

# The Effect of Cost-Elasticity Choice on Loss Reversal

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**ABSTRACT:** Although the prevalence of losses has been increasing over the years, little is known regarding managerial decisions resulting in reversing losses back to profits. We find cost-elasticity choices implied by operating actions made in advance significantly increase the likelihood of loss reversal. The results are robust to different estimation procedures and a battery of sensitivity analyses. The results are stronger for losses reported during an exogenous shock, the 2008 financial crisis, suggesting a causal effect. The contributions are twofold. First, we shed light on a mechanism underlying loss reversal. Particularly, we promote our understanding of how cost-elasticity choices made in advance affect the likelihood of loss reversal. Moreover, we demonstrate the likelihood of exercising the abandonment option is negatively and significantly related to cost elasticity. Second, the findings enrich the cost-accounting literature by demonstrating a meaningful implication of cost-elasticity choice.

**Keywords:** *cost elasticity; losses; loss reversal.*

# **The Effect of Cost-Elasticity Choice on Loss Reversal**

## **I. INTRODUCTION**

Prior research documents that reporting losses has significantly increased over time (e.g., Hayn 1995; Klein and Marquardt 2006; Gu, Lev, and Zhu 2023). However, the mechanism underlying loss reversal has received limited attention in the literature, and little is known regarding how managerial decisions help firms reverse losses back to profits. Joos and Plesko (2005) consider financial profile, past losses, and dividends in modeling loss reversal. Li (2011) modified Joos and Plesko's model by incorporating quarterly performance effects. Neither model incorporates information on firms' operating choices. Addressing this knowledge gap, this study explores the effect of cost-elasticity choices implied by operating actions on the likelihood of loss reversal.

We propose a loss-reversal prediction model utilizing cost-elasticity choices firms make before reporting losses. Our motivation to focus on cost functions derives from the neoclassical firm theory, suggesting cost functions mirror decisions on quantities and prices of resources and products (Kreps 2013). Firms with more elastic costs require lower sales revenue to break even than do firms with less elastic costs (Balakrishnan, Sivaramakrishnan, and Sprinkle 2013; Holzhacker, Krishnan, and Mahlendorf 2015b), resulting in a greater likelihood of reversing losses to profits. That is, we expect that firms with higher cost elasticity have a greater likelihood of reporting profits than firms with lower cost elasticity. Similarly, Aboody, Levi, and Weiss (2018) show low cost elasticity (i.e., high operating leverage) intensifies the downside potential of earnings. Accordingly, we hypothesize that cost elasticity is positively associated with loss reversal.

Testing the hypothesis, we use a sample of loss firm-year observations from 1992 to 2021. We utilize two estimates used in prior studies for estimating cost elasticity. Cost elasticity is the percentage change in costs divided by a percentage change in output quantity (Besanko and

Braeutigam 2020). The first cost-elasticity estimate employs changes in operating costs and sales revenue (e.g., Banker, Byzalov, and Plehn-Dujowich 2014; Holzhacker, Krishnan, and Mahlendorf 2015a, 2015b; Siciliano and Weiss 2023). The second cost-elasticity estimate utilizes a linear relation between levels of operating costs and sales revenue (e.g., Holzhacker et al. 2015a; Aboody et al. 2018). Kallapur and Eldenburg (2005, p. 745) refer to this estimate as “the ratio of variable to fixed costs”, which serves as a proxy for cost elasticity (Holzhacker et al. 2015a).

Applying a univariate analysis using the first estimate, we find the likelihood of loss reversal for high-cost-elasticity firms (above-median) is 34.66%, whereas the likelihood of loss reversal for low-cost-elasticity firms (below-median) is 22.50%. The difference, 12.16%, is highly significant ( $p\text{-value}<0.01$ ), suggesting a significant relation between cost elasticity and loss reversal. We find similar results when we apply the second cost-elasticity estimate. Furthermore, we use employee intensity as a crude proxy for labor cost elasticity set before incurring a loss, reflecting managerial decisions of hiring and firing employees (Holzhacker et al. 2015b). Firms with greater employee intensity are expected to be less sensitive to changes in revenue (Hall 2016). The evidence indicates a significantly greater likelihood of loss reversal in firms with low employee intensity (below-median) than in firms with high employee intensity (above-median). Again, the difference, 7.65%, is highly significant ( $p\text{-value}<0.01$ ) and further supports our hypothesis.

Next, we extend the multivariable regression model in Joos and Plesko (2005). We also control for an alternative explanation, financial leverage, because high financial leverage impedes loss reversal (Titman and Wessels 1998; Wald 1999). We find a positive and significant association between cost elasticity and loss reversal. The results from estimating the multivariable regression models are robust to different estimation procedures. Overall, the

results from the empirical evidence strongly support a positive and significant association between cost elasticity and loss reversal.

Notably, we further test the hypothesis for loss firms during the 2008 financial crisis because this exogenous shock allows for testing a potential causal effect (Armstrong, Kepler, Samuels, and Taylor 2022). As before, we find a positive and highly significant association between cost elasticity and loss reversal. Taken as a whole, the empirical evidence strongly supports our hypothesis and is consistent with a causal effect.

Gaining insights into future survival rate of firms after reversing losses, we find a positive and significant incremental five-year-ahead survival rate for high-cost-elasticity firms (above-median) compared with low-cost-elasticity firms (below-median). The results suggest a positive relation between cost elasticity and firms' survival rate, consistent with a long-lasting relation between cost elasticity and the survival of loss firms.

Integrating the cost-accounting concept of cost elasticity with loss reversal allows us to contribute to both the losses and cost-accounting stream of studies. First, the results highlight the association between cost-elasticity choices, implied by operating actions taken before incurring a loss, and the likelihood of loss reversal. Specifically, the results emphasize a mechanism underlying loss reversal by showing cost-elasticity choices have a significant and economically meaningful impact on the likelihood of reversing losses back to profits. Particularly, empirical evidence from an exogenous shock of the 2008 financial crisis suggests a causal effect of cost elasticity on loss reversal.

The evidence extends the literature on losses by adding a novel perspective to prior studies on loss-reversal prediction. Specifically, the findings extend Joos and Plesko (2005) and Li (2011) by focusing on cost-elasticity choices made by firms' management prior to experiencing a loss. Employing information on cost elasticity in loss firms is an innovative approach to

understanding how cost-elasticity decisions made prior to experiencing a loss influence the likelihood of loss reversal.

Similarly, the findings on five-year-ahead firm survival draw attention to the link between cost elasticity and the likelihood of exercising the abandonment option. Prior studies corroborate the abandonment option solidified by Hayn (1995): Pinnuck and Lillis (2007) and Lawrence, Sloan, and Sun (2018). Joos and Plesko (2005) show the likelihood of exercising the abandonment option is inversely related to loss reversal. Our findings expand these studies, suggesting the likelihood of exercising the abandonment option is negatively and significantly related to loss firms' cost-elasticity choices.

Second, the results extend the cost-accounting literature, which has demonstrated both costs and benefits of high cost elasticity. On one hand, Banker et al. (2014) report that to reduce congestion costs, firms choose low cost elasticity when uncertainty increases. They emphasize the disadvantage of high cost elasticity when high realizations of demand become more likely. In an early study, Lev (1974) reports that high cost elasticity (i.e., low operating leverage) decreases the overall and systematic risk of stocks, suggesting lower expected stock returns.

On the other hand, Aboody et al. (2018) report that managers facing a decrease in risk-taking incentives adjust cost elasticity upward because high cost elasticity alleviates the downside potential of earnings. Both Kallapur and Eldenburg (2005) and Holzhacker et al. (2015a) show firms increased cost elasticity to accommodate a regulatory change. Holzhacker et al. (2015b) report that firms increase cost elasticity in response to demand uncertainty (contrary to Banker et al. 2014). Recently, Siciliano and Weiss (2023) report that family-owned firms benefit from choosing high cost elasticity.

Our findings extend this stream of studies by highlighting the effect of cost-elasticity choices on the likelihood of loss reversal. Highlighting a cost-elasticity mechanism underlying the bounce-back from losses to profits, we conclude that the level of cost elasticity chosen by

loss firms matters in reversing losses back to profits. Moreover, the prediction model of reversing losses into profits will help researchers, investors, and financial analysts in expanding the understanding of loss reversal.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops the hypothesis. Section 3 lays out the research design and the data used in this study. Section 4 presents the empirical results. Section 5 offers robustness checks, and section 6 focuses on the exogenous shock of the 2008 financial crisis. Section 7 poses a further analysis of the effect of cost elasticity on survival rate. A summary is presented in the last section.

## **II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT**

### **Loss-Reversal Prediction Models**

The proportion of firms reporting losses has increased from 2% in the early 1950s to over 40% in recent years (Klein and Marquardt 2006; Darrough and Ye 2007; Gu et al. 2023), indicating the growing number of firms reporting losses is a long-lasting phenomenon.<sup>1</sup> Yet, little is known about the mechanism underlying managerial decisions supporting loss reversal back to profits because loss reversal has received limited attention in the literature. Joos and Plesko (2005) offer a loss-reversal prediction model, which includes variables related to the firm's business environment consisting of three categories: financial profile, past losses, and dividend behavior. Li (2011) modifies Joos and Plesko's loss-reversal model using forecasted future quarterly earnings instead of reported annual losses, because future earnings are expected to be more informative regarding loss reversal. Li incorporates additional variables beyond the ones used by Joos and Plesko to address forecasted earnings in future quarters. Neither model specification has addressed potential effects of operational choices on the

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<sup>1</sup> Balkrishna, Coultonb, and Taylor (2007) report about 40% of public firms in Australia report losses from 1993 to 2003.

likelihood of loss reversal. Later, Gu et al. (2023) reported that expensing investments in intangible assets, rather than capitalizing them, enhances the frequency of loss reports. They focus on a financial-reporting issue, not on the managerial choice to make these investments.

Overall, the stream of studies on loss reversal has not explored a potential mechanism underlying the reversal of losses back to profits. Addressing this knowledge gap, we explore the link between cost-elasticity choices made in advance by loss firms and the likelihood of reversing a loss back into profit.

### **Cost Elasticity as a Manifestation of Operating Actions**

A cost function is a manifestation of a management's operational choices, because cost functions mirror production functions, reflecting choices of both the quantities of resources and products, that is, inputs and outputs, and their prices (Kreps 2013; Varian 2014). Shephard's duality theorem states that these choices may be represented by either a production function or a cost function (Shephard 1967).

Prior studies argue cost functions reflect the management's choices of the technology in hand, resource commitments, consumption of various inputs, output mix and levels, and other important operational choices (Banker et al. 2014; Holzhacker et al. 2015b). Managerial actions such as outsourcing or using subcontractors augment variable costs, whereas acquiring new machines or infrastructure influence the level of fixed costs. Therefore, managerial actions affect cost elasticity because cost elasticity captures the proportion between variable and fixed costs (Chen, Kama, and Lehavy 2024).

Particularly, cost elasticity is the percentage change in costs divided by a percentage change in output quantity. It is interpreted as a percentage change in costs for a one-percent change in output (Besanko and Braeutigam 2020). Several studies indicate managers take actions to increase the level of cost elasticity. Sedatole, Vrettos, and Widener (2012) find aircraft maintenance is often outsourced to suppliers, increasing variable costs, which, in turn,

increases cost elasticity. Kallapur and Eldenburg (2005) report that hospital managers prefer technologies that involve low fixed and high variable costs in response to a regulatory change. Holzhacker et al. (2015a) find hospitals modify their cost elasticity in response to price regulation, in line with Kallapur and Eldenburg (2005). Abowd, Corbel, and Kramarz (1999) find managers adjust labor resources by hiring employees based on short-term contracts rather than long-term contracts (see also Abowd and Kramarz 2003; Kramarz and Michaud 2010). These short-term contracts allow firms to scale down their labor when demand decreases, thereby increasing variable costs and increasing cost elasticity.

Further, Holzhacker et al. (2015b) report that hospitals make resource procurement choices to increase cost elasticity by outsourcing, leasing equipment instead of purchasing, and increasing the extent of short-term contracts. Overall, prior studies document how various managerial actions influence the level of cost elasticity.

### Cost Elasticity and the Proportion of Variable and Fixed Costs

We demonstrate the linkage between cost elasticity and the proportion of variable and fixed costs, using linear cost functions for two firms,  $i = 1, 2$ . Suppose Firm 1 has lower fixed costs,  $FC_i$ , than Firm 2 ( $FC_1 < FC_2$ ) and higher variable costs per unit,  $V_i$ , than Firm 2 ( $V_1 > V_2$ ). Also,  $Q$  is product quantity, and total cost (TC) is the sum of fixed and variable costs ( $TC = FC + V \cdot Q$ ). Then, when subtracting the cost elasticity of Firm 2 from the cost elasticity of Firm 1, we obtain the following:

$$\text{Cost Elasticity} = \epsilon_{FC,V,Q} = \frac{\text{percentage change in costs}}{\text{percentage change in quantity}} = \frac{\frac{\Delta TC}{TC}}{\frac{\Delta Q}{Q}} = \frac{\frac{V \cdot \Delta Q}{FC + V \cdot Q}}{\frac{\Delta Q}{Q}} \quad (1)$$

$$\epsilon_1 - \epsilon_2 = \frac{\frac{V_1 \cdot \Delta Q}{FC_1 + V_1 \cdot Q} - \frac{V_2 \cdot \Delta Q}{FC_2 + V_2 \cdot Q}}{\frac{\Delta Q}{Q}} = \frac{Q(V_1 \cdot FC_2 - V_2 \cdot FC_1)}{(FC_1 + V_1 \cdot Q)(FC_2 + V_2 \cdot Q)} \quad (2)$$

$$FC_1 < FC_2 \quad \& \quad V_1 > V_2 \Rightarrow \epsilon_1 > \epsilon_2.$$

For a given quantity level  $Q$ , the cost elasticity of Firm 1,  $\epsilon_1$ , is larger than the cost elasticity of Firm 2,  $\epsilon_2$ , that is,  $\epsilon_1 > \epsilon_2$ , if Firm 1 has lower fixed costs and a higher variable cost per unit than Firm 2.

Figure 1 compares the profit functions of two firms facing the same selling price per product to demonstrate the influence of variable versus fixed costs on the level of cost elasticity. Firm 1 with lower fixed costs and a higher variable cost per unit (moderate slope) has greater cost elasticity, whereas Firm 2 with higher fixed costs and a lower variable cost per unit (steep slope) has lower cost elasticity. Whereas high cost elasticity (Firm 1 in Figure 1) alleviates demand shocks on firms' earnings, low cost elasticity (Firm 2 in Figure 1) results in a strong sensitivity of earnings to change in demand, and as a result, firms experience high earnings volatility (Garrison et al. 2021). Thus, a higher cost-elasticity level chosen by the firm mirrors greater adjustments of the costs of variable costs, such as adjustments of the labor force and procurement of various resources.<sup>2</sup>

[See Figure 1]

### **The Relation between Cost Elasticity and Loss Reversal**

The amount of sales revenue needed to break even increases as cost elasticity decreases. That is, firms with more elastic costs require lower sales revenue to break even than do firms with less elastic costs (Balakrishnan et al. 2013; Holzhacker et al. 2015b), because greater fixed costs triggered by high resource commitments made in advance together with irreversible obligations result in a higher break-even point. That is, firms with a lower cost elasticity are exposed to a higher risk of losses and debt default (Chen et al. 2024). Figure 1 depicts the lower break-even point for Firm 1 with higher cost elasticity. The bold line between the firms' break-

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<sup>2</sup> Taking a more general approach, a non-linear cost function can be approximated by a linear cost function within a range of activity levels known as the relevant range (Garrison et al. 2021). Walters (1963) and Banker and Hughes (1994) indicate a cost function is approximately linear until capacity is reached. Accordingly, the above argument holds at the relevant range around an activity level.

even points indicates a range in which Firm 1 is profitable and Firm 2 suffers a loss. The figure suggests a greater likelihood of reporting profits for the firm with higher cost elasticity than for the firm with lower cost elasticity. Consequently, for all sales-revenue distributions, the likelihood of the high-cost-elasticity firm reporting a profit is higher than the likelihood of the low-cost-elasticity firm reporting a loss. Therefore, high cost elasticity is likely to enhance the reversal of a loss into a profit. Taken together, the following hypothesis summarizes:

*Hypothesis: Cost elasticity is positively associated with loss reversal.*

### III. RESEARCH DESIGN

#### Measuring Cost Elasticity

We utilize two cost-elasticity estimates used in prior studies. The first cost-elasticity estimate uses changes in operating costs and sales revenue. That is, cost elasticity is estimated as the slope coefficient of the relation between the logarithm change in costs and the logarithm change in sales revenue (e.g., Anderson et al. 2003; Chen et al. 2012; Kama and Weiss 2013; Banker et al. 2014; Holzhacker et al. 2015a, 2015b; Siciliano and Weiss 2023). Sales revenue is used as an imperfect proxy for output quantity because output quantities are not observable (Anderson et al. 2003; Banker and Chen 2006; Weiss 2010; Chen et al. 2012; Aboody et al. 2018). We focus on operating costs because they reflect operating decisions and constitute the majority of expenses, in line with Weiss (2010), Kama and Weiss (2013), and Aboody et al. (2018).

Following these studies, we regress the natural logarithm change in operating costs on the natural logarithm change in sales revenue for each firm  $i$  and estimate the following regression model 1:

### Model 1

$$\ln\left(\frac{OC_{i,j}}{OC_{i,j-1}}\right) = \beta_0 + \beta_{i,t} \ln\left(\frac{REV_{i,j}}{REV_{i,j-1}}\right) + \varepsilon_{i,j}, \quad j = t - 5, \dots, t,$$

where  $OC$  denotes total operating costs calculated as total sales revenue (Compustat item “SALE”) minus income from operations (Compustat item “OIADP”).  $REV$  denotes total sales revenue (Compustat item “SALE”). Cost elasticity for firm  $i$  in year  $t$  is estimated as the slope  $\beta_{i,t}$  over a six-year window ( $t-5$  to  $t$ ) using a firm-specific time-series model. That is, the first cost-elasticity estimate based on operating cost and sales-revenue changes is termed  $CELST_{i,t} = \beta_{i,t}$  and interpreted as the percentage decrease in operating costs for a one-percent change in sales revenue (Anderson et al. 2003; Chen et al. 2012; Holzhacker et al. 2015a, 2015b; Siciliano and Weiss 2023).

The second cost-elasticity estimate follows Aboody et al. (2018), who build on Kallapur and Eldenburg (2005) and run a firm-specific time-series regression of operating costs on sales revenue. They use the estimated coefficient on sales revenue as an estimate of the ratio of variable costs to fixed costs. Aboody et al. (2018) and Lev et al. (1974) relate the fixed-to-variable cost ratio to operating leverage because it mirrors the impact of a wide range of operative decisions. Similarly, Noreen and Soderstrom (1994, 1997) use the log-linear specification for estimating the time-series regressions of costs on sales revenue. Importantly, the log-log cost-function specification is consistent with the generalized Cobb-Douglas production function (Heathfield and Wibe 1987), which allows for a reflection of a firm’s labor and capital choices, consistent with choices of labor force and investments in capital assets. Assuming the generalized Cobb-Douglas is the dual production function, it allows for an explicit manifestation of operating choices. Both regression models use a log-log specification, in line with prior studies because it largely eliminates heteroscedasticity (Noreen and

Soderstrom 1994; Anderson et al. 2003; Kallapur and Eldenburg 2005; Holzhacker et al. 2015a; Aboody et al. 2018).

Specifically, cost elasticity is estimated as the slope coefficient of the relation between the natural logarithm of operating-cost levels and the natural logarithm of sales-revenue levels. We build on Aboody et al. (2018) and regress the following regression model 2 over a six-year window ( $t-5$  to  $t$ ) using a time-series model:

### **Model 2**

$$\ln(OC_{i,j}) = \beta_0 + \beta_{i,t} \ln(REV_{i,j}) + \varepsilon_{i,j}, \quad j = t - 5, \dots, t,$$

where cost elasticity for firm  $i$  in year  $t$  is estimated as the slope  $\beta_{i,t}$ . Thus, the second cost-elasticity estimate is based on operating-cost and sales-revenue levels and termed  $LELST_{i,t} = \beta_{i,t}$ . Kallapur and Eldenburg (2005) and Aboody et al. (2018) interpret this coefficient as the proportion of variable costs to fixed costs. Further, Noreen and Soderstrom (1994) argue this coefficient “roughly... quantifies how much of a given percentage change in volume translates into a percentage change in costs” (ibid, p. 258). Based on prior studies, we attribute  $\beta_{i,t}$  to cost elasticity.

### **Adjusting Labor Costs**

Labor costs play a significant role in driving cost-behavior patterns (Golden, Mashruwala, and Pevzner 2020) and represent the largest expense category for many firms (Hall 2016). Prior studies indicate adjustments of labor costs are subject to managerial discretion (Pinnuck and Lillis 2007). Hall (2016) finds managers of public banks adjust more labor resources than managers of private banks, choosing a more elastic labor-cost structure. Further, Dierynck, Landsman, and Renders (2012) document that managers cut labor costs to avoid a loss when sales revenue decrease, and they limit the increase in labor costs when sales revenue increases.

Specifically, they report that managers adjust both the number of employees and the number of working hours of each employee.

Hiring an employee or increasing working hours involves a commitment to pay more salaries, and cost outflows will occur regardless of the sales turnover servicing these costs (Holzhacker et al. 2015b). On the other hand, firing employees saves salaries but induces severance payments, reputational damage in the labor market, and decreased morale among remaining employees (Pindyck 1988). Fixed labor costs include salaries and benefits, whereas variable labor costs consist of salaries for overtime work, hourly employees, and commissions (Hall 2016).

The costs of adjusting committed labor resources are higher for firms using more employees to support a given volume of sales (Anderson et al. 2003), suggesting adjustment costs of firms with high employee intensity are larger than the adjustment costs of firms with low employee intensity. That is, firms with greater employee intensity are expected to be less sensitive to changes in revenue (Hall 2016), and thus have lower labor cost elasticity. In our setting, we use employee intensity as a crude proxy for labor cost elasticity set in advance, before incurring a loss, reflecting managerial decisions to hire and fire employees. We expect employee intensity to be negatively correlated with labor cost elasticity (i.e., firms with greater employee intensity have lower labor cost elasticity).

Utilizing an indicator of labor-force intensity, we use average employee intensity over a six-year period prior to incurring a loss.  $EMP_{i,t}$  is the average employee intensity of firm  $i$  in year  $t$  over the six years ( $t-5$  to  $t$ ), computed as the average ratio of the number of employees (Compustat item “EMP”) scaled by sales revenue (Compustat item “SALE”). Our approach for estimating employee intensity follows prior studies (Anderson et al. 2003; Dierynck et al. 2012; Hall 2016; Chen et al. 2024), and the six-year window is consistent with the time window used for both earlier estimates of cost elasticity.

### **Testing the Hypothesis: Univariate Analysis**

The hypothesis predicts cost elasticity is positively associated with loss reversal. We perform a univariate analysis that compares loss-reversal probabilities between loss firms with high (above-median) versus low (below-median) cost elasticity, utilizing both cost-elasticity estimates. The hypothesis is consistent with loss firms with high cost elasticity having a significantly higher loss-reversal probability than loss firms with low cost elasticity. We repeat the univariate analysis using employee intensity as a proxy for cost elasticity.

### **Testing the Hypothesis – Extending Joos and Plesko (2005)**

The univariate analysis does not control for other potential determinants of loss reversal. We build on Joos and Plesko's (2005) prediction model for testing the hypothesis, which includes three categories of variables of a firm's financial profile, frequency of historical losses, and dividend behavior. Above and beyond testing the incremental prediction power of cost elasticity as in Joos and Plesko (2005), we add a meaningful alternative explanation by incorporating financial leverage as another alternative determinant of loss reversal. High financial leverage leads to high financial expenses and is likely to lead a firm to report a loss (Titman and Wessels 1998; Wald 1999). Particularly, high financial leverage represents the risk of a firm's inability to bear its interest costs, pay off its financial liabilities due to high financial expenses, diminishing the probability of loss reversal. Together, we follow Joos and Plesko's loss-reversal prediction model and add cost elasticity and financial leverage as predictors. We estimate the following logistic regression model 3 using the Fama and MacBeth (1973) estimation procedure:

### Model 3

$$\begin{aligned} REVERSAL_{i,t+1} = & \beta_0 + \beta_1 ELST_{i,t} + \beta_2 ROA_{i,t} + \beta_3 PASTROA_{i,t} \\ & + \beta_4 SIZE_{i,t} + \beta_5 SALESGROWTH_{i,t} + \beta_6 FIRSTLOSS_{i,t} \\ & + \beta_7 LOSSSEQ_{i,t} + \beta_8 DIVDUM_{i,t} + \beta_9 DIVSTOP_{i,t} \\ & + \beta_{10} FINLEV_{i,t} + \varepsilon_{i,t+1}, \end{aligned}$$

where  $ELST_{i,t} = \{CELST_{i,t}, LELST_{i,t} \text{ or } EMP_{i,t}\}$ ;

$REVERSAL_{i,t+1}$  = a dummy variable that equals 1 if firm  $i$  becomes profitable in the consecutive year  $(t+1)$ , and 0 otherwise;

$ROA_{i,t}$  = return on assets measured as income before extraordinary items and discontinued operations (Compustat item “IB”) scaled by lagged total assets (Compustat item “AT”);

$PASTROA_{i,t}$  = past five-year average of return on assets;

$SIZE_{i,t}$  = measured as the natural logarithm of the current market value of common equity at year end  $(t)$  (Compustat item “PRCC\_F” multiplied by Compustat item “CSHO”);

$SALESGROWTH_{i,t}$  = measured as the percentage growth in sales revenue (Compustat item “SALE”) during the current year;

$FIRSTLOSS_{i,t}$  = a dummy variable that equals 1 if a firm reports a loss in the current year  $(t)$  and was profitable in the previous year  $(t-1)$ , and 0 otherwise;

$LOSSSEQ_{i,t}$  = the number of sequential losses over the past five years before the current loss  $(t)$ ;

$DIVDUM_{i,t}$  = a dummy variable that equals 1 if a firm pays dividends in the current year  $(t)$  (Compustat item “DVC”), and 0 otherwise;

$DIVSTOP_{i,t}$  = a dummy variable that equals 1 if a firm stops paying dividends in the current year  $(t)$ , and 0 otherwise; and

$FINLEV_{i,t}$  = financial leverage calculated as the ratio of long-term debt at year end ( $t$ ) (Compustat item “DLTT”) to market value of common equity at year end (Compustat item “PRCC\_F” multiplied by Compustat item “CSHO”).

The hypothesis predicts the estimated coefficient of interest  $\beta_1$  is positive and significant. We also expect  $\beta_{10}$  to be negative and significant. As for the other control variables, we expect the coefficients on  $ROA$  and  $PASTROA$  to be positive because higher profitability indicates a higher likelihood of loss reversal (Joos and Plesko 2005). Moreover, Balakrishnan, Bartov, and Faurel (2010, Table 6) show a high probability of reporting a loss in the subsequent quarter if a large loss is reported in the current quarter. Following Balakrishnan et al. (2010), we use  $ROA$  to control for large losses to alleviate a concern that the predictive power of cost elasticity is derived from a size effect of observations with large losses. Because large firms are financially stronger than small firms, and therefore have a higher likelihood of reversing losses, we expect a positive coefficient on  $SIZE$ . We also expect a positive coefficient on  $SALESGROWTH$  because a firm with higher sales revenue has a higher probability of returning to profitability (Joos and Plesko 2005). Also, we expect the coefficient on  $FIRSTLOSS$  to be positive because a firm reporting a profit a year before reporting a loss is more likely to return to profitability in the next year (Joos and Plesko 2005). We expect the coefficient on  $LOSSSEQ$  to be negative. Further, we expect a positive coefficient on  $DIVDUM$  and a negative coefficient on  $DIVSTOP$  because a firm continuing to pay dividends when reporting a loss indicates an expectation that losses will be a short-time event (Joos and Plesko 2005).

We implement the Fama-MacBeth (1973) procedure (as in Joos and Plesko 2005) for estimating the probability of loss reversal in the consecutive year ( $t+1$ ) after reporting a loss in year ( $t$ ) using information from the six years ( $t-5$  to  $t$ ). We repeat the procedure using a rolling window of six consecutive observations for each firm.

## Data and Sample Selection

We obtain data from Compustat annual industrial files for the years 1992–2021. We exclude financial institutions (SIC codes between 6000 and 6999) and public utilities (SIC codes between 4900 and 4999). Table 1 presents our sample-selection procedure. We start with 229,167 firm-year observations in Compustat for fiscal years 1992–2021. We require that firm-year observations have positive values for sales revenue (Compustat item “SALE”), operating costs calculated as total sales revenue (Compustat item “SALE”) minus income from operations (Compustat item “OIADP”), total assets (Compustat item “AT”), book value (Compustat item “CEQ”), market value (Compustat item “PRCC\_F” multiplied by item “CSHO”), and with total assets more than \$5 million. To ensure estimates are not driven by outliers, we winsorize financial-statement variables at the 1<sup>st</sup> and 99<sup>th</sup> percentiles. We require firms to have at least seven consecutive firm-year observations with data on earnings defined as income (loss) before extraordinary items and discontinued operations (Compustat item “IB”) (Hayn 1995; Joos and Plesko 2005; Li 2011). These criteria result in a total of 112,182 firm-year observations for 7,410 firms, of which 78,181 firm-year observations have positive earnings for 6,923 firms labeled as the profit-firms sample, and 34,001 firm-year observations have negative earnings for 6,293 firms labeled as the loss-firms sample.

Focusing on the association between cost elasticity and loss reversal, for each estimate, *CELST*, *LELST*, or *EMP*, we set up a sample of loss observations. For the first estimate of cost elasticity, *CELST*, we further require each firm-year observation in the loss-firms sample to have available sales revenue and operating-cost data for six years ( $t-6$  to  $t-1$ ) prior to the year in which cost elasticity is estimated ( $t$ ), which is necessary for the estimation of cost elasticity. The result is 19,220 firm-year observations for 5,340 firms labeled as the first loss sample. For the second estimate of cost elasticity, *LELST*, we require sales revenue and operating-cost data for five years ( $t-5$  to  $t-1$ ) prior to estimating cost elasticity ( $t$ ) for each firm-year observation in

the loss-firms sample, resulting in 21,743 firm-year observations for 5,604 firms labeled as the second loss sample. For the crude proxy of cost elasticity, *EMP*, we require the number of employees and sales-revenue data for five years ( $t-5$  to  $t-1$ ) prior to estimating employee intensity ( $t$ ) for each firm-year observation in the loss-firms sample. This requirement results in 22,162 firm-year observations for 5,641 firms labeled as the third loss sample. We use these three samples for testing the association between cost elasticity and loss reversal.

[See Table 1]

Table 2 presents the proportion of losses per year for firm-year observations from 1992 to 2020. We omit year 2021 because firm-year observations are required to have data on earnings in the year following the year in which a loss is reported. The proportion of loss firms increases in the year following the year in which a loss is reported. The proportion of loss firms increases from 21.91% in 1992 to 41.65% in 2020. The estimated trend slope over the 29-year period is 0.0048, significantly different from zero ( $p$ -value<0.01), indicating a growing number of firms reporting losses over time. The evidence suggests reporting losses is a growing phenomenon, consistent with Klein and Marquardt (2006), Darrough and Ye (2007), and Gu et al. (2023).

[See Table 2]

Following Joos and Plesko (2005), we report the distribution of the number of per-firm losses in our sample. Table 3 documents that only 15.07% of our sample firms did not experience a loss during the 29-year period. An accumulation of the reported figures indicates 76.68% of the firms reported 1–10 losses during the 29-year period, and 8.25% of the firms reported more than 10 losses. Further, we document 47 (0.63%) firms out of 7,410 reported 20 losses or more during the 29-year period, indicating these firms can sustain losses for a long period of time without being liquidated.<sup>3</sup> These findings indicate losses became more widespread in our 1992–2021 sample than in the 1971–2000 sample used by Joos and Plesko

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<sup>3</sup> Two firms reported the largest number of losses—27 annual losses during a 29-year period: American Superconductor Corporation (AMSC) and NTN Buzztime Ltd (NTN).

(2005). For instance, they report that 27.21% of the firms never experienced a loss and 65.53% of the firms reported between 1–10 losses. The findings in Table 3 highlight the increasing prevalence of losses.

[See Table 3]

Panel A of Table 4 documents the loss-reversal probability in our loss-firms sample—28.81% of firms reporting a loss in the current year ( $t$ ) report profits in the consecutive year ( $t+1$ ). Panel B of Table 4 shows loss-reversal probabilities as a function of the sequence of past uninterrupted losses in past years. We find 42.30% of the firms reporting a first loss, that is, a loss after being profitable in the previous year ( $t-1$ ), reverse the loss and report profits in the next consecutive year ( $t+1$ ). However, only 20.61% of the firms experiencing five consecutive losses report profits in the next consecutive year ( $t+1$ ). The evidence indicates the likelihood of loss reversal decreases monotonically as the sequence of losses becomes longer. Consistent with Joss and Plesko (2005), these findings indicate that the longer the loss sequence that the firms recorded in the past, the lower the reversal probability of the current loss.

[See Table 4]

## Descriptive Statistics

Table 5 compares descriptive statistics between the profit-firms sample and the loss-firms sample. We observe that the mean of *SIZE*, for firms reporting profits, is 6.3878, whereas the mean of *SIZE* is 4.7416 for firms reporting losses, significantly smaller relative to profit firms ( $p$ -value<0.01). These statistics are in line with Hayn (1995), Darrough and Ye (2007), and Kim, Saha, and Bose (2021). Also, the mean of financial leverage, *FINLEV*, for the profit firms is 0.6760, whereas the mean of *FINLEV* for the loss firms is 0.9088, significantly higher than for the profit firms ( $p$ -value<0.01). These statistics are in line with Kim et al. (2021).<sup>4</sup> The

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<sup>4</sup> We observe that firms reporting losses have, on average, a significantly lower level of cost elasticity (*CELST* and *LELST*) than firms reporting profits. These descriptive statistics are in line with Banker et al. (2014). While

differences between the means of the variables reported in Table 5 for the profit-firms sample and the loss-firms sample are significant ( $p$ -value<0.01). Overall, these findings document that profit firms have different characteristics than loss firms, consistent with prior studies (Darrough and Ye 2007; Kim et al. 2021).

Table 6 presents Pearson and Spearman correlations for the variables employed in model 3 for the loss-firms sample. We find the first estimate of cost elasticity, *CELST*, is highly and positively correlated with the second estimate of cost elasticity, *LELST*, as expected (Pearson and Spearman correlations are 0.4943 and 0.5891, respectively,  $p$ -value<0.01). Also, we find the first estimate of cost elasticity, *CELST*, is positively correlated with loss reversal, *REVERSAL* (Pearson and Spearman correlations are 0.1182 and 0.1440, respectively,  $p$ -value<0.01). Similarly, we find the correlation for the second estimate of cost elasticity, *LELST*, is positively correlated with loss reversal, *REVERSAL* (Pearson and Spearman correlations are 0.1126 and 0.1414, respectively,  $p$ -value<0.01). These correlations are consistent with the hypothesis.

Notably, the correlation matrix indicates the employee intensity, *EMP*, is negatively associated with the first estimate of cost elasticity, *CELST* (Pearson and Spearman correlations are -0.1821 and -0.0875, respectively,  $p$ -value<0.01). Similarly, we find a negative correlation between employee intensity, *EMP*, and the second estimate of cost elasticity, *LELST* (Pearson and Spearman correlations are -0.1962 and -0.1244, respectively,  $p$ -value<0.01). The figures suggest employee intensity is significantly and negatively correlated with the first and second estimates of cost elasticity. Also, the correlation between employee intensity, *EMP*, and loss reversal, *REVERSAL* (Pearson and Spearman correlations are -0.1158 and -0.1062,

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Banker et al. (2014) view high cost elasticity as a drawback, other studies see high cost elasticity as an advantage (Holzhacker et al. 2015a; Aboody et al. 2018; Weiss 2023).

respectively,  $p\text{-value} < 0.01$ ). These descriptive statistics are consistent with the hypothesis because employee intensity is negatively associated with cost elasticity.<sup>5</sup>

[See Tables 5 and 6]

## IV. EMPIRICAL FINDINGS

### Univariate Analysis

To utilize a univariate analysis, we classify loss firms into low- versus high-cost-elasticity firms using the median of each of our two cost-elasticity estimates. Specifically, for the first, second, and third loss samples, we sorted the sample firms into two equal portfolios based on their median cost-elasticity estimate for the current year ( $t$ ). Table 7 presents the loss-reversal probabilities of the portfolios in the following year ( $t+1$ ) for each sample. For the first cost-elasticity estimate, *CELST*, 34.66% of the losses in the current year ( $t$ ) of firms with high cost elasticity are reversed in the consecutive year ( $t+1$ ). However, for the low-cost-elasticity firms, only 22.50% of the losses are reversed. The difference between these loss-reversal probabilities is 12.16% and significant ( $p\text{-value} < 0.01$ ).

For the second cost-elasticity estimate, *LELST*, 34.61% of the firms with high cost elasticity report a loss reversal in the year following a loss, whereas merely 22.40% of the firms with low cost elasticity report a loss reversal. The difference of 12.21% is significant ( $p\text{-value} < 0.01$ ). The findings based on both cost-elasticity estimates are in line with the hypothesis indicating an economically meaningful and highly significant difference in loss-reversal probabilities between high- versus low-cost-elasticity firms.

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<sup>5</sup> The descriptive statistics also indicate the alternative determinant of loss reversal, financial leverage, *FINLEV*, is positively correlated with loss reversal, *REVERSAL* (Pearson and Spearman correlations are 0.0334 and 0.1386, respectively,  $p\text{-value} < 0.01$ ), which is inconsistent with our alternative explanation. However, results from estimating the multivariate regression model reported in section IV will shed light on the relation between financial leverage and cost elasticity.

Similarly, for employee intensity, *EMP*, 32.30% of the low-employee-intensity firms reverse their losses, whereas only 24.65% of the high-employee-intensity firms reverse their losses. The difference, 7.65%, is significant ( $p\text{-value}<0.01$ ). The finding indicates employee intensity is inversely associated with loss reversal. To the extent that low employee intensity induces high cost elasticity, the findings further corroborate the hypothesis.

[See Table 7]

### **Multivariate Regression Analyses**

Table 8 depicts the results from estimating model 3 using the Fama and MacBeth (1973) procedure. Extending Joos and Plesko's (2005) specification with cost elasticity and financial leverage, the estimated coefficient on *CELST* reported in column (2) is 0.2047, which is positive and significant ( $p\text{-value}<0.01$ ). This result suggests cost elasticity is positively associated with loss reversal, in support of our hypothesis. We further interpret the economic significance of this result by computing the average incremental likelihood of loss reversal associated with a 10% increase in cost elasticity. Holding other variables at a fixed value, a 10% increase in cost elasticity, *CELST*, increases the likelihood of reporting loss reversal by 2.27%.<sup>6</sup>

The estimated coefficient on *LELST* reported in column (3) is 0.1525, which is positive and significant ( $p\text{-value}<0.01$ ). Again, this result suggests cost elasticity is positively associated with loss reversal, in support of our hypothesis. This estimated coefficient indicates an increase of 10% in cost elasticity, *LELST*, increases the likelihood of loss reversal by 1.65%.

The estimated coefficient on *EMP* reported in column (4) is -13.7198, which is negative and significant ( $p\text{-value}<0.01$ ). The evidence suggests the level of employee intensity is negatively and significantly associated with loss reversal. That is, loss firms with low employee

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<sup>6</sup> The likelihood of the dependent variable can be estimated by exponentiating regression coefficients estimated by a logistic regression (Hosmer and Lemeshow 2000).

intensity in the current year ( $t$ ) are significantly more likely to reverse a loss reversal in the following year ( $t+1$ ) than loss firms with high employee intensity. To the extent that low employee intensity proxies for cost elasticity, the findings further support the hypothesis.

Regarding the control variables, the estimated coefficients are reported in column (1). The estimated coefficients are in line with Joos and Plesko (2005). Further, the pseudo R-squared figures reported in columns (2) and (3) are 0.1331 and 0.1295, respectively, and larger than the pseudo R-squared figure in Joos and Plesko's specification reported in column (1), 0.1256, indicating the incremental prediction power of cost elasticity and financial leverage.

The estimated coefficients on *FINLEV* reported in columns (2), (3), and (4) are -0.1651, -0.1628, and -0.1618, respectively, which are all negative and significant ( $p$ -value $<0.01$ ). These findings suggest financial leverage is negatively and significantly associated with loss reversal, in line with viewing high financial leverage as detrimental to loss reversal (Titman and Wessels 1998; Wald 1999).

[See Table 8]

Taken together, the findings suggest cost elasticity is positively and significantly associated with loss reversal. Remarkably, the difference in the likelihood of loss reversal between high-versus low-cost-elasticity firms is statistically significant and economically meaningful. The empirical evidence supports our hypothesis and demonstrates its economic significance.

## V. ROBUSTNESS CHECKS

We conduct several robustness checks to further corroborate the positive association of cost elasticity with loss reversal.

### Cross-Sectional Regression

We estimate model 3 using cross-sectional estimation with year and industry fixed effects, and cluster observations by industry to provide standard errors that are robust to autocorrelation

and heteroscedasticity (Petersen 2009). This regression analysis increases our confidence that the findings are not derived by industry-specific characteristics or by a time trend.

Results of estimating model 3 are reported in Table 9. The estimated coefficients of cost elasticity, *CELST*, reported in column (2) is 0.1422 ( $p$ -value<0.05). Similarly, the estimated coefficients of cost elasticity, *LELST*, reported in column (3) is 0.1286 ( $p$ -value<0.05). That is, we find positive and significant coefficients. The estimated coefficient of employee intensity, *EMP*, reported in column (4) is -10.8475, which is negative and significant ( $p$ -value<0.01). The results from the cross-sectional estimation further support the hypothesis.

[See Table 9]

### **Operating Income after Depreciation**

Both estimates of cost elasticity use operating costs and exclude financial expenses. Loss reversal, on the other hand, is determined using firm-year observations of income before extraordinary items and discontinued operations, that is, after financial income or expenses. In the previous section, we control for financial leverage as a driver of loss reversal to mitigate a concern that the findings are driven by financial expenses.

Now, we take a different perspective and examine reversal of income from operations, excluding financial income or expenses, to gain direct insights on the reversal of income from operations per se. We repeat the univariate and multivariate analyses for operating income after depreciation (Compustat item “OIADP”), where the dependent variable, *REVERSAL*, is a dummy variable that equals 1 if a negative income from operations after depreciation in the current year ( $t$ ) becomes positive in the consecutive year ( $t+1$ ), and 0 otherwise.

The results for the univariate analysis are reported in Table 10. For the first and second cost-elasticity estimates, the difference in probabilities of reversal of income from operations between firms with high (above-median) versus low (below-median) cost elasticity is 9.58% and 10.89%, respectively, which are positive and significant ( $p$ -value<0.01). For employee

intensity, the difference is -7.90%, which is negative and significant ( $p$ -value<0.01). The results further support our hypothesis. The results from estimating a multivariate regression model are presented in Table 11. The estimated coefficients on *CELST*, *LELST*, and *EMP* reported in columns (2), (3), and (4) are 0.2508 ( $p$ -value<0.05), 0.2150 ( $p$ -value<0.01), and -20.9538 ( $p$ -value<0.01), respectively. As before, the empirical evidence is in line with our conclusion.

[See Tables 10 and 11]

Taken as a whole, the results support the hypothesis. The robustness tests further corroborate the positive association between cost elasticity and loss reversal, suggesting this association is significant and insensitive to using income before extraordinary items and discontinued operations or operating income after depreciation as the dependent variable, *REVERSAL*.

## **VI. Exogenous Shock: The 2008 Financial Crisis**

We gain further insights into a potential causal relation by utilizing an exogenous shock (Armstrong et al. 2022). Specifically, we investigate the effect of the cost elasticity of firms experiencing a loss reversal after the exogenous shock of the 2008 financial crisis. This financial crisis is an exogenous shock, because all major industrialized countries experienced extraordinarily large and synchronized contractions in real and financial aggregates. This crisis was marked by decreases in safe market rates of interest, increases in the interest rate spreads between risky and safe debt, and reductions in the credit market (Williamson 2012; Perri and Quadrini 2018). As before, we conduct a univariate analysis, classifying firms reporting a loss in 2008 into low- and high-cost-elasticity firms based on the cost-elasticity median (separately for each of our two cost-elasticity estimates). That is, for each of the first, second, and third loss samples, we assign firms into two equal portfolios based on their median cost-elasticity estimate in 2008. Table 12 presents the loss-reversal probabilities.

Utilizing the first cost-elasticity estimate, *CELST*, 37.66% of the high-cost-elasticity firms reporting losses in 2008 were reversed in 2009. However, only 19.29% of the low-cost-elasticity firms reporting losses in 2008 were reversed in 2009. The difference is 18.37% and significant ( $p\text{-value}<0.01$ ). Similarly, utilizing the second cost-elasticity estimate, *LELST*, 39.05% of the high-cost-elasticity firms reporting losses in 2008 were reversed in 2009, compared to merely 17.49% of firms with low cost elasticity. Again, the difference, 21.56%, is significant ( $p\text{-value}<0.01$ ). Also, for employee intensity, *EMP*, 31.67% of the low-employee-intensity firms reverse their losses, whereas only 24.91% of the high-employee-intensity firms reverse their losses. The difference, 6.76%, is also significant ( $p\text{-value}<0.01$ ). The results are consistent with a causal effect: an increase in cost elasticity leads to a higher likelihood of loss reversal (Armstrong et al. 2022).

[See Table 12]

Second, we re-estimate the cross-sectional regression model 3 using loss-firm observations in 2008 with industry fixed effects and cluster observations by industry. Table 13 reports the results. Similarly, the estimated coefficient on *CELST* is 0.8243, which is positive and significant ( $p\text{-value}<0.01$ ). This estimated coefficient is 4.03 times larger than the corresponding estimated coefficient reported in Table 8 (0.2047). The difference between these estimated coefficients is significant ( $p\text{-value}<0.01$ ).<sup>7</sup> Again, the coefficient on *LELST* is 0.5365, which is positive and significant ( $p\text{-value}<0.1$ ) and 3.52 times larger than the corresponding estimated coefficient reported in Table 8 (0.1525). Additionally, the coefficient on *EMP* is -16.8983, which is negative and significant ( $p\text{-value}<0.05$ ) and 1.23 times larger than the corresponding estimated coefficient reported in Table 8 (-13.7183).

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<sup>7</sup> The Z-statistic to test for the difference between estimated coefficients is computed as follows (see Holzhaecker et al. 2015a):  $Z = \frac{\hat{\beta}_1 - \hat{\beta}_2}{\sqrt{se(\hat{\beta}_1)^2 + se(\hat{\beta}_2)^2}}$ .

Overall, the results indicate greater economic significance of the effect of cost elasticity under the financial crisis on the likelihood of loss reversal. We conclude the phenomenon at hand is more pronounced under the 2008 financial crisis and consistent with a causal effect.

[See Table 13]

## **VII. THE ABANDONMENT OPTION**

Hayn (1995) emphasizes the phenomenon of an increasing number of firms reporting losses in previous decades and distinguishes between the information content of losses versus profits. Hayn recognizes that losses are not expected to perpetuate due to the abandonment option – the notion that shareholders can liquidate or redeploy the assets of the firm if they expect the loss to continue. A number of subsequent studies corroborate Hayn’s findings regarding the abandonment option (Pinnuck and Lillis 2007; Lawrence, Sloan, and Sun 2018).

The abandonment option implies shareholders can liquidate or redeploy the assets of the firm. The rationale underlying the abandonment-option concept assumes losses are temporary and are not expected to perpetuate over a long term. Joos and Plesko (2005) contend that the probability of loss reversal represents a proxy for the likelihood of exercising the abandonment option. They show that the longer the loss sequence, the lower the ex-ante probability of reversal, in line with the abandonment-option theory. They conclude the loss-reversal likelihood inversely corresponds to the likelihood of exercising the abandonment option. Together, Joos and Plesko (2005) conclude loss reversal is a proxy for exercising the abandonment option. Following Joos and Plesko (2005), Li (2011) differentiates between transitory and persistent losses. However, Li finds no evidence that loss persistence impounded in the stock prices is associated with exercising the abandonment option. Taking a different perspective, Gu et al. (2023) distinguish between losses generated by expensing intangible investments versus real losses generated by other expenses. Gu et al. (2023) show firms with real losses have a lower likelihood of loss reversal and a higher likelihood of exercising the

abandonment option. Prior studies, however, have not examined how pre-determined cost elasticity affects the likelihood of exercising the abandonment option.

Next, we examine the effect of cost elasticity on the survival rate of firms over up to five consecutive years. Prior studies view the delisting of public firms as a negative outcome of bankruptcy or of the stock market survival, by being acquired as a substitute for the hazard of bankruptcy (Xia, Dawley, Jiang, Ma, and Boal 2016).<sup>8</sup> We measure the survival rate of firm  $i$  in year  $t$  by the probability of the firm not being deleted from Compustat in consecutive years ahead (Franzen, Rodgers, and Simin 2007). As before, we classify the loss firms into low- versus high-cost-elasticity firms using the median of each of our two cost-elasticity estimates for both the first and second loss samples. Thus, exercising the abandonment option for a loss firm is captured by its survival rate.

Results from comparing the accumulated survival-rate portfolios for high versus low cost elasticity are reported in Table 14. The incremental survival rate of loss firms with low cost elasticity over loss firms with high cost elasticity for the first cost-elasticity estimate, *CELST*, is 0.48% for one year ahead, 0.95% for two consecutive years ahead, 1.63% for three consecutive years ahead, 1.55% for four consecutive years ahead, and 1.81% for five consecutive years ahead. Whereas the incremental survival rate is insignificant for one year and two consecutive years ahead, the incremental survival rate for three, four, and five years is significant ( $p$ -value<0.05), indicating firms with high cost elasticity have a significantly higher survival rate two years after reporting a loss.

For the second cost-elasticity estimate, *LELST*, the incremental survival rate is 1.54% for one year ahead, 3.31% for two consecutive years ahead, 4.42% for three consecutive years

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<sup>8</sup> Some loss firms may delist due to a choice to go private or to an acquisition that does not follow poor performance (Leuz, Triantis, and Wang 2008; Martinez and Serve 2011). Addressing this issue in the abandonment-option context, we replicate the analysis using only 153 deletion observations from Compustat, due to bankruptcy and liquidation (Compustat item DLRSN, codes 02 and 03). The results, not reported due to the small sample, further support our conclusion.

ahead, 4.22% for four consecutive years ahead, and 4.80% for five consecutive years ahead. All these differences in survival rate among low- versus high-elasticity firms are highly significant ( $p$ -value $<0.01$ ). Overall, the findings suggest the survival rate of loss firms is significantly reduced by low cost elasticity from three to five years in the future. Moreover, the results suggest cost elasticity of loss firms is positively and significantly associated with survival rate. Extending Joos and Plesko (2005), we conclude cost elasticity is positively and significantly related to exercising the abandonment option. Importantly, the findings draw attention to a compelling effect of cost-elasticity choices on the likelihood of exercising the abandonment option.

[See Table 14]

## **VIII. SUMMARY**

This study highlights the mechanism underlying the effect of cost elasticity induced by operating actions on the likelihood of loss reversal. We find cost elasticity has a positive and significant impact on the likelihood of loss reversal. The significant relation is robust to different estimation procedures and sensitivity analyses. Utilizing the exogenous shock of the 2008 financial crisis, we find the results are more pronounced after the 2008 financial crisis exogenous shock, providing empirical evidence in line with causality of the effect. The findings extend both the losses and cost-accounting stream of studies by showing cost elasticity matters in predicting loss reversal.

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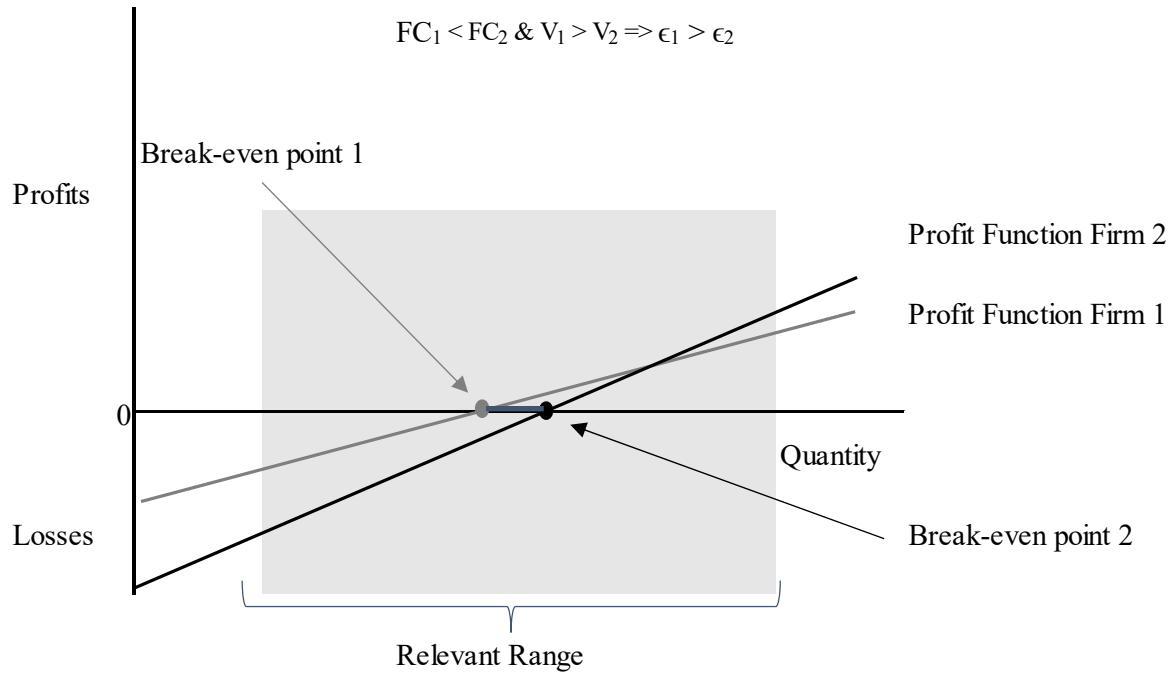
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**FIGURE 1**  
**Cost Elasticity and Break-Even-Point**



This figure depicts two profit functions with both firms facing the same selling price per a single product. Firm 1 has lower fixed costs than Firm 2 ( $FC_1 < FC_2$ ) and higher variable costs per unit than Firm 2 ( $V_1 > V_2$ ). Therefore, Firm 1 has more elastic costs than Firm 2. For all product quantity distributions, the break-even point is lower for Firm 1 than for Firm 2, and the probability of a loss in Firm 1 (with high cost elasticity) is lower than the probability of a loss in Firm 2 (with low cost elasticity).

**TABLE 1**  
**Sample Selection Procedure**

<b>Sample Criteria</b>	<b>No. of Obs.</b>	<b>Firms</b>
Observations in Compustat annual database for firms with 4-digit Standard Industry Classification (SIC) codes from 1000 to 9999 excluding 6000 to 6999 and 4900 to 4999, fiscal years from 1992 to 2021	229,167	22,237
Less observations without positive values for sales revenue, operating costs, total assets, book value, and market value	(74,568)	(4,720)
Less observations with total assets less than \$5 million	(6,800)	(785)
Less observations of firms with fewer than 7 consecutive observations over the sample period and without information on income before extraordinary items and discontinued operations in the year following the year in which a loss is reported	(35,617)	(9,322)
<b>Full Sample</b>	<b>112,182</b>	<b>7,410</b>
<b>Profit-Firms Sample</b> – observations of firms reporting positive earnings	<b>78,181</b>	<b>6,923</b>
<b>Loss-Firms Sample</b> – observations of firms reporting negative earnings	<b>34,001</b>	<b>6,293</b>
Less observations of firms in the loss-firms sample without data on sales revenue and operating costs six years prior to the year in which the first cost-elasticity estimate is computed	(14,781)	(953)
<b>First Loss Sample for Computing the First Cost-Elasticity Estimate (CELST)</b>	<b>19,220</b>	<b>5,340</b>
Less observations of firms in the loss-firms sample without data on sales revenue and operating costs five years prior to the year in which the second cost-elasticity estimate is computed	(12,258)	(689)
<b>Second Loss Sample for Computing the Second Cost-Elasticity Estimate (LELST)</b>	<b>21,743</b>	<b>5,604</b>
Less observations of firms in the loss-firms sample without data on sales revenue and the number of employees five years prior to the year in which employee intensity is computed	(11,839)	(652)
<b>Third Loss Sample for Computing Employee Intensity (EMP)</b>	<b>22,162</b>	<b>5,641</b>

**TABLE 2**  
**Proportion of Losses per Year**

<b>Year</b>	<b>Firm-year Obs.</b>	<b>Losses</b>	<b>% of Losses</b>
1992	2,652	581	21.91%
1993	3,101	676	21.80%
1994	3,433	671	19.55%
1995	3,773	813	21.55%
1996	4,167	940	22.56%
1997	4,433	1,055	23.80%
1998	4,689	1,389	29.62%
1999	4,713	1,417	30.07%
2000	4,712	1,539	32.66%
2001	4,554	1,908	41.90%
2002	4,455	1,663	37.33%
2003	4,385	1,465	33.41%
2004	4,346	1,218	28.03%
2005	4,269	1,169	27.38%
2006	4,237	1,125	26.55%
2007	4,148	1,244	29.99%
2008	3,972	1,562	39.33%
2009	3,882	1,514	39.00%
2010	3,818	1,054	27.61%
2011	3,726	1,004	26.95%
2012	3,668	1,101	30.02%
2013	3,629	1,161	31.99%
2014	3,594	1,164	32.39%
2015	3,461	1,288	37.21%
2016	3,266	1,179	36.10%
2017	3,096	1,046	33.79%
2018	2,926	970	33.15%
2019	2,769	1,020	36.84%
2020	2,557	1,065	41.65%
<b>Total</b>	<b>110,431</b>	<b>34,001</b>	<b>30.79%</b>
Trend Coefficient		0.0048***	
( <i>t</i> -statistic)		(4.4215)	

This table presents the proportion of losses per year for firm-year observations from 1992 to 2020. This table excludes the year 2021 because we require firm-year observations to have data on income before extraordinary items and discontinued operations (Compustat item “IB”) in the year following the year in which a loss is reported (see Table 1).

**TABLE 3**  
**Distribution of the Number of Losses per Firm**

<b>No. of Losses</b>	<b>No. of Firms</b>	<b>% of Firms</b>
0	1,117	15.07%
<b>Subtotal</b>	<b>1,117</b>	<b>15.07%</b>
1	887	11.97%
2	777	10.49%
3	726	9.80%
4	685	9.24%
5	610	8.23%
6	554	7.48%
7	532	7.18%
8	432	5.83%
9	266	3.59%
10	213	2.87%
11	151	2.04%
12	110	1.48%
13	81	1.09%
14	68	0.92%
15	54	0.73%
16	43	0.58%
17	21	0.28%
18	15	0.20%
19	21	0.28%
20	10	0.13%
21	12	0.16%
22	7	0.09%
23	4	0.05%
24	3	0.04%
25	4	0.05%
26	5	0.07%
27	2	0.03%
28	0	0.00%
29	0	0.00%
30	0	0.00%
<b>Subtotal</b>	<b>6,293</b>	<b>84.93%</b>
<b>Total</b>	<b>7,410</b>	<b>100%</b>

This table presents the distribution of the number of per-firm losses in the sample. A loss is defined as negative income before extraordinary items and discontinued operations (Compustat item “IB”).

**TABLE 4**  
**Loss-Reversal Probabilities**

**Panel A: Loss-Reversal Probability**

No. of Obs.	No. of Firms	Reversal Prob. in $t+1$
34,001	6,293	28.81%

**Panel B: Loss-Reversal Probabilities Conditional on Length of Loss Sequence**

Length of Loss Sequence	No. of Firms	No. of Obs.	Reversal Prob. in $t+1$
1	5,480	10,650	42.30%
2	3,846	5,342	32.57%
3	2,586	3,047	27.96%
4	1,661	1,809	21.78%
5	1,087	1,145	20.61%

This table presents the analysis of loss-reversal probabilities for the loss-firms sample. Panel A presents the loss-reversal probability. Panel B presents the loss-reversal probabilities conditional on the sequence of past uninterrupted losses in the past one to five years. *Loss Reversal* indicates the likelihood that a firm reporting a loss in the current year ( $t$ ) becomes profitable in the consecutive year ( $t+1$ ). *Loss sequence* indicates the number of uninterrupted annual losses. A loss is defined as negative income before extraordinary items and discontinued operations (Compustat item “IB”).

**TABLE 5**  
**Descriptive Statistics**

Profit-Firms Sample							Loss-Firms Sample					
Variables	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
<i>REVERSAL</i>	--	--	--	--	--	--	34,001	0.2881	0.4529	0.0000	0.0000	1.0000
<i>ΔREV</i>	72,885	0.1224	0.2379	0.0106	0.0916	0.2042	31,681	0.0108***	0.4243	(0.1773)	(0.0036)	0.1727
<i>ΔOC</i>	72,885	0.1065	0.2122	0.0066	0.0841	0.1874	31,681	0.0446***	0.3142	(0.1138)	0.0247	0.1846
<i>CELST</i>	47,262	0.8600	0.3270	0.7461	0.9187	1.0176	19,220	0.6744***	0.4234	0.4830	0.7550	0.9346
<i>REV</i>	78,181	6.2751	2.1229	4.7397	6.2279	7.7380	34,001	4.4038***	2.2595	2.8828	4.2791	5.9129
<i>OC</i>	78,181	6.1384	2.1134	4.5971	6.0865	7.6050	34,001	4.7428***	1.9159	3.3096	4.4734	5.9676
<i>LELST</i>	51,587	0.9163	0.9102	0.8387	0.9603	1.0274	21,743	0.7739***	0.4931	0.5776	0.8636	1.0217
<i>EMP</i>	52,764	0.0058	0.0069	0.0023	0.0042	0.0068	22,162	0.0085***	0.0120	0.0028	0.0049	0.0084
<i>ROA</i>	72,885	0.0832	0.0701	0.0348	0.0651	0.1094	31,681	- 0.1616***	0.1791	(0.2224)	(0.0922)	(0.0326)
<i>PASTROA</i>	47,262	0.0573	0.0764	0.0237	0.0562	0.0944	19,224	- 0.0571***	0.1523	(0.1016)	(0.0125)	0.0338
<i>SIZE</i>	78,181	6.3878	2.2752	4.7210	6.3772	7.9631	34,001	4.7416***	1.9989	3.2715	4.6127	6.0250
<i>SALESGROWTH</i>	72,885	0.1663	0.3468	0.0107	0.0959	0.2265	31,681	0.1160***	0.5964	(0.1625)	(0.0036)	0.1885
<i>FIRSTLOSS</i>	--	--	--	--	--	--	31,681	0.3359	0.4723	0.0000	0.0000	1.0000
<i>LOSSSEQ</i>	--	--	--	--	--	--	21,901	2.4170	1.7576	1.0000	2.0000	4.0000
<i>DIVDUM</i>	77,887	0.4730	0.4993	0.0000	0.0000	1.0000	33,882	0.1385***	0.3454	0.0000	0.0000	0.0000
<i>DIVSTOP</i>	72,885	0.0179	0.1327	0.0000	0.0000	0.0000	31,681	0.0298***	0.1700	0.0000	0.0000	0.0000
<i>FINLEV</i>	77,921	0.6760	1.0910	0.0566	0.3705	0.8263	33,857	0.9088***	1.6612	0.0142	0.2995	0.9877

**TABLE 5 (continued)**

This table reports the descriptive statistics of the variables employed in this study for the profit-firms sample and loss-firms sample. The profit-firms sample and loss-firms sample include 78,181 and 34,001 firm-year observations, respectively.

**REVERSAL** is a dummy variable that equals 1 if a loss firm in the current year ( $t$ ) becomes profitable in the consecutive year ( $t+1$ ), and 0 otherwise;  **$\Delta REV$**  is the natural logarithm of the change in sales revenue (Compustat item “SALE”) in the current year ( $t$ ) relative to the previous year ( $t-1$ );  **$\Delta OC$**  is the natural logarithm of the change in total operating costs in the current year ( $t$ ) relative to the previous year ( $t-1$ ), where operating costs are calculated as total sales revenue (Compustat item “SALE”) minus income from operations after depreciation (Compustat item “OIADP”); **CELST** is a firm’s cost elasticity as estimated in model 1 over a six-year window ( $t-5$  to  $t$ ); **REV** is the natural logarithm of total sales revenue (Compustat item “SALE”); **OC** is the natural logarithm of total operating costs calculated as total sales revenue (Compustat item “SALE”) minus income from operations after depreciation (Compustat item “OIADP”); **LELST** is a firm’s cost elasticity as estimated in model 2 over a six-year window ( $t-5$  to  $t$ ); **EMP** is the employee intensity calculated as the average ratio of the number of employees to sales revenue over a six-year window ( $t-5$  to  $t$ ); **ROA** is return on assets measured as income before extraordinary items and discontinued operations (Compustat item “BI”) scaled by lagged total assets (Compustat item “AT”); **PASTROA** is the past five-year average of return on assets; **SIZE** is measured as the natural logarithm of current market value of common equity at year end ( $t$ ) (Compustat item “PRCC\_F” multiplied by Compustat item “CSHO”); **SALESGROWTH** is measured as the percentage growth in sales revenue (Compustat item “SALE”) during the current year; **FIRSTLOSS** is a dummy variable that equals 1 if a firm reports a loss in the current year ( $t$ ) and was profitable in the previous year ( $t-1$ ), and 0 otherwise; **LOSSSEQ** is the number of sequential losses over the past five years before the current loss ( $t$ ); **DIVDUM** is a dummy variable that equals 1 if a firm is paying dividends (Compustat item “DVC”), and 0 otherwise; **DIVSTOP** is a dummy variable that equals 1 if a firm stopped paying dividends in the current year ( $t$ ), and 0 otherwise; and **FINLEV** is financial leverage calculated as the ratio of long-term debt at year end ( $t$ ) (Compustat item “DLTT”) to market value of common equity at year end (Compustat item “PRCC\_F” multiplied by Compustat item “CSHO”). A t-test is used for testing the difference in means. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed test.

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**TABLE 6**  
**Correlation Matrix for the Variables Employed in the Logistic Regression**

Variables	<i>REVERSAL</i>	<i>CELST</i>	<i>LELST</i>	<i>EMP</i>	<i>ROA</i>	<i>PASTROA</i>	<i>SIZE</i>	<i>SALES GROWTH</i>	<i>FIRSTLOSS</i>	<i>LOSSSEQ</i>	<i>DIVDUM</i>	<i>DIVSTOP</i>	<i>FINLEV</i>
<i>REVERSAL</i>		0.1440***	0.1414***	- 0.1062***	0.3026***	0.2576***	0.1080***	0.0108*	0.2133***	- 0.2662***	0.1892***	0.0282***	0.1386***
<i>CELST</i>	0.1182***		0.5891***	- 0.0875***	0.3397***	0.2866***	0.0507***	0.0298***	0.1448***	- 0.2751***	0.1541***	0.0519***	0.2640***
<i>LELST</i>	0.1126***	0.4943***		- 0.1244***	0.2965***	0.3404***	0.1032***	0.0887***	0.1941***	- 0.3448***	0.1104***	0.0135**	0.2366***
<i>EMP</i>	- 0.1158***	- 0.1821***	- 0.1962***		- 0.2056***	- 0.2380***	- 0.1865***	0.0827***	- 0.1313***	0.2136***	- 0.1793***	- 0.0384***	- 0.1324***
<i>ROA</i>	0.2673***	0.3221***	0.2574***	- 0.3177***		0.4379***	0.1891***	0.0096*	0.3287***	- 0.4023***	0.2691***	0.0656***	0.3140***
<i>PASTROA</i>	0.2378***	0.3188***	0.2870***	- 0.3693***	0.5806***		0.2212***	- 0.1130***	0.5102***	- 0.8449***	0.3516***	0.0998***	0.2392***
<i>SIZE</i>	0.1218***	0.0356***	0.0614***	- 0.1134***	0.1406***	0.1591***		0.1416***	0.1244***	- 0.1821***	0.2859***	0.0039	0.1002***
<i>SALES GROWTH</i>	- 0.0481***	- 0.0722***	- 0.0569***	0.1950***	- 0.1732***	- 0.2038***	0.0822***		- 0.1130***	0.1274***	- 0.0819***	- 0.0572***	- 0.0130**
<i>FIRSTLOSS</i>	0.2133***	0.1206***	0.1417***	- 0.1391***	0.2971***	0.4158***	0.1365***	- 0.1349***		- 0.5761***	0.2771***	0.0015	0.1605***
<i>LOSSSEQ</i>	- 0.2636***	- 0.2452***	- 0.2569***	0.2523***	- 0.4061***	- 0.7497***	- 0.1808***	0.1635***	- 0.5550***		- 0.3689***	- 0.1008***	- 0.2458***
<i>DIVDUM</i>	0.1892***	0.1216***	0.0863***	- 0.1298***	0.2214***	0.2800***	0.3161***	- 0.0912***	0.2771***	- 0.3551***		- 0.0708***	0.2319***
<i>DIVSTOP</i>	0.0282***	0.0476***	0.0183***	- 0.0281***	0.0701***	0.0925***	0.0053	- 0.0471***	0.0015	- 0.1026***	- 0.0708***		0.0820***
<i>FINLEV</i>	0.0334***	0.1233***	0.1009***	- 0.0852***	0.1963***	0.1701***	- 0.0500***	- 0.0726***	0.0694***	- 0.1496***	0.1213***	0.0783***	

This table presents pooled Pearson (below diagonal) and Spearman (above diagonal) correlations of the variables employed in this study for the loss-firms sample. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed test. Notes of Table 5 provide variable definitions.

**TABLE 7**  
**Loss-Reversal Probabilities Conditional on Cost-Elasticity Estimates and Employee Intensity**

	<b>First Loss Sample</b>		<b>Second Loss Sample</b>		<b>Third Loss Sample</b>	
	<b>Cost Elasticity</b>				<b>Employee Intensity</b>	
	<i>CELST</i>		<i>LELST</i>		<i>EMP</i>	
	<b>No. Of Obs.</b>	<b>Reversal Prob. in t+1</b>	<b>No. Of Obs.</b>	<b>Reversal Prob. in t+1</b>	<b>No. Of Obs.</b>	<b>Reversal Prob. in t+1</b>
<b>Above Median</b>	9,610	34.66%	10,872	34.61%	11,081	24.65%
<b>Below Median</b>	9,610	22.50%	10,871	22.40%	11,081	32.30%
<b>Diff. in Mean (Above-Below)</b>		12.16%***		12.21%***		- 7.65%***

This table presents loss-reversal probabilities conditional on the cost-elasticity-estimates median computed for the first and the second loss samples, and conditional on the employee-intensity median computed for the third loss sample. A t-test is used for testing the difference in means. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed test.

**TABLE 8**  
**Logistic Regression of Loss Reversal – Time-Series Estimation**

Independent Variables	<i>REVERSAL<sub>i,t+1</sub></i>			
	(1)	(2)	(3)	(4)
<i>INTERCEPT</i>	- 0.8017*** -8.0001	- 0.8336*** -7.3100	- 0.7902*** -7.1617	- 0.5493*** -5.4124
<i>CELS<i>T<sub>i,t</sub></i></i>	--	0.2047*** 2.9300	--	--
<i>LELS<i>T<sub>i,t</sub></i></i>	--	--	0.1525*** 3.2222	--
<i>EMP<i>T<sub>i,t</sub></i></i>	--	--	--	- 13.7198*** -5.7754
<i>ROA<i>T<sub>i,t</sub></i></i>	4.1805*** 13.2023	4.2388*** 13.2529	4.2903*** 13.7848	4.2889*** 13.2707
<i>PASTROA<i>T<sub>i,t</sub></i></i>	0.7046** 2.2088	0.7488** 2.3948	0.6958** 2.1638	0.6371* 2.0302
<i>SIZE<i>T<sub>i,t</sub></i></i>	0.0935*** 6.1486	0.0888*** 5.8909	0.0846*** 5.5147	0.0822*** 5.4707
<i>SALES<i>GROWTH<sub>i,t</sub></i></i>	0.2164*** 3.5533	0.2355*** 3.9499	0.2278*** 3.8463	0.2621*** 4.4183
<i>FIRSTLOSS<i>T<sub>i,t</sub></i></i>	0.2307*** 4.3251	0.2226*** 4.1690	0.2211*** 4.0713	0.2205*** 4.1456
<i>LOSSSEQ<i>T<sub>i,t</sub></i></i>	- 0.1458*** -6.8299	- 0.1466*** -7.0289	- 0.1445*** -6.9040	- 0.1511*** -7.2739
<i>DIVDUM<i>T<sub>i,t</sub></i></i>	0.2815*** 4.4200	0.3021*** 4.8796	0.3173*** 5.1227	0.3116*** 4.9267
<i>DIVSTOP<i>T<sub>i,t</sub></i></i>	- 0.6706 -1.0354	- 0.6346 -0.9921	- 0.6243 -0.9749	- 0.6368 -0.9921
<i>FINLEV<i>T<sub>i,t</sub></i></i>	--	- 0.1651*** -5.8918	- 0.1628*** -5.6890	- 0.1618*** -5.6471
<b>No. of Obs.</b>	19,146	19,065	18,935	19,069
<b>Average No. of Annual Obs.</b>	832	829	823	829
<b>Average Pseudo R-Squared</b>	0.1256	0.1331	0.1295	0.1328
<b>Average LR <i>p</i>-value</b>	0.0000	0.0000	0.0000	0.0000

This table presents results from estimating logistic regression model 3. Reported coefficients are the average coefficient of the annual estimation of logistic regression over the estimation period from 1992 to 2021 and *t*-statistics with robust standard errors (in parentheses) derived using the Fama-MacBeth (1973) procedure. Pseudo R-squared is measured by the proportion reduction of error (log-likelihood) achieved from the use of the set of independent variables relative to the null model (McFadden 1973). Variable definitions are in Table 5. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed test.

**TABLE 9**  
**Logistic Regression of Loss Reversal – Cross-Section Estimation**

Independent Variables	<i>REVERSAL<sub>i,t+1</sub></i>			
	(1)	(2)	(3)	(4)
<i>CELST<sub>i,t</sub></i>	--	0.1422** 2.0971	--	--
<i>LELST<sub>i,t</sub></i>	--	--	0.1286** 2.3934	--
<i>EMP<sub>i,t</sub></i>	--	--	--	- 10.8475*** -3.3128
<i>ROA<sub>i,t</sub></i>	3.7863*** 16.5112	3.8156*** 18.2139	3.8470*** 19.4026	3.8458*** 17.9162
<i>PASTROA<sub>i,t</sub></i>	0.9094*** 3.2882	0.9037*** 3.5187	0.8757*** 3.4253	0.8094*** 3.4694
<i>SIZE<sub>i,t</sub></i>	0.0963*** 7.1651	0.0894*** 7.0059	0.0854*** 6.7951	0.0854*** 6.6736
<i>SALESGROWTH<sub>i,t</sub></i>	0.2305*** 3.4529	0.2304*** 3.8188	0.2271*** 3.6510	0.2598*** 3.9208
<i>FIRSTLOSS<sub>i,t</sub></i>	0.2227*** 4.7823	0.2150*** 4.5031	0.2158*** 4.7559	0.2146*** 4.6235
<i>LOSSSEQ<sub>i,t</sub></i>	- 0.1428*** -16.0420	- 0.1445*** -15.2825	- 0.1413*** -15.2253	- 0.1474*** -16.0324
<i>DIVDUM<sub>i,t</sub></i>	0.3178*** 4.5008	0.3281*** 4.7923	0.3363*** 4.9691	0.3370*** 4.7926
<i>DIVSTOP<sub>i,t</sub></i>	0.0156 0.3916	0.0348 0.7950	0.0417 0.9787	0.0475 1.0534
<i>FINLEV<sub>i,t</sub></i>	--	- 0.1033*** -6.3555	- 0.1036*** -5.6210	- 0.1019*** -5.6058
<b>Year Fixed Effects</b>	Yes	Yes	Yes	Yes
<b>Industry Fixed Effects</b>	Yes	Yes	Yes	Yes
<b>No. of Obs.</b>	19,146	19,065	18,935	19,069
<b>Pseudo R-Squared</b>	0.1274	0.1298	0.1271	0.1306

This table presents the estimation of logistic regression model 3. Reported coefficients are estimated using cross-sectional regression over the estimation period from 1992 to 2021 and the associated *t*-statistics (in parentheses) calculated using standard errors clustered by industry (SIC one digit). We include year dummies and industry (SIC one digit) dummies to control for fixed effects. Pseudo R-squared is measured by the proportion reduction of error (log-likelihood) achieved from the use of the set of independent variables relative to the null model (McFadden 1973). Variable definitions are in Table 5. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed test.

**TABLE 10**  
**Reversal of Negative Operating Income**

	First Loss Sample		Second Loss Sample		Third Loss Sample	
	Cost Elasticity				Employee Intensity	
	CELST		LELST		EMP	
		Reversal Prob. in t+1		Reversal Prob. in t+1		Reversal Prob. in t+1
	No. Of Obs.		No. Of Obs.		No. Of Obs.	
Above Median	7,204	28.18%	8,236	28.90%	8,412	19.39%
Below Median	7,203	18.60%	8,236	18.01%	8,411	27.29%
Diff. in Mean (Above-Below)	9.58%***		10.89%***		- 7.90%***	

This table presents probabilities of negative operating income conditional on the cost-elasticity median computed for the first and second loss samples for income from operations after depreciation as the dependent variable that equals 1 if a negative income from operations after depreciation in the current year ( $t$ ) becomes positive in the consecutive year ( $t+1$ ), and 0 otherwise. A t-test is used for testing the difference in means. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed test.

TABLE 11

## Logistic Regression of Reversal of Negative Operating Income – Time Series

Independent Variables	Operating Income after Depreciation			
	<i>REVERSAL<sub>i,t+1</sub></i>			
	(1)	(2)	(3)	(4)
<i>INTERCEPT</i>	- 0.6744*** -7.9364	- 0.8921*** -7.5752	- 0.8541*** -8.1599	- 0.5096*** -6.3136
<i>CELS<sub>i,t</sub></i>	--	0.2508** 2.6528	--	--
<i>LELS<sub>i,t</sub></i>	--	--	0.2150*** 4.1297	--
<i>EMP<sub>i,t</sub></i>	--	--	--	- 20.9538*** -4.0474
<i>ROA<sub>i,t</sub></i>	4.4522*** 12.4437	4.3809*** 11.8270	4.4254*** 12.2568	0.6645* 2.0005
<i>PASTROA<sub>i,t</sub></i>	0.8518** 2.6113	0.7677** 2.2377	0.7404** 2.2382	0.0691*** 4.7145
<i>SIZE<sub>i,t</sub></i>	0.0786*** 5.1819	0.0844*** 5.5872	0.0753*** 4.9677	0.3392*** 4.5212
<i>SALESGROWTH<sub>i,t</sub></i>	0.2609*** 4.1840	0.2705*** 4.1838	0.2627*** 4.2368	0.0691 1.0407
<i>FIRSTLOSS<sub>i,t</sub></i>	0.0612 0.9022	0.0724 1.0102	0.0628 0.9001	- 0.1509*** -5.2764
<i>LOSSSEQ<sub>i,t</sub></i>	- 0.1495*** -5.1430	- 0.1475*** -5.0769	- 0.1411*** -4.8603	0.2830*** 3.1496
<i>DIVDUM<sub>i,t</sub></i>	0.2848*** 3.1900	0.2748*** 3.0699	0.2877*** 3.1835	0.0886 0.8224
<i>DIVSTOP<sub>i,t</sub></i>	0.0924 0.8330	0.0757 0.6771	0.0868 0.7710	0.4563*** 33.2716
<b>No. of Obs.</b>	13,229	13,225	13,124	13,229
<b>Average No. of Annual Obs.</b>	575	575	571	575
<b>Average Pseudo R-Squared</b>	0.1241	0.1243	0.1243	0.1293
<b>Average LR <i>p</i>-value</b>	0.0000	0.0000	0.0000	0.0000

This table presents the estimation of logistic regression model 3 for operating income after depreciation as the dependent variable that equals 1 if a negative operating income after depreciation in the current year ( $t$ ) becomes positive in the consecutive year ( $t+1$ ), and 0 otherwise. Reported coefficients are the average coefficient of the annual estimation of logistic regression over the estimation period from 1992 to 2021 and  $t$ -statistics with robust standard errors (in parentheses) derived using the Fama-MacBeth (1973) procedure. Pseudo R-squared is measured by the proportion reduction of error (log-likelihood) achieved from the use of the set of independent variables relative to the null model (McFadden 1973). Variable definitions are in Table 5. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed test.

**TABLE 12**  
**Exogenous Shock: The 2008 Financial Crisis**

	<b>First Loss Sample</b>		<b>Second Loss Sample</b>		<b>Third Loss Sample</b>	
	<b>Cost Elasticity</b>				<b>Employee Intensity</b>	
	<i>CELST</i>		<i>LELST</i>		<i>EMP</i>	
	<b>No. Of Obs.</b>	<b>Reversal Prob. in t+1</b>	<b>No. Of Obs.</b>	<b>Reversal Prob. in t+1</b>	<b>No. Of Obs.</b>	<b>Reversal Prob. in t+1</b>
<b>Above Median</b>	539	37.66%	566	39.05%	582	24.91%
<b>Below Median</b>	539	19.29%	566	17.49%	581	31.67%
<b>Diff. in Mean (Above-Below)</b>		18.37%***		21.56%***		- 6.76%**

This table presents loss-reversal probabilities conditional on the cost-elasticity median for the firms reporting a loss on the 2008 financial crisis year for the first and second loss samples. A t-test is used for testing the difference in means. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed test.

**TABLE 13**  
**Exogenous Shock: The 2008 Financial Crisis**

Independent Variables	<i>REVERSAL<sub>i,t+1</sub></i>			
	(1)	(2)	(3)	(4)
<i>CELST<sub>i,t</sub></i>	--	0.8243*** 3.8563	--	--
<i>LELST<sub>i,t</sub></i>	--	--	0.5365* 1.7674	--
<i>EMP<sub>i,t</sub></i>	--	--	--	- 16.8983** - 1.9799
<i>ROA<sub>i,t</sub></i>	1.3950*** 3.3410	1.3567*** 3.3291	1.4673*** 3.2956	1.4298*** 3.1608
<i>PASTROA<sub>i,t</sub></i>	3.3646*** 2.6265	3.1472*** 2.6038	2.8896** 2.5456	3.1609*** 2.6166
<i>SIZE<sub>i,t</sub></i>	0.1817*** 4.8172	0.1820*** 4.2526	0.1776*** 4.0640	0.1745*** 4.0718
<i>SALESGROWTH<sub>i,t</sub></i>	0.5256*** 4.1783	0.5479*** 4.2294	0.5010*** 3.5678	0.5759*** 3.5467
<i>FIRSTLOSS<sub>i,t</sub></i>	0.4703*** 3.0894	0.4689*** 3.0081	0.4893*** 3.1465	0.4755*** 2.9258
<i>LOSSSEQ<sub>i,t</sub></i>	- 0.0975** - 2.2882	- 0.0892** - 2.0616	- 0.0745* - 1.9239	- 0.1005** - 2.2204
<i>DIVDUM<sub>i,t</sub></i>	0.3824 1.4617	0.2970 1.0990	0.3858 1.5251	0.3892 1.5401
<i>DIVSTOP<sub>i,t</sub></i>	- 0.2586 - 0.5578	- 0.2728 - 0.6018	- 0.2140 - 0.4615	- 0.2378 - 0.5263
<i>FINLEV<sub>i,t</sub></i>	--	- 0.0012 - 0.0281	0.0082 0.1988	0.0214 0.5478
<b>Industry Fixed Effects</b>	Yes	Yes	Yes	Yes
<b>No. of Obs.</b>	1,072	1,068	1,061	1,068
<b>Pseudo R-Squared</b>	0.1624	0.1727	0.1643	0.1650

This table presents the estimation of logistic regression model 3 for firms reporting a loss on the 2008 financial crisis year. Reported coefficients are estimated from cross-sectional regressions and the associated *t*-statistics (in parentheses) calculated using standard errors clustered by industry (SIC one digit). We include industry (SIC one digit) dummies to control for fixed effects. Pseudo R-squared is measured by the proportion reduction of error (log-likelihood) achieved from the use of the set of independent variables relative to the null model (McFadden 1973). Variable definitions are in Table 5. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed test.

**TABLE 14**  
**Survival Rates Conditional on Cost Elasticity**

<b>Cost-Elasticity Estimate</b>	<b>Survival rate from year t to t+1</b>	<b>Survival rate from year t to t+2</b>	<b>Survival rate from year t to t+3</b>	<b>Survival rate from year t to t+4</b>	<b>Survival rate from year t to t+5</b>
<b><i>CELST</i></b>	<b>First Loss Sample</b>				
<b>Above Median</b>	86.96%	72.32%	61.28%	52.21%	48.48%
<b>Below Median</b>	86.48%	71.37%	59.65%	50.66%	46.66%
<b>Diff. in Mean (Above-Below)</b>	0.48%	0.95%	1.63%**	1.55%**	1.81%**
<b><i>LELST</i></b>	<b>Second Loss Sample</b>				
<b>Above Median</b>	89.10%	74.93%	63.67%	54.28%	50.65%
<b>Below Median</b>	87.56%	71.61%	59.25%	50.06%	45.85%
<b>Diff. in Mean (Above-Below)</b>	1.54%***	3.31%***	4.42%***	4.22%***	4.80%***

This table presents accumulated survival rates over up to five years ahead ( $t$  to  $t+5$ ) conditional on the cost-elasticity median computed for the first and second loss samples. A t-test is used for testing the difference in means. \*, \*\*, and \*\*\* denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed test.