

Panel A: 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 B: 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 are collected from *Compustat*'s Industrial and Research Annual Data Bases and cover 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

Length of 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[b]

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 are collected from *Compustat*'s Industrial and Research Annual Data Bases and cover 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] *Loss sequence* refers to an uninterrupted sequence of annual losses. *Reversal* indicates the loss firm becomes profitable.

Table 3: Logistic Regression Model of Loss Reversal: Descriptive Statistics[a]

Panel A: Indicator Variables[b]

Variable	*Value*	*Obs.*	*Reversal (%)*	*χ^2 p-value*
FIRSTLOSS	0	11,253	25.19	.000
	1	7,021	44.65	
DIVDUM	0	15,374	28.70	.000
	1	2,900	53.72	
DIVSTOP	0	17,486	32.57	.196
	1	776	34.79	

Panel B: Continuous and Ordinal Variables[c]

Variable[d]	Sample	*Obs.*	*Mean*	*Std. Dev.*	*Median*
ROA	Full Sample	18,192	-0.206	0.466	-0.082
	No Reversal	11,562	-0.259	0.540	-0.116
	Reversal	5,966	-0.097***	0.215	-0.044***
PAST_ROA	Full Sample	17,162	-0.439	1.231	-0.045
	No Reversal	11,562	-0.615	1.405	-0.138
	Reversal	5,600	-0.076***	0.607	0.058***
CFO	Full Sample	16,627	-0.682	4.967	-0.029
	No Reversal	11,265	-0.988	6.035	-0.055
	Reversal	5,362	-0.039*	0.578	0.008***
ACC	Full Sample	16,627	-0.130	4.258	-0.074
	No Reversal	11,265	-0.155	5.166	-0.074
	Reversal	5,362	-0.078*	0.305	-0.074
PAST_CFO	Full Sample	14,416	-0.197	1.156	0.097
	No Reversal	9,547	-0.355	1.333	0.023
	Reversal	4,869	0.113***	0.571	0.198***
PAST_ACC	Full Sample	14,416	-0.206	0.467	-0.191
	No Reversal	9,547	-0.219	0.524	-0.197
	Reversal	4,869	-0.182***	0.327	0.179***
SIZE	Full Sample	18,026	3.218	1.897	3.055
	No Reversal	12,133	3.058	1.804	2.923
	Reversal	5,893	3.550***	2.031	3.348***

Panel C: Continuous and Ordinal Variables[c] (continued)

Variable[d]	Sample	*Obs.*	*Mean*	*Std. Dev.*	*Median*
SALESGROWTH	Full Sample	17,868	0.613	3.311	-0.021
	No Reversal	11,940	0.456	9.179	-0.031
	Reversal	6,399	0.930	5.600	-0.004***
LOSS_SEQ	Full Sample	18,274	2.440	1.754	2.000
	No Reversal	12,304	2.763	1.753	3.000
	Reversal	5,970	1.775***	1.560	1.000***

[a] The data are collected from *Compustat*'s Industrial and Research Annual Data Bases and cover 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] *FIRSTLOSS* is an indicator variable equal to one if the current year's loss is the first in a sequence (i.e., the firm was profitable last year) 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.

[c] *ROA* is return-on-assets and calculated as income before extra-ordinary items (annual *Compustat* data item # 18) scaled by lagged total assets (annual *Compustat* data item # 6). PAST_ROA is average ROA over the past five years (i.e., *t-5* through *t-1*); CFO is cash flow from operations scaled by lagged total assets, where CFO is net income (annual *Compustat* data item # 172) – accruals ACC; ACC is (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), scaled by lagged total assets. PAST_CFO and PAST_ACC are average CFO and ACC over the past five years (i.e., *t-5* through *t-1*); SIZE is log of current market value (annual *Compustat* data item # 199 * annual *Compustat* data item # 25). SALESGROWTH is percentage growth in sales (annual *Compustat* data item # 12) over the current year; LOSS_SEQ is an ordinal variable that counts the number of sequential losses over the past five years before the current loss.

[d] ***, **, * indicate the difference between the No Reversal and Reversal subsample means or medians is significant at the 1%, 5%, or 10% level.

Table 4: Logistic regression models of loss reversal[a]

Variable	Predicted Sign	Specification I	Specification II
ROA	+	2.321	---
		(8.331)	
PAST_ROA	+	0.166	---
		(0.730)	
CFO	+	---	1.284
			(5.130)
ACC	+	---	1.283
			(3.453)
PAST_CFO	+	---	0.174
			(1.102)
PAST_ACC	+	---	-0.189
			(1.222)
SIZE	+	0.074	0.069
		(3.258)	(3.149)
SALESGROWTH	?	0.126	0.217
		(1.058)	(2.156)
FIRSTLOSS	+	0.125	0.124
		(1.866)	(1.874)
LOSS_SEQ	-	-0.128	-0.183
		(3.493)	(4.668)
DIVDUM	+	0.280	0.287
		(4.044)	(3.623)
DIVSTOP	-	-0.251	-0.195
		(2.218)	(1.906)
Average Number of Annual Observations		662	556
Average LR *p*-value		0.001	0.001
Average % Concordance		69%	69%

[a] The table presents the results of the annual estimation of logistic regressions where the dependent variable that takes the value of one when the firm becomes profitable one-year into the future, and zero otherwise. Definitions of the variable are provided in the notes to Table 3. Reported coefficients are the *average* coefficient over the estimation period (1971 – 2000) and associated *t*-statistic derived using the Fama-Macbeth (1973) procedure. The table further reports the average number of observations used in

the estimations, the average *p*-value of the Likelihood Ratio Statistic (LR) of the models and the average % concordant pairs, i.e., the within-sample percentage of observations correctly classified by the model.

Table 5: Predicted Reversal Probabilities: Descriptive Statistics

Panel A: Predicted Reversal Probabilities[a]

Sample[b]		Specification I	Specification II
Persistent	No. Obs.	3,796	3,135
	Mean	0.148	0.166
	Median	0.151	0.172
	St. Dev.	0.086	0.085
Transitory	No. Obs.	3,784	3,121
	Mean	0.530	0.538
	Median	0.517	0.519
	St. Dev.	0.074	0.086

Panel B: Time-series evidence: Predicted Reversal Trend[c]

Sample[b]	Specification I Coeff. (*t*-stat)	Specification II Coeff. (*t*-stat)
Persistent	-0.013	-0.012
	(-20.161)	(-21.271)
Transitory	-0.000	-0.001
	(-0.100)	(-0.302)

Panel C: Out-of-Sample Classification Accuracy[d]

Sample[b]	Specification I Mean (Median)	Specification II Mean (Median)
Persistent	83%	82%
	(83%)	(81%)
Transitory	51%	49%
	(52%)	(51%)

[a] Panel A shows the predicted probabilities of loss reversal using the models estimated in Table 4. We average the annual equation (1) coefficients over consecutive five-year panels to compute predicted reversal probabilities. As an example, we average the coefficients of the annual coefficients of 1976 through 1980 to obtain predicted reversal probabilities for losses occurring in 1981. We repeat this procedure using successive panels of data, each time dropping the oldest year and adding a new year, until we reach the end of the sample period.

[b] We define two samples of losses based on the distribution of the predicted reversal probabilities. We sort the loss observations annually into quartiles based on their estimated probability of reversal and define persistent (transitory) losses as those with probabilities in the first (fourth) quartile of the distribution: persistent losses are therefore those least likely to reverse, and transitory losses those most likely to reverse.

[c] Panel B of the table shows the coefficients and associated *t*-statistics of a regression of annual median predicted reversal probability on year-indicator variables.
[d] Panel C reports the results of a test of the classification accuracy of the predicted reversal probabilities *out-of-sample*. We use the *ex post* sample proportion of reversals versus non-reversals as a benchmark. .

Table 6: Earnings Response Coefficient Analysis[a]

Panel A: Descriptive Statistics[b]

Variable	Sample[c]	No. Obs.	Mean	St. Dev.	Median
IB	Persistent	3,796	-0.371	0.402	-0.225
	Transitory	3,784	-0.087***	0.133	-0.048***
RET	Persistent	3,796	0.193	1.401	-0.196
	Transitory	3,784	-0.050***	0.646	-0.162**

Panel B: Earnings Response Coefficients[d]

		Raw Data			Rank Regression	
Sample[c]	Average No. Obs.	Intcpt (*t-stat*)	ERC (*t-stat*)	Adj. R^2	ERC (*t-stat*)	Adj. R^2
Persistent	188	0.080	-0.181	0.006	-0.017	0.007
		(0.656)	(2.793)		(0.491)	
Transitory	187	-0.037	0.166	0.007	0.081	0.004
		(0.938)	(1.672)		(3.773)	

Panel C: Rank Regression: Coefficient Time-series Evidence[e]

Sample[c]	Coefficient	*t*-statistic
Persistent	-0.017	-2.892
Transitory	-0.005	-1.071

[a] The data are collected from *Compustat*'s Industrial and Research Annual Data Bases and cover 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 shows descriptive statistics of the variables included in the ERC regressions. 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-1*. ***, **, * indicate the difference between the persistent and transitory sample means or medians is significant at the 1%, 5%, or 10% level.

[c] We define two samples of losses based on the distribution of the predicted reversal probabilities. We sort the loss observations annually into quartiles based on their estimated probability of reversal and define persistent (transitory) losses as those with probabilities in the first (fourth) quartile of the distribution: persistent losses are therefore those least likely to reverse, and transitory losses those most likely to reverse.

[d] Panel B reports the results of the estimation of the following regression:

$$RET_t = \alpha + \beta IB_t + \varepsilon_t \qquad (2).$$

We estimate equation (2) in each year of the sample period and assess the significance of the ERCs using the Fama-Macbeth procedure (1973). The panel shows the results of the estimation of equation (2) using the raw data and using rank data.

[e] Panel C shows the coefficient and associated *t*-statistics of regressions of the annual ERCs obtained using rank regressions (see Panel B) on year-indicator variables.

Table 7: Additional results: Loss Components[a]

Panel A: Descriptive Statistics

Variable[b]	Sample[c]	No. Obs.	Mean	St. Dev.	Median
CFO	Persistent	3,683	-0.426	0.762	-0.266
	Transitory	3,322	0.012***	0.139	0.022***
ACC	Persistent	3,683	-0.106	0.438	-0.102
	Transitory	3,322	-0.055***	0.130	-0.060***
R&D	Persistent	3,675	-0.182	0.336	-0.052
	Transitory	3,573	-0.029***	0.065	0.000***
SPI	Persistent	3,670	-0.061	0.205	0.000
	Transitory	3,503	-0.035***	0.061	-0.008***

Panel B: Time-series Evidence on Loss Components[d]

Sample[c]	CFO Coeff. (*t*-stat)	ACC Coeff. (*t*-stat)	R&D Coeff. (*t*-stat)	SPI Coeff. (*t*-stat)
Persistent	-0.030	0.001	-0.012	-0.000
	(-12.613)	(1.982)	(-8.693)	(-0.250)
Transitory	-0.000	-0.000	N/A	-0.001
	(-0.742)	(-0.632)		(-4.363)

[a] The data are collected from *Compustat*'s Industrial and Research Annual Data Bases and cover the period 1971-2000.
[b] Panel A shows descriptive statistics for the loss component variables. CFO is cash flow from operations or net income (annual *Compustat* data item # 172) – ACC; ACC is (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); R&D is annual *Compustat* data item #46; SPI is data item #17. All variables are scaled by lagged total assets (annual *Compustat* data item # 6).
***, **, * indicate the difference between the persistent and transitory sample means or medians is significant at the 1%, 5%, or 10% level.
[c] We define two samples of losses based on the distribution of the predicted reversal probabilities. We sort the loss observations annually into quartiles based on their estimated probability of reversal and define persistent (transitory) losses as those with probabilities in the first (fourth) quartile of the distribution: persistent losses are therefore those least likely to reverse, and transitory losses those most likely to reverse.
[d] Panel B of the table shows the coefficients and associated *t*-statistics of a regression of annual median loss components on year-indicator variables.

Table 8: Additional Results: Rank Regressions on Loss Components[a]

Panel A: Cash Flow and Accruals

Sample[e]	Response Coefficients[b]				Time-series Evidence[d]	
	Average No. Obs.	Cash Flows Coeff. (*t*-stat)	Accruals Coeff. (*t*-stat)	Adj. R^2	Cash Flows Coeff. (*t*-stat)	Accruals Coeff. (*t*-stat)
Persistent	195	-0.056	0.080	0.019	-0.023	-0.005
		(-1.310)	(3.206)		(-3.382)	(-1.043)
Transitory	175	0.137	0.038	0.023	-0.017	-0.011
		(4.265)	(0.908)		(-3.463)	(-1.374)

Panel B: Earnings, R&D, and SPI[c]

Sample[e]	Response Coefficients[c]					Time-series Evidence[d]		
	Average No. Obs.	OTHIB Coeff. (*t*-stat)	R&D Coeff. (*t*-stat)	SPI Coeff. (*t*-stat)	Adj. R^2	OTHIB Coeff. (*t*-stat)	R&D Coeff. (*t*-stat)	SPI Coeff. (*t*-stat)
Persistent	186	0.053	-0.067	0.119	0.022	-0.011	-0.014	-0.004
		(1.747)	(-1.938)	(5.407)		(-2.002)	(-2.323)	(-1.012)
Transitory	174	0.176	0.012	0.063	0.027	0.000	-0.010	-0.000
		(5.387)	(0.351)	(2.925)		(0.021)	(-1.503)	(-0.071)

[a] The data are collected from *Compustat*'s Industrial and Research Annual Data Bases and cover the period 1971-2000[b] We obtain the response coefficients in Panel A by estimating the following regression:

$$RET_t = \alpha + \beta\, CFO_t + \gamma\, ACC_t + \varepsilon_t \qquad (3)$$

where we define RET as before; we measure CFO and ACC per share and scale them by share price (annual *Compustat* data item #199) at the end of year *t-1*. We estimate equation (3) in each year of the sample period using the ranks of the observations and assess the significance of the ERCs using the Fama-Macbeth procedure (1973).

[c] We obtain the response coefficients in Panel B by estimating the following regression:

$$RET_t = \alpha + \beta\, OTHIB_t + \gamma\, R\&D_t + \delta\, SPI_t + \varepsilon_t \qquad (4)$$

where we define RET as before; OTHIB is (IB-R&D-SPI); we measure OTHIB, R&D, and SPI per share and scale them by share price (annual *Compustat* data item #199) at the end of year *t-1*. We estimate equation (4) in each year of the sample period using the ranks of the observations and assess the significance of the ERCs using the Fama-Macbeth procedure (1973).

[d] Each of the panels shows the coefficients and associated *t*-statistics of regressions of the annual response coefficients on year-indicator variables.

[e] We define two samples of losses based on the distribution of the predicted reversal probabilities. We sort the loss observations annually into quartiles based on their estimated probability of reversal and define persistent (transitory) losses as those with probabilities in the first (fourth) quartile of the distribution: persistent losses are therefore those least likely to reverse, and transitory losses those most likely to reverse.