LOSS FIRMS DURING THE COVID-19 CRISIS AND THE SUBSEQUENT REVERSAL

Wan-Ting Wu *

* Department of Accounting and Finance, College of Management, University of Massachusetts Boston (UMass Boston), Boston, USA
Contact details: Department of Accounting and Finance, College of Management, UMass Boston, 100 William T. Morrissey Blvd., Boston, 02125-3393 MA, USA

OPEN ACCESS

How to cite this paper: Wu, W.-T. (2023). Loss firms during the COVID-19 crisis and the subsequent reversal. *Corporate Ownership & Control, 20*(2), 8–20. https://doi.org/10.22495/cocv20i2art1

ISSN Online: 1810-3057
ISSN Print: 1727-9232

Received: 19.09.2022
Accepted: 06.01.2023

JEL Classification: G32, M41
DOI: 10.22495/cocv20i2art1

Abstract

The COVID-19 pandemic has caused significant disruptions to the global economy. This paper examines firms that reported losses during the first year of the COVID-19 crisis (i.e., 2020) and their subsequent reversals to profitability in 2021. A comparison of data on the COVID-19 crisis with the Global Financial Crisis (GFC) and a general sample period (1976–2021) shows a high frequency and magnitude of losses reported during the COVID-19 crisis. Although the magnitude of losses reported during the COVID-19 crisis is not significantly higher than the losses reported during the GFC, the percentage of loss firms that reversed to profitability is greater after the COVID-19 crisis than after the GFC. This result applies to firms that suffered from the first year of loss as well as to firms with consecutive loss periods of two, three, or four years. While the reversal models based on Joos and Plesko (2005) are able to predict loss reversals in general, the prediction performance of these models is weaker for the GFC and the COVID-19 crisis, especially for firms that incurred more transitory losses. Further analysis shows that the negative relation between market value and earnings in loss firms is reduced when additional value drivers such as research and development (R&D), sales growth, and sustainability are considered.

Keywords: Losses, Loss Reversal, COVID-19, Prediction, Valuation

Authors' individual contribution: The Author is responsible for all the contributions to the paper according to CRediT (Contributor Roles Taxonomy) standards.

Declaration of conflicting interests: The Author declares that there is no conflict of interest.

1. INTRODUCTION

The COVID-19 pandemic has brought significant shocks to the global economy. The government-imposed lockdowns, the disruption of production and supply chains, the social-distancing practices, and their impacts on customer demand led to a dramatic decrease in companies' revenues and profits during the pandemic. Unsurprisingly, the percentage of firms that reported losses increased significantly during 2020, the first year of the COVID-19 crisis. The purpose of this paper is to examine firms that reported losses during 2020 and the recovery of these loss firms to a profit status one year later (i.e., 2021). Based on Joos and Plesko (2005), this paper uses two models to predict loss reversals and evaluates the models' prediction performance for the COVID-19 crisis relative to the Global Financial Crisis, GFC (2008–2009) and a general sample period (1976–2021). To understand the valuation of loss firms, this paper further examines the relation between market value and earnings for loss firms and tests additional value drivers that are not reflected in a firm's book value and earnings.

A growing number of studies examine the extreme disruptions of the COVID-19 crisis on the stock market (Alfaro et al., 2020; Ramelli & Wagner, 2020; Fahlenbrach et al., 2021) and the bond market (Kargar et al., 2021; Schrimpf et al., 2020; Haddad et al., 2021). The evidence on the impact of corporate social responsibility (CSR) on stock returns during the COVID-19 crisis is mixed. Garel and Petit-Romec (2020), Albuquerque et al. (2020), Ding et al. (2021), and Li et al. (2021) show that firms with higher CSR scores have significantly higher stock returns. However, Bae et al. (2021) and Demers et al. (2021) find that CSR has no explanatory power for stock returns during the COVID-19 crisis.

This paper differs from these prior studies by focusing on the reporting of losses on the financial statements during the first year of the COVID-19 crisis (i.e., 2020) and the reversal to profitability in 2021. Previous studies have documented a notable increase in the number of firms reporting losses over time (Hayn, 1995; Givoly & Hayn, 2000; Joos & Plesko, 2005). In line with these findings, this paper shows that the percentage of firms reporting losses in a given year has increased markedly over the last five decades: from 10.8% in 1970 to more than 34% after 2000. The Dot-com bubble, the GFC, and the COVID-19 crisis caused almost half of all firms to report a loss (46.85% in 2001, 47.34% in 2008–2009, and 47.04% in 2020, respectively)[1].

Further analysis shows that the magnitude of losses reported during the COVID-19 crisis is significantly larger than in the non-COVID period (1976–2019). In addition, although the magnitude of losses reported during the two crises (the COVID-19 crisis and the GFC) are similar, the percentage of loss firms that reversed to profitability is greater after the COVID-19 crisis than after the GFC. This result applies to firms that suffered from the first year of loss as well as to firms having consecutive loss periods of two, three, or four years. These findings suggest that the nature of losses incurred during the COVID-19 crisis differs from that in the other periods.

Based on the reversal models in Joos and Plesko (2005), this paper finds that the following types of loss firms are more likely to return to profitability subsequently: firms with higher profitability (or lower magnitude of loss), larger firms, firms with higher sales growth, firms experiencing the first year of loss, firms having a shorter loss sequence, dividend-paying firms, and firms that do not decrease dividend payments to shareholders. However, when the analysis focuses on the COVID-19 crisis alone, the explanatory ability of these variables for the loss reversal is not as significant as in other periods.

The out-of-sample analysis shows that the estimated probability of loss reversals aligns with the actual frequency of loss reversals in general. However, the model's prediction performance deteriorates significantly during the GFC period and the COVID-19 crisis period, especially for firms which are predicted to have more transitory losses. An analysis based on firms reporting transitory losses during the COVID-19 crisis shows that while the model predicts the probability of loss reversal to be 51.7%, more than three-quarters of these firms (76.8%) returned to profitability in 2021. This result suggests that even though the pandemic caused many firms to lose sales and to report a loss, the losses reported during the first year of the COVID-19 crisis (2020) tend to be more transitory than expected and a significant percentage of these losses firms were able to reverse to profitability in the next year.

Several studies (Burgstahler & Dichev, 1997; Collins et al., 1999) examine the negative relation between market value and earnings for loss firms and argue that book value plays an important role in the valuation of loss firms. Darrough and Ye (2007) suggest that including additional drivers such as R&D expensing and sustainability eliminates the negative relation between market value and earnings. This paper shows that including additional value drivers (R&D, sales growth, and proxies for sustainability) increases the explanatory power of the models and reduces the negative relation between market value and earnings in loss firms.

Overall, this paper documented a significant frequency of loss firms and a drastic decrease in sales during the COVID-19 crisis. While the reversal models in Joos and Plesko (2005) can predict the loss reversal in a general sample period (1976–2021), the prediction performance of these models is weaker for the GFC and the COVID-19 crisis, especially for firms with transitory losses. When it comes to valuation, it is crucial to consider additional factors that drive the value of loss firms, such as R&D, sales growth, and sustainability.

This paper contributes to the literature on loss firms in several aspects. First, while most recent literature focuses on the effects of the COVID-19 pandemic on the stock market or bond market, this paper adds to evidence from the accounting perspective, specifically about firms reporting losses during the first year of the COVID-19 crisis and their reversal to profitability one year later. Second, this paper documents that the loss reversals after the COVID-19 crisis differ from that after the GFC. This finding implies the results of the GFC do not necessarily apply to the COVID-19 crisis. Lastly, this paper finds that the loss reversal models used in prior literature have differing prediction abilities for firms with transitory losses relative to firms with permanent losses, and those models' performance declines during the crisis periods. This suggests that future studies can work on improving the models' performance for firms with transitory losses and crisis periods.

The remainder of the paper is organized as follows. Section 2 reviews the prior studies related to losses and the COVID-19 crisis. Data and samples are described in Section 3. Empirical results are presented and discussed in Section 4. Section 5 concludes the paper.

2. LITERATURE REVIEW

This study is related to prior literature on the reporting of losses and the prediction of the reversal to profitability. Hayn (1995) examines the information content of losses and shows that losses are not as informative as profits about future earnings because shareholders have a liquidation option. Hayn (1995) argues that when losses are reported, investors do not evaluate firms strictly on earnings, which leads to a weak association between stock returns and reported earnings. The results show that when only profit firm years are considered, the relation between stock price and earnings is much higher than when both profit and loss years are considered.

[1] The increase in loss reporting during these periods coincide with a significant decrease in sales, suggesting that the decrease in sales in these financially distressed periods is a major cause for the reporting of losses.

A number of studies use book value as a proxy for the abandonment value of the firm (Burgstahler & Dichev, 1997; Collins et al., 1997; Collins et al., 1999; Darrough & Ye, 2007). By regressing market value on book value and earnings, these studies find that book value has a substantially higher coefficient for loss firms than for-profit firms. Collins et al. (1999) explain this result as book value serving as a proxy for the loss firm's expected future normal earnings or as a proxy for the loss firms' abandonment value.

Instead of using book value as a proxy for a firm's abandonment value, Joos and Plesko (2005) develop prediction models to measure expected loss reversals and use it as a proxy for the likelihood of investors' exercise of the abandonment option. They show that investors value persistent losses differently from transitory losses and that when persistent losses contain R&D, investors value the R&D component as an asset and the non-R&D component as if it is a transitory loss. Consistent with Joos and Plesko (2005), Darrough and Ye (2007) find that R&D plays an important role in the valuation of loss firms. They show that accounting earnings and book values do not fully capture the firm value and that including R&D in the analysis significantly reduces the negative relation between earnings and market value. Based on UK loss-making firms, Jiang and Stark (2013) show that book value plays less of a role in the valuation of high R&D-intensive firms and dividend-paying firms than in the valuation of low R&D-intensive firms and firms with zero dividend payments. They note that the valuation models used in Darrough and Ye (2007) do not remove the negative relation between earnings and market value for UK loss-making firms.

A number of studies examine the impacts of COVID-19 crisis on the stock market (Alfaro et al., 2020; Bretscher et al., 2020; Gormsen & Koijen, 2020; Pástor & Vorsatz, 2020; Ramelli & Wagner, 2020; Ding et al., 2021; Mazur et al., 2021) and the bond market (Kargar et al., 2021; Schrimpf et al., 2020; Haddad et al., 2021; O'Hara & Zhou, 2021). Alfaro et al. (2020) show that unanticipated changes in predicted COVID-19 infections forecast next-day aggregate-level US stock returns. In the firm-level analysis, they find that firms with higher capital intensity and leverage, and firms in industries more conducive to disease transmission suffer from deeper losses in market value during the COVID-19 crisis. Fahlenbrach et al. (2021) find that during the COVID-19 shock, firms with high financial flexibility experienced a smaller stock price drop than those with low financial flexibility. They argue that firms with higher financial flexibility are more able to fund a cash flow shortfall caused by the dramatic decrease in revenues created by the COVID-19 shock. Haddad et al. (2021) document that the COVID-19 crisis brought extreme disruption to the bond market and those the Federal Reserve's interventions improved the liquidity in the bond market.

The evidence of the impact of CSR on stock returns during the COVID-19 crisis is mixed. Garel and Petit-Romec (2020), Albuquerque et al. (2020), and Ding et al. (2021) show that firms with higher CSR scores have significantly higher stock returns. However, Bae et al. (2021) find no relation between CSR and stock returns and show a weak relation between CSR and stock returns only when CSR is congruent with a firm's institutional environment. Similarly, Demers et al. (2021) show that CSR has no explanatory power for stock returns during the COVID-19 crisis once industry affiliation, market-based measures of risk, and accounting-based measures of performance, financial position, and intangibles investments have been controlled for. Instead of using pre-crisis CSR ratings, Li et al. (2021) develops a firm-level measure of exposure and response related to the COVID-19 crisis based on information collected from earnings calls over the period January 22 to April 30, 2020. They show that stock returns during the three-month crisis period in 2020 are higher in firms with a strong corporate culture than in their peers that do not have a strong culture.

This paper builds on the findings in these prior studies and examines the losses reported in the first year of the COVID-19 crisis and the loss firms' subsequent recovery to profitability.

3. RESEARCH FRAMEWORK

This section explains how the sample in this study is constructed, the characteristics of sample firms, and the frequency of loss and sales growth of loss firms during the sample period. The sample is collected from Compustat-Capital IQ North America fundamentals annual database for the years 1971–2021, and each firm is required to have at least seven years of non-missing data to calculate the key variables in the paper. Following Hayn (1995) and Joos and Plesko (2005), the loss is measured based on the report of negative income before extraordinary items (Compustat data item: *IB*). The initial sample contains 62,670 firm-year observations that reported losses between 1971 and 2021. Appendix A provides detailed definitions of the key variables in this study.

Figure 1 shows that consistent with the findings in the prior literature (Joos & Plesko, 2005), the frequency of firms reporting losses has increased significantly over the last five decades: from 10.8% in 1970 to more than 34% after 2000. It is noteworthy that during the Dot-com bubble, the GFC, and the COVID-19 crisis, almost half of all firms reported a loss (46.85% in 2001, 47.34% in 2008–2009, and 47.04% in 2020, respectively). The percentage of firms reporting losses during the first year of the COVID-19 crisis (47.04% in the fiscal year 2020) is similar to that during the GFC (47.34% during the fiscal year 2008–2009). However, the frequency of loss firms is lower in 2021 (35.30%) than after the GFC (38.92%). This result implies that more loss firms reverse to profitability after the first year of the COVID-19 crisis than after the GFC. In other words, the losses incurred during the first year of the COVID-19 crisis are more transitory than the losses incurred during the GFC.

Figure 1. Frequency of loss firms by year

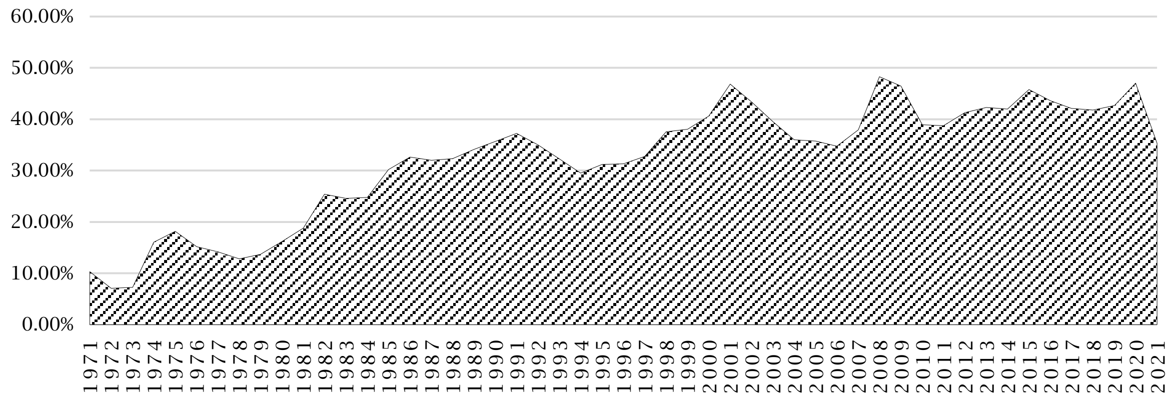
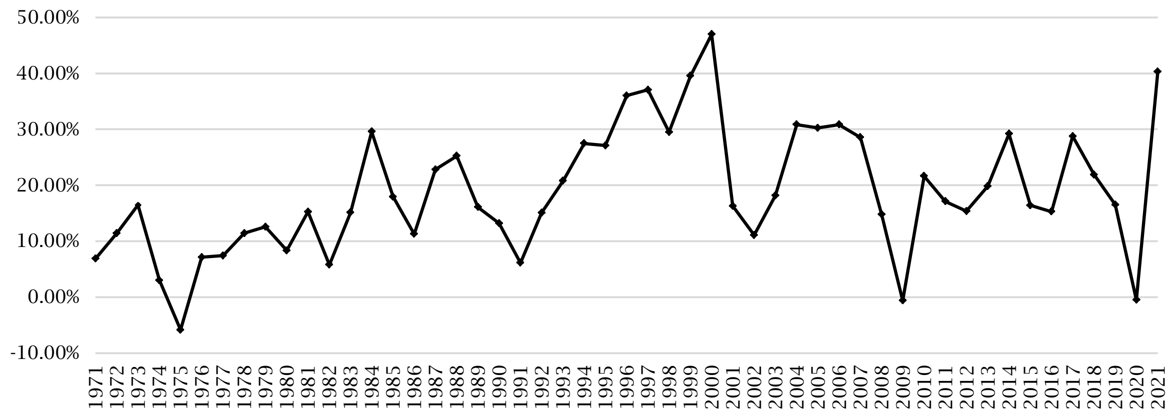


Figure 2 reports the sales growth of loss firms by fiscal year. The drastic decrease in sales growth in the years 2002, 2009, and 2020 is consistent with the higher incidence of losses during these recession periods. While the GFC and the COVID-19 crisis both caused negative sales growth among loss firms, their recoveries after the crisis differs significantly: sales growth is 21.64% in 2010 versus 40.30% in 2021.

Figure 2. Average sales growth of loss firms by year



Overall, Figures 1 and 2 show that in contrast to loss firms during the Dot-com bubble and the GFC, loss firms that survived the first year of the COVID-19 crisis reported higher sale growth and have a higher incidence of returning to profitability subsequent to the crisis.

Table 1 reports the descriptive statistics of the key variables in this paper. Panel A shows that compared to profit firms, loss firms have lower *ROA*, smaller *Size*, lower sales growth (*SaleGR*), lower accrual (*ACC*), and lower cash flows from operations (*CFO*). However, loss firms report more special items (*SPIW*) and research and development (*RD*) and have higher balances in cash, stock issuance (*StkIss*), and debt issuance (*DbtIss*) than profit firms. These findings suggest that loss firms are likely start-up companies that are smaller in size, sales growth, and cash flows from operations relative to profit firms, but these start-up companies invest more in R&D expenditures and have more capital raised from stock and debt issuance than profit firms.

Panel B of Table 1 documents the descriptive statistics of the key variables during the non-COVID-19 period (1976–2019), the GFC (2008–2009), and the COVID-19 crisis (2020). The last two columns compare the differences between the COVID-19 crisis and the other periods. Compared to the non-COVID-19 periods, firms reporting losses during the COVID-19 crisis are more likely to reverse to profitability (0.359 vs. 0.263). The magnitude of losses during the COVID-19 crisis is significantly larger than that during the non-COVID-19 period (*ROA* = -0.372 vs. -0.313), but is not significantly different from that during the GFC (*ROA* = -0.354). In addition, firms reporting losses during the COVID-19 crisis have lower sale growth, are larger, report more R&D, and have more stock issuance and debt issuance than loss firms in the non-COVID-19 periods. Compared to loss firms in the GFC, loss firms in the COVID-19 crisis have worse past performance (lower *Past_ROA*), larger size, lower operating cash flows (*CFO*), lower special items and R&D, and more stock issuance and debt issuance. These results suggest that the nature of losses incurred during the COVID-19 crisis differs from those incurred in the other periods, so it is crucial to provide more detailed analyses of firms that report a loss during the pandemic.

Table 1. Descriptive statistics of key variables

Panel A. *Loss firms vs. profit firms*

Variable	Loss Firms			Profit Firms			Differences
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
ROA	62,670	-0.318	0.686	149,904	0.072	0.076	-0.390***
Size	62,670	3.755	2.373	149,904	5.757	2.456	-2.002***
SaleGR	62,670	0.093	0.842	149,904	0.144	0.406	-0.051***
ACC	54,471	-0.215	0.505	108,599	-0.029	0.113	-0.185***
CFO	54,472	-0.149	0.474	108,601	0.101	0.126	-0.250***
SPIW	61,350	0.044	0.081	142,050	0.008	0.023	0.037***
RD	62,670	0.080	0.167	149,904	0.020	0.054	0.060***
Cash	60,121	0.159	0.287	138,488	0.097	0.160	0.062***
StkIss	61,349	0.158	0.528	140,718	0.027	0.138	0.131***
DbtIss	60,286	0.122	0.286	138,729	0.107	0.232	0.015***

Panel B. *Loss firms during non-COVID-19 period (1976–2019), GFC (2008–2009), and COVID-19 crisis (2020)*

Variable	Non-COVID-19 period (1976–2019)			Global Financial Crisis (2008–2009)			COVID-19 crisis (2020)			Diff. from non-COVID-19	Diff. from GFC
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.		
Reversal	0.263	0.000	0.440	0.292	0.000	0.455	0.359	0.000	0.480	0.097***	0.067***
ROA	-0.313	-0.097	0.678	-0.354	-0.095	0.784	-0.372	-0.087	0.796	-0.059***	-0.018
Past_ROA	-0.232	-0.030	0.581	-0.282	-0.011	0.710	-0.326	-0.035	0.737	-0.094***	-0.045**
Size	3.664	3.531	2.338	3.960	3.844	2.370	5.420	5.348	2.475	1.756***	1.460***
SaleGR	0.090	-0.033	0.831	0.009	-0.100	0.778	-0.008	-0.136	0.860	-0.098***	-0.017
ACC	-0.214	-0.105	0.501	-0.250	-0.114	0.566	-0.232	-0.105	0.548	-0.019	0.018
CFO	-0.146	-0.008	0.470	-0.125	0.006	0.469	-0.161	0.005	0.518	-0.015	-0.036***
Past_ACC	-0.173	-0.077	0.384	-0.192	-0.065	0.446	-0.191	-0.078	0.428	-0.019**	0.000
Past_CFO	-0.140	0.009	0.427	-0.131	0.021	0.462	-0.158	0.027	0.491	-0.018*	-0.027**
SPIW	0.044	0.007	0.081	0.054	0.010	0.093	0.044	0.012	0.076	0.000	-0.010***
RD	0.079	0.000	0.166	0.080	0.000	0.169	0.089	0.000	0.184	0.010***	0.009**
StkIss	0.149	0.001	0.508	0.102	0.001	0.417	0.285	0.001	0.764	0.136***	0.183***
DbtIss	0.121	0.001	0.286	0.104	0.000	0.270	0.145	0.048	0.270	0.024***	0.042***

*Note: This table provides descriptive statistics of the key variables in this paper. Panel A compares the differences in the key variables between loss firms and profit firms. Panel B reports the descriptive statistics of loss firms during the Non-COVID-19 period, the GFC, and the COVID-19 crisis. ***, **, * indicates statistical significance at the 1, 5, and 10 percent levels, respectively, using two-sided t-tests.*

4. EMPIRICAL RESULTS

4.1. Frequency of losses and loss reversals

Table 2 reports the distribution of losses and their reversals in the next year. Panel A shows that over 1971–2021, only 17.6% of the firms have *never* reported a loss. This percentage is significantly lower than the 27.21% of firms that never had a loss over the period 1971–2000 noted by Joos and Plesko (2005). Panel A further shows that the frequency of loss firms that report more than ten losses over 1971–2021, 16.74%, is higher than the 10% reported in Joos and Plesko (2005) over the period 1971–2000. This finding suggests that losses have become more persistent over time.

Panel B of Table 2 reports the likelihood of loss reversals based on whether it is the first year of loss reporting. $Reversal_{t+1}$ is a dummy variable that equals one if the loss firm becomes profitable in the next year (*t+1*) and zero otherwise. *FirstLoss* is a dummy variable equal to 1 if the current loss is the first in a sequence, and 0 otherwise. The results can be summarized as follows. First, based on the whole sample period (1976–2021), firms reporting the first loss are more likely to reverse to profitability the next year than firms with consecutive years of losses (35.13% vs. 17.11%). Second, during the COVID-19 crisis, firms reporting the first year of loss are much more likely to reverse to profitability than those in the other periods: $Reversal_{t+1}$ in the COVID-19 crisis, 57.98%, is higher than in 35.13% in the whole sample period and 41.70% in the GFC. This result suggests that losses incurred during the COVID-19 crisis are more transitory than losses incurred in the other periods.

Panel C of Table 2 shows the relation between the length of loss sequence (*LossSEQ*) and the likelihood of loss reversals one year later. The length of loss sequence (*LossSEQ*) measures the number of consecutive years of losses over the past five years. Firms with *LossSEQ* = 1 are firms experiencing the first year of loss; in contrast, firms with *LossSEQ* = 5 are those experiencing consecutive five years of losses. Based on the whole sample period (1976–2021), the likelihood of loss reversals decreases monotonically from 35.13% to 14.63% when the length of the loss sequence increases from one year to five years. The negative relation between the length of loss sequence (*LossSEQ*) and the likelihood of loss reversal within a year suggests that firms suffering from a longer period of losses are less likely to reverse to profitability than firms experiencing a shorter period of losses.

The negative relation between the sequence of prior losses and the likelihood of loss reversals also exists during the COVID-19 crisis and the GFC. It is noteworthy that firms reporting consecutive years of losses by the time of the COVID-19 crisis have a higher ability to reverse profitability than the other periods. For example, when $LossSEQ_t$ = 2 years, $Reversal_{t+1}$ = 37.43% for the COVID-19 crisis, which is much higher than that during GFC (27.67%) and in the whole sample period (24.70%)[2].

[2] Similarly, while 29.67% of firms reporting three consecutive years of losses by the first year of the COVID-19 crisis reverse to profitability, this frequency decreases notably during the GFC (23.35%) and in the whole sample period (20.49%).

Table 2. Frequency of losses and reversals

Panel A. *Distribution of the total number of years with losses*

Total number of years with losses	*N of firms*	*% of firms*
0	3,820	17.6
1	2,107	9.71
2	1,761	8.12
3	1,523	7.02
4	1,482	6.83
5	1,389	6.4
6	1,318	6.07
7	1,476	6.8
8	1,220	5.62
9	1,031	4.75
10	942	4.34
11–20	3,106	14.31
20 or more	525	2.43
Total	21,700	100

Panel B. *Relation between* $FirstLoss_t$ *and* $Reversal_{t+1}$

$FirstLoss_t$	*Whole sample period (1976–2021)*		*COVID-19 crisis (2020)*		*Global Financial Crisis (2008–2009)*	
	N of obs.	$Reversal_{t+1}$	*N of obs.*	$Reversal_{t+1}$	*N of obs.*	$Reversal_{t+1}$
No	80,515	17.11%	2075	18.02%	4788	18.15%
Yes	37,248	35.13%	752	57.98%	2410	41.70%

Panel C. *Relation between length of loss sequence* ($LossSEQ_t$) *and* $Reversal_{t+1}$

$LossSEQ_t$	*Whole sample period (1976–2021)*		*COVID-19 crisis (2020)*		*Global Financial Crisis (2008–2009)*	
	N of Obs.	$Reversal_{t+1}$	*N of obs.*	$Reversal_{t+1}$	*N of obs.*	$Reversal_{t+1}$
1 year	37,248	35.13%	752	57.98%	2410	41.70%
2 years	21,821	24.70%	350	37.43%	1431	27.67%
3 years	14,769	20.49%	209	29.67%	805	23.35%
4 years	10,596	16.61%	143	27.97%	494	15.79%
5 years	7,989	14.63%	179	14.53%	327	12.84%

Note: This table reports the distribution of the total number of years with losses (Panel A), the relation between $FirstLoss_t$ *and* $Reversal_{t+1}$ *(Panel B), and the relation between* $LossSEQ_t$ *and* $Reversal_{t+1}$ *(Panel C) based on the whole sample period (1976–2021), the GFC (2008–2009), and the COVID-19 crisis (2020).*

Table 3 reports the frequency of losses by industries. Industries are formed according to the Fama and French's twelve-industry classification scheme. Panel A shows that over the whole sample period (1976–2021), firms in the Energy, Business Equipment, and Healthcare industries are more likely to report a loss (44.41%, 46.66%, and 65.06%, respectively). Among these industries, the Healthcare industry has the largest magnitude of losses measured by *ROA* (-0.854), the longest sequence of loss reporting (an average of 4.009 years), and the lowest likelihood of returning to profitability following the loss reporting (0.104). Panels B and C document the loss reporting across industries during the COVID-19 crisis and the GFC.

Table 3. Frequency of losses and reversals (Part 1)

Panel A. *Frequency of losses by industry: Whole sample period (1976–2021)*

Industry	*Frequency of loss*	ROA_t	$FirstLoss_t$	$LossSEQ_t$	$Reversal_{t+1}$
Consumer nondurables	27.37%	-0.359	0.385	2.651	0.281
Consumer durables	34.04%	-0.553	0.325	2.959	0.232
Manufacturing	29.88%	-0.329	0.384	2.658	0.308
Energy	44.41%	-0.330	0.308	3.085	0.255
Chemicals and allied products	32.83%	-0.698	0.301	3.253	0.226
Business equipment	46.66%	-0.557	0.296	3.098	0.220
Telephone and television	34.75%	-0.313	0.278	3.218	0.218
Utilities	6.61%	-0.059	0.531	2.095	0.452
Wholesale & retail	30.04%	-0.275	0.377	2.601	0.273
Healthcare	65.06%	-0.854	0.172	4.009	0.104
Finance	19.38%	-0.222	0.407	2.565	0.323
Other	30.85%	-0.425	0.334	2.940	0.231

Panel B. *Frequency of losses by industry during the COVID-19 crisis (2020)*

Industry	*Frequency of loss*	ROA_t	$FirstLoss_t$	$LossSEQ_t$	$Reversal_{t+1}$
Consumer nondurables	38.92%	-0.391	0.492	2.600	0.508
Consumer durables	51.35%	-0.390	0.211	3.579	0.474
Manufacturing	38.15%	-0.296	0.429	2.743	0.429
Energy	82.83%	-0.234	0.366	2.762	0.494
Chemicals and allied products	43.64%	-0.638	0.229	3.479	0.333
Business equipment	40.70%	-0.637	0.208	3.893	0.259
Telephone and television	38.54%	-0.034	0.486	2.351	0.541
Utilities	6.25%	-0.052	0.692	1.769	0.615
Wholesale & retail	41.29%	-0.153	0.516	2.344	0.531
Healthcare	77.38%	-0.893	0.102	4.982	0.084
Finance	19.13%	-0.128	0.582	2.121	0.526
Other	58.24%	-0.617	0.212	4.092	0.241

Table 3. Frequency of losses and reversals (Part 2)

Panel C. *Frequency of losses by industry during the Global Financial Crisis (2008–2009)*

Industry	*Frequency of loss*	ROA_t	$FirstLoss_t$	$LossSEQ_t$	$Reversal_{t+1}$
Consumer nondurables	33.59%	-0.384	0.424	2.360	0.349
Consumer durables	54.29%	-0.525	0.316	2.632	0.263
Manufacturing	37.69%	-0.343	0.454	2.602	0.408
Energy	52.17%	-0.349	0.401	2.721	0.282
Chemicals and allied products	43.48%	-0.664	0.300	3.517	0.267
Business equipment	52.46%	-0.553	0.293	3.203	0.282
Telephone and television	37.39%	-0.180	0.373	2.976	0.333
Utilities	7.57%	-0.047	0.571	1.952	0.429
Wholesale & retail	34.87%	-0.241	0.429	2.492	0.369
Healthcare	64.46%	-0.872	0.135	4.426	0.121
Finance	36.84%	-0.135	0.521	1.941	0.337
Other	55.07%	-0.440	0.302	3.064	0.221

Note: This table reports industrial descriptive statistics related to losses. Industries are formed according to the Fama-French 12 industry classification. Panel A reports the descriptive statistics of the whole sample period (1976–2021), Panel B documents the descriptive statistics during the COVID-19 crisis (2020), and Panel C shows the results during the GFC (2008–2009).

The results during these two periods are different from those over the whole sample period in several ways. First, in addition to the aforementioned three industries that have the largest frequency of loss firms (Energy, Business Equipment, and Healthcare), the Consumer Durables industry also reports a high frequency of losses during the COVID-19 crisis (51.35%), and the GFC (54.29%). Second, during the COVID-19 crisis, the frequency of losses in the Energy industry (82.83%) and the Healthcare industry (77.38%) is much higher than the loss frequency of these industries during the GFC or over the whole sample period.

In summary, the results in Tables 2 and 3 suggest that the impacts of the COVID-19 crisis on firm's earnings are distinctive from the GFC and other periods, and the effects also differ across industries.

4.2. Analysis of loss reversals

The following models are used to examine loss reversals in the year subsequent to the loss reporting year.

Model I

$$Reversal_{t+1} = \beta_0 + \beta_1 ROA_t + \beta_2 Past\_ROA_t + \\ + \beta_3 Size_t + \beta_4 SaleGR_t + \beta_5 FirstLoss_t + \\ + \beta_6 LossSEQ_t + \beta_7 DivDum_t + \beta_8 DivDec_t + \varepsilon_{1t} \quad (1)$$

Model II

$$Reversal_{t+1} = \gamma_0 + \gamma_1 CFO_t + \gamma_2 ACC_t + \\ + \gamma_3 Past\_CFO_t + \gamma_4 Past\_ACC_t + \gamma_5 Size_t + \\ + \gamma_6 SaleGR_t + \gamma_7 FirstLoss_t + \gamma_8 LossSEQ_t + \\ + \gamma_9 DivDum_t + \gamma_{10} DivDec_t + \varepsilon_{2t} \quad (2)$$

The dependent variable $Reversal_{t+1}$ is a dummy variable that equals one if the loss firm becomes profitable in the next year (t+1) and zeroes otherwise[3]. The explanatory variables are composed of three categories: 1) financial measures such as profitability (*ROA* and *Past_ROA*), *Size*, and growth in sales (*SaleGR*); 2) measures related to losses (the first occurrence of loss (*FirstLoss*), and the sequence of losses (*LossSEQ*); and 3) dividend-related variables (*DivDum* and *DivDec*).

Among the first category of explanatory variables, *ROA* and *Past_ROA* are both expected to carry a positive sign, because firms with higher profitability are more likely to reverse to profitability. *Size*, measured as the log of market value (price close ($PRCC\_F_t$) x common shares outstanding ($CSHO_t$)), is also expected to have a positive sign, as larger firms are financially healthier and more likely to return to profitability than smaller firms (Joos & Plesko, 2005). Following Hayn (1995) and Joos and Plesko (2005), this paper includes growth in sales ($SaleGR_t$) in the models. $SaleGR_t$ is expected to carry a positive sign because firms with stronger sales growth are more likely to return to profitability following a loss year[4].

The second category of explanatory variables includes *FirstLoss* and *LossSEQ*. *FirstLoss* is a dummy variable equal to 1 if the loss in the current year is the first in a sequence, and 0 otherwise. *FirstLoss* is expected to carry a positive coefficient because compared to firms that suffer from a series of losses, firms incurring the first year of loss are more likely to suffer from temporary losses in operations and have a higher ability to solve the issues and return to profitability[5]. *LossSEQ* measures the number of sequential losses over the past five years. Firms experiencing a longer period of losses are less likely to reverse to profitability in the next year, so the coefficient of *LossSEQ* is expected to be negative.

The third category of explanatory variables is associated with the dividend-paying behavior of firms. Skinner and Soltes (2011) show that losses of firms that continue to pay dividends are less persistent than losses of firms that do not pay dividends. Two indicator variables are used to measure the dividend-paying behavior of firms. The first variable, *DivDum*, is a dummy variable equal to 1 if a firm pays dividends in year t, and 0 otherwise. Loss firms that continue to pay dividends send a signal that their losses are more likely to be transitory and thus are more capable of keeping paying dividends to shareholders. *DivDum* is expected to have a positive coefficient. The second

[3] Although the loss reversal may not necessarily occur in the immediate future, the results in Table 1 show that the majority of loss firms were able to reverse to profitability in the next year (with a frequency of 35.13%). As such, this paper follows the method in Joos and Plesko (2005) and focuses on the loss reversal in the year following the loss-reporting year.

[4] However, sales growth may not be a good predictor of reversals for young firms that have high growth yet stayed unprofitable for a number of years.

[5] This expectation is also consistent with the results in Table 1 that firms experiencing the first year of loss are more likely to revert to profitability in the following year.

variable, *DivDec*, is an indicator variable that measures whether a firm reduces dividend payments. *DivDec* equals 1 if the amount of a firm's dividend payment in year t is lower than that in year *t–1*, and 0 otherwise. The results in DeAngelo et al. (1992) suggest loss firms that do not reduce dividends are more likely to revert to profitability. Therefore, *DivDec* is expected to carry a negative sign.

Table 4 shows the logistic regression results of Model I. The coefficients are calculated based on the Fama-MacBeth (Fama & MacBeth, 1973) procedure and the significance is adjusted for autocorrelation using the Newey-West method. When the whole sample (1976–2021) is used in the analysis, the results are consistent with the expectations. The coefficients of *ROA*, *Past_ROA*, and *Size* are positive as expected, suggesting that loss firms with higher profitability (or lower magnitude of loss) and larger firms are more likely to return to profitability in the next year. The variable *SaleGR* also carries a positive coefficient, suggesting that loss firms with stronger sales growth are more likely to return to profitability. The result of the second category of the independent variables (*FirstLoss* and *LossSEQ*) are consistent with expectations as well: *FirstLoss* has a positive coefficient 0.151 and *LossSEQ* has a negative coefficient -0.123, which implies that firms experiencing the first year of loss and firms with a shorter loss sequence are more likely to return to profitability. Consistent with expectations, *DivDum* has a positive coefficient and *DivDec* has a negative coefficient, suggesting that firms with the ability to pay dividends to shareholders and firms not decreasing dividend payments are more likely to return to profitability. The results based on the GFC sample (2008–2009) are similar to those based on the whole sample period, except that the coefficient of *SaleGR* is not as significantly positive in the GFC sample as in the whole sample. The results of the COVID-19 crisis (2020) show the least significant results; the coefficients of *Size*, *SaleGR*, *FirstLoss*, and *DivDec* are not statistically significant, and the significance levels of *ROA* and *Past_ROA* are lower than those based on the whole sample period or the GFC.

The logistic regression results of Model II where *ROA* is decomposed into cash flows from operations (*CFO*) and accruals (*ACC*) are provided in Appendix B. The results show that cash flows from operations *CFO* are more associated with the loss reversals than accruals *ACC*. The rest of the results are generally similar to Table 4. In general, these findings suggest that the loss reversal models in Joos and Plesko (2005) are able to explain the loss reversals in the whole sample period (1976–2021), but their performance is worse for the GFC and the COVID-19 crisis.

4.3. Out-of-sample prediction of loss reversal

This section evaluates the prediction accuracy of the models using the out-of-sample tests. A two-step, rolling-window procedure is used to predict the probabilities of loss reversals only based on the predictors available at the time of prediction: In the first step, Model I and Model II are run separately annually to obtain the coefficients of each predictor. In the second step, the annual coefficients are averaged over the previous consecutive five-year period (*t–5* to *t–1*) and are then applied to the predictors in year *t* to generate the predicted probabilities of loss reversals in *t+1*[6]. The evaluation of the model's prediction performance is based on the difference between predicted reversals and actual reversals (*Diff* equals predicted reversal $\hat{R}$ minus actual reversal *R*).

Table 5 reports the results of the out-of-sample predictions. In Panel A, the prediction of loss reversals is estimated based on Model I. The loss observations are then sorted annually into deciles based on the estimated probability of loss reversal ($\hat{R}$). Decile 1(10) has observations with the most persistent (transitory) losses[7]. Based on the whole sample, the predicted reversal ($\hat{R}$) is generally consistent with the actual reversal (*R*). The actual loss reversal increases monotonically from 7.0% in Decile 1 to 53.3% in Decile 10, and the absolute value of prediction error (measured by *Diff*) is less than 3% in each decile. The larger *Diff* in Decile 1 (*Diff* = -2.9%) than in the other deciles (*Diff* varies from -1.5% to 1.2%) implies that the prediction performance of Model I is lower for firms with permanent losses (Decile 1) than for the other firms with more transitory losses (Decile 2–10).

During the GFC, the prediction performance of Model I declines significantly for firms with more transitory losses. For firms in Deciles 6–10 that have more transitory losses, the model significantly under-estimate the loss firms' ability to reverse to profitability in the next year. For example, while the model predicts the probability of loss reversals for Decile 10 to be 46.4%, a much higher percentage, 62.5%, of these loss firms reversed to profitability in the next year. The results show the differences between the predicted reversal and the actual reversal vary from -4.0% in Decile 7 to -16.1% in Decile 10, and the differences are significantly larger than those based on the whole sample period when the absolute value of *Diff* is less than 3%.

The underperformance of Model I in predicting reversals for transitory losses is notably observed during the COVID-19 crisis. For firms in Decile 6, while the model predicts the probability of loss reversals to be 25.1%, a significantly larger percentage (40.2%) of these loss firms reversed to profitability in 2021. For firms in Decile 10 that have the most transitory losses, while the model predicts the probability of loss reversal to be 51.7%, more than three-quarters of these firms (76.8%) reversed to profitability in 2021. This result suggests that while the pandemic caused many firms to lose sales and to report a loss, the losses are more transitory than expected and a significant percentage of these loss firms reversed to profitability in the next year. Panel B of Table 5 reports the results when Model II is used to predict the probability of loss reversals. The results are generally consistent with Panel A.

[6] For example, the annual coefficients of 2013 through 2017 are averaged and applied to the value of the predictors of 2018 to predict the reversal probabilities in year 2019 (i.e., the probabilities of the losses reported in 2018 to return to profit in 2019).

[7] Decile 1 has the observations with the lowest estimated likelihood of loss reversals (e.g., 4.1% based on the whole sample), which means their losses are more persistent than losses in the other deciles. In contrast, Decile 10 has observations with the highest estimated likelihood of loss reversals (e.g., 51.9% based on the whole sample), which means their losses are more transitory than those in the other deciles.

In general, the results show that Model I and Model II are able to predict loss reversals for the whole sample period (1976–2021), but their out-of-sample prediction performance for the GFC and the COVID-19 crisis is not as accurate. One year subsequent to these two crisis periods, more loss firms reversed to profitability than predicted by the models.

Table 4. Logistic regressions of loss reversal based on Model I

Variable	*Expected sign*	*Estimates (p-value)*		
		Whole sample period	*Global Financial Crisis*	*COVID-19 crisis*
ROA_t	+	1.444*** (<0.0001)	0.479** (0.010)	0.478** (0.030)
$Past\_ROA_t$	+	0.747*** (0.010)	0.328* (0.050)	0.511** (0.019)
$Size_t$	+	0.084*** (<0.0001)	0.179*** (<0.0001)	0.020 (0.419)
$SaleGR_t$	?	0.075*** (0.003)	0.106 (0.520)	0.080 (0.283)
$Firstloss_t$	+	0.151*** (0.001)	0.354*** (0.007)	0.265 (0.111)
$LossSEQ_t$	-	-0.123*** (<0.0001)	-0.172** (0.043)	-0.245*** (<0.0001)
$DivDum_t$	+	0.424*** (<0.0001)	0.338* (0.085)	0.743*** (<0.0001)
$DivDec_t$	-	-0.167*** (<0.0001)	-0.254* (0.075)	0.071 (0.651)
No. of observations		61,385	4,697	1,988
Average pseudo R-square		0.148	0.213	0.292
Average Likelihood ratio (LR)		157.222	379.327	475.091
Average LR p-value		0.012	<0.0001	<0.0001

*Note: This table presents the results from the annual logistic regressions of loss reversals based on Model I over the whole sample period (1976–2021), the GFC (2008–2009), and the COVID-19 crisis (2020). The dependent variable $Reversal_{t+1}$ equals 1 if a loss firm becomes profitable one year later. The definitions of the independent variables are provided in Appendix A. The coefficients are the mean of the coefficients from annual regressions, and the p-value (in parentheses) are calculated using the Fama-MacBeth method, adjusted for autocorrelation using the Newey-West method. ***, **, * indicates statistical significance at the 1, 5, and 10 percent levels, respectively, using two-sided t-tests.*

Table 5. Out-of-sample prediction of loss reversal

Panel A. *Out-of-sample prediction based on Model I*

	Whole sample period			*Global Financial Crisis*			*COVID-19 crisis*		
	$\hat{R}$	*R*	*Diff*	$\hat{R}$	*R*	*Diff*	$\hat{R}$	*R*	*Diff*
Decile 1	4.1%	7.0%	-2.9%***	2.8%	5.8%	-3.0%***	3.4%	6.6%	-3.2%*
Decile 2	10.9%	10.0%	0.9%**	9.4%	9.4%	0.1%	8.8%	12.6%	-3.7%
Decile 3	15.5%	14.4%	1.1%**	13.8%	13.2%	0.5%	11.9%	12.6%	-0.6%
Decile 4	19.3%	18.5%	0.9%*	18.3%	21.0%	-2.8%	15.5%	23.6%	-8.2%***
Decile 5	23.2%	22.0%	1.2%**	23.0%	20.3%	2.8%	20.1%	27.6%	-7.6%**
Decile 6	27.2%	27.1%	0.1%	27.2%	31.5%	-4.3%**	25.1%	40.2%	-15.1%***
Decile 7	31.4%	33.0%	-1.5%**	31.2%	35.2%	-4.0%*	30.5%	42.7%	-12.2%***
Decile 8	36.0%	35.1%	0.9%	35.1%	42.9%	-7.8%***	36.4%	54.8%	-18.4%***
Decile 9	41.6%	41.8%	-0.3%	39.1%	50.0%	-10.9%***	43.0%	61.8%	-18.8%***
Decile 10	51.9%	53.3%	-1.4%**	46.4%	62.5%	-16.1%***	51.7%	76.8%	-25.1%***

Panel B. *Out-of-sample prediction based on Model II*

	Whole sample period			*Global Financial Crisis*			*COVID-19 crisis*		
	$\hat{R}$	*R*	*Diff*	$\hat{R}$	*R*	*Diff*	$\hat{R}$	*R*	*Diff*
Decile 1	1.9%	4.5%	-2.6%***	2.4%	6.7%	-4.3%***	2.4%	4.6%	-2.2%
Decile 2	7.4%	6.6%	0.8%**	8.4%	7.8%	0.6%	7.8%	10.2%	-2.4%
Decile 3	12.2%	10.6%	1.6%***	13.5%	10.2%	3.3%**	11.8%	14.1%	-2.3%
Decile 4	16.5%	16.0%	0.5%	18.4%	20.0%	-1.5%	16.0%	23.4%	-7.4%**
Decile 5	20.8%	20.3%	0.4%	23.2%	23.7%	-0.6%	20.5%	28.3%	-7.8%**
Decile 6	25.0%	24.8%	0.1%	27.3%	31.6%	-4.3%**	25.1%	40.6%	-15.5%***
Decile 7	29.4%	29.9%	-0.4%	31.4%	36.4%	-5.0%**	30.9%	41.9%	-11.0%***
Decile 8	34.3%	33.3%	0.9%	35.5%	41.4%	-5.9%**	36.6%	53.3%	-16.7%***
Decile 9	40.3%	40.1%	0.2%	39.8%	51.7%	-11.8%***	42.5%	65.2%	-22.6%***
Decile 10	51.2%	53.2%	-2.0%***	47.7%	66.0%	-18.3%***	51.2%	77.2%	-25.9%***

*Note: This table presents the out-of-sample prediction results for loss reversals. Panel A shows the results based on Model I, and Panel B reports the results based on Model II. The loss observations are sorted annually into deciles based on the estimated probability of loss reversals ($\hat{R}$). R measures the actual percentage of loss firms that reverse to profitability in t+1. Diff equals $\hat{R}$ minus R. ***, **, * indicates statistical significance at the 1, 5, and 10 percent levels, respectively, using two-sided t-tests.*

4.4. Valuation of loss firms

Ohlson (1995) and Feltham and Ohlson (1995) model a firm's value as a function of the book value of equity and earnings. They suggest a positive relation between firm value and earnings. For loss firms, however, several studies such as Burgstahler and Dichev (1997) and Collins et al. (1999) have shown a negative relation between earnings and firms' market value and argue that book value plays an important role in the valuation of loss firms. Darrough and Ye (2007) explore additional value drivers of loss firms and suggest that the inclusion of R&D expensing and sustainability together in the equity valuation analyses helps address the issues of a negative relation between market value and earnings.

Following Darrough and Ye (2007), this paper uses the following equation to examine the valuation of earnings and other accounting measures:

Model III

$$MVE_t = \alpha_0 + \alpha_1 BVE_t + \alpha_2 ROA_t + \alpha_3 SPIW_t + \\ + \alpha_4 RD_t + \alpha_5 SaleGR_t + \alpha_6 NegSGR_t + \alpha_7 Cash_t + \\ + \alpha_8 StkIss_t + \alpha_9 LagStkIss_t + \alpha_{10} DbtIss_t + \varepsilon_{3t} \quad (3)$$

where, *MVE* (*BVE*) is the market (book) value of equity scaled by lagged total assets; *ROA* is calculated as earnings before extraordinary items scaled by lagged total assets; *SPIW* is measured as the absolute value of special items scaled by lagged total assets; *RD* is calculated as research and development expenses scaled by lagged total assets; *SaleGR* measures sales growth; *NegSGR* equals *SaleGR* if *SaleGR* is less than zero, and zero otherwise; *Cash* is scaled by lagged total assets; *StkIss* (*LagStkIss*) is defined as new stock issues in year *t* (*t-1*) scaled by lagged total assets; *DbtIss* equals new long-term debt issuance in year *t* scaled by lagged total assets.

Table 6 presents the results of equation (3) based on the Fama-MacBeth (1973) procedure and the significance is adjusted for autocorrelation using the Newey-West method. Industry dummies are included in the analysis. In the benchmark model (Model 1), the coefficient of earnings (proxied by *ROA*) is negative (-4.17, t-stat = -11.22), consistent with the findings in the previous studies on loss firms. When special items are added to the analysis (Model 2), the coefficient of earnings becomes slightly more negative (-4.44 with t-stat = -11.41), similar to the findings in Darrough and Ye (2007). Compared to the benchmark model, the inclusion of R&D (Model 3), sales growth (Model 4), proxies for sustainability (Model 5), or R&D together with sustainability measures (Model 6) reduces the negative relation between market value and earnings. When all the variables are included in the analysis (Model 7), the coefficient of earnings is the least negative and the least significant among all the models considered (-1.15 with t-stat = -4.22). The result of the significantly negative coefficient of the variable *ROA* in Models 6 and 7, however, is inconsistent with Darrough and Ye (2007) which find an insignificant coefficient for their earnings variable.

Overall, the results in Table 6 suggest that including additional variables such as R&D, sales growth, and proxies for sustainability reduces the negative relation between market value and earnings in loss firms. These variables also increase the explanatory power of the models (the adjusted *R*-square increases from 56.46% in Model 1 to 61.82% in Model 7).

Table 6. Valuation of accounting measures

Variable	Models						
	1	2	3	4	5	6	7
Intercept	-1.15 (-8.40)	-1.07 (-8.50)	-1.12 (-8.03)	-0.92 (-7.00)	-0.52 (-6.71)	-0.52 (-5.42)	-0.34 (-4.92)
BE	3.46 (10.10)	3.44 (10.18)	3.27 (9.93)	3.31 (9.63)	1.81 (9.62)	1.76 (9.30)	1.68 (9.04)
ROA	-4.17 (-11.22)	-4.44 (-11.41)	-3.73 (-9.33)	-3.55 (-8.66)	-2.06 (-6.07)	-1.75 (-4.95)	-1.15 (-4.22)
SPIW		-2.50 (-3.51)					-0.63 (-2.11)
RD			2.93 (4.20)			2.66 (3.78)	3.51 (6.19)
SaleGR				0.32 (3.53)			0.20 (3.42)
NegSGR				0.38 (1.62)			0.38 (1.52)
Cash					1.09 (3.87)	0.88 (3.54)	0.82 (2.65)
StkIss					2.11 (9.48)	2.06 (8.55)	1.99 (8.65)
LagStkIss					0.47 (2.81)	0.43 (2.78)	0.32 (2.67)
DbtIss					0.47 (3.88)	0.46 (3.57)	0.35 (3.52)
Industry dummies	included	included	included	included	included	included	included
Adj. R-square	56.46%	57.07%	58.76%	54.17%	61.13%	62.81%	61.82%

Note: This table presents regression results of equation (3) (Model III) over 1976–2021. The coefficients and the t-statistics (in parentheses) are based on Fama–MacBeth annual regression, and the significance is adjusted for autocorrelation using the Newey-West method. The definitions of the variables are provided in Appendix A.

5. CONCLUSION

This paper provides important evidence on the high frequency of loss firms during the first year of the COVID-19 crisis and the higher-than-expected frequency of reversals to profitability in the subsequent year. Differing from the existing literature on the impacts of the COVID-19 crisis on the stock market and the bond market (Alfaro et al., 2020; Ramelli & Wagner, 2020; Ding et al., 2021; Fahlenbrach et al., 2021; Haddad et al., 2021), this paper focuses on its impacts on financial reporting. Consistent with prior studies (Hayn, 1995; Joos & Plesko, 2005; Darrough & Ye, 2007), this paper shows that the frequency of firms reporting losses has increased markedly over time. The increasing trend of loss reporting has continued into the 21st century, well beyond the years of the prior studies, with peaks in the Dot-com bubble, the GFC, and the COVID-19 crisis when almost half of all firms in the Compustat database reported a loss (46.85% in 2001, 47.34% in 2008–2009, and 47.04% in 2020, respectively).

A comparison of loss reporting during the COVID-19 crisis, the GFC, and a general sample period (1976–2021) reveals several interesting features of the losses reported during the COVID-19 crisis. First, the magnitude of losses reported during the COVID-19 crisis is significantly larger than in the non-COVID period, and the associated sales growth is also significantly lower during the COVID-19 crisis. Second, the magnitude of losses reported during the two crises (the COVID-19 crisis and the GFC) are similar, but the percentage of loss firms that reverse to profitability is higher after the COVID-19 crisis. Third, the higher likelihood of reversing to profitability after the COVID-19 crisis than the other periods apply to firms that are reporting their first year of loss as well as to firms that have reported consecutive years of loss. Last, the distribution of industries that suffered from losses during the COVID-19 crisis is different from the other periods.

Based on the reversal models in Joos and Plesko (2005), this paper shows that the following types of loss firms are more likely to return to profitability in the next year: firms with higher profitability (or lower magnitude of loss), larger firms, firms with stronger sales growth, firms experiencing the first year of loss, firms with fewer consecutive years of loss, dividend-paying firms, and firms that do not decrease dividend payments to shareholders. When the analysis focuses on the COVID-19 year alone, however, the significance of the explanatory variables is weaker relative to the other periods. The out-of-sample analysis indicates that the estimated probability of loss reversal is generally consistent with the actual frequency of loss reversal. However, the model's prediction performance declines significantly during the GFC and the COVID-19 crisis, especially for firms which incurred transitory losses. The analysis of equity valuation shows that the inclusion of additional value drivers such as R&D, sales growth, and sustainability reduces the negative relation between market value and earnings in loss firms. Overall, the findings suggest that while the COVID-19 pandemic caused many firms to lose sales and to report a loss, the losses are more transitory than expected and a significant percentage of these loss firms reversed to profitability in the next year. These results provide complementary evidence to the observations of faster-than-expected recovery in the stock market and the economy after the COVID-19 crisis (Carlsson-Szlezak et al., 2020; Kaplan, 2021).

A limitation of this study is the potential survivorship bias caused by the requirement of seven years of non-missing data. In addition, while this paper attempts to examine the long-term effect of the COVID-19 crisis, the data availability of loss reversals is limited to 2021. Thus, the results of this study may not be generalized to the long-term effects of the COVID-19 crisis. Future research can examine the long-term effects of the COVID-19 crisis on corporate financial reporting and investigate how to improve the prediction models for loss reversals during financially distressing periods and for firms suffering from transitory losses.

REFERENCES

1. Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C., (2020). Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies, 9*(3), 593–621. https://doi.org/10.1093/rcfs/cfaa011
2. Alfaro, L., Chari, A., Greenland, A., & Schott, P. (2020). *Aggregate and firm-level stock returns during pandemics, in real time* (NBER Working Paper No. 6950). National Bureau of Economic Research. https://doi.org/10.3386/w26950
3. Bae, K.-H., Ghoul, S., Gong, J., & Guedhami, O. (2021). Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. *Journal of Corporate Finance, 67*, Article 101876. https://doi.org/10.1016/j.jcorpfin.2020.101876
4. Bretscher, L., Hsu, A., Simasek, P., & Tamoni, A., (2020). COVID-19 and the cross-section of equity returns: Impact and transmission. *The Review of Asset Pricing Studies, 10*(4), 705–741. https://doi.org/10.1093/rapstu/raaa017
5. Burgstahler, D., & Dichev, I. (1997). Earnings, adaptation, and equity value. *The Accounting Review, 72*(2), 187–215. https://www.jstor.org/stable/248552
6. Carlsson-Szlezak, P., Swartz, P., & Reeves, M. (2020, November 3). *Why the global economy is recovering faster than expected*. Harvard Business Review. https://hbr.org/2020/11/why-the-global-economy-is-recovering-faster-than-expected
7. Collins, D., Maydew, E., & Weiss, I. (1997). Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics*, *24*(1), 39–67. https://doi.org/10.1016/S0165-4101(97)00015-3
8. Collins, D., Pincus, M., & Xie, H. (1999). Equity valuation and negative earnings: The role of book value of equity. *The Accounting Review, 74*(1), 29–61. https://doi.org/10.2308/accr.1999.74.1.29
9. Darrough, M., & Ye, J. (2007). Valuation of loss firms in a knowledge-based economy. *Review of Accounting Studies, 12*, 61–93. https://doi.org/10.1007/s11142-006-9022-z
10. DeAngelo, H., DeAngelo, L., & Skinner, D. (1992). Dividends and losses. *The Journal of Finance, 47*(5), 1837–1863. https://doi.org/10.1111/j.1540-6261.1992.tb04685.x
11. Demers, E., Hendrikse, J., Joos, P, & Lev, B. (2021). ESG did not immunize stocks during the COVID-19 crisis, but investments in intangible assets did. *Journal of Business Finance & Accounting, 48*(3–4), 433–462. https://doi.org/10.1111/jbfa.12523
12. Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics, 141*(2), 802–830. https://doi.org/10.1016/j.jfineco.2021.03.005

13. Fahlenbrach, R., Rageth, K., & Stulz, R. (2021). How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis. *The Review of Financial Studies, 34*(11), 5474–5521. https://doi.org/10.1093/rfs/hhaa134
14. Fama, E., & MacBeth, J. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607–636. https://doi.org/10.1086/260061
15. Feltham, G., & Ohlson, J. (1995). Valuation and clean surplus accounting for operating and financial activities. *Contemporary Accounting Research, 11*(2), 689–731. https://doi.org/10.1111/j.1911-3846.1995.tb00462.x
16. Garel, A., & Petit-Romec, A. (2020). Investor rewards to environmental responsibility: Evidence from the COVID-19 crisis. *Journal of Corporate Finance, 68*, Article 101948. https://doi.org/10.2139/ssrn.3620109
17. Givoly, D., & Hayn, C. (2000). The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative? *Journal of Accounting and Economics, 29*(3), 287–320. https://doi.org/10.1016/S0165-4101(00)00024-0
18. Gormsen, N., & Koijen, R. (2020). Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies, 10*(4), 574–597. https://doi.org/10.1093/rapstu/raaa013
19. Haddad, V., Moreira, A., & Muir, T. (2021). When selling becomes viral: Disruptions in debt markets in the COVID-19 crisis and the fed's response. *The Review of Financial Studies, 34*(11), 5309–5351. https://doi.org/10.1093/rfs/hhaa145
20. Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics, 20*(2), 125–153. https://doi.org/10.1016/0165-4101(95)00397-2
21. Jiang, W., & Stark, A. (2013). Dividends, research and development expenditures, and the value relevance of book value for UK loss-making firms. *The British Accounting Review, 45*(2), 112–124. https://doi.org/10.1016/j.bar.2013.03.003
22. Joos, P., & Plesko, G. (2005). Valuing loss firms. *The Accounting Review, 80*(3), 847–870. https://doi.org/10.2308/accr.2005.80.3.847
23. Kaplan, P. (2021, March 9). *In long history of market crashes, coronavirus crash was the shortest.* Morningstar. https://www.morningstar.com/articles/1028407/in-long-history-of-market-crashes-coronavirus-crash-was-the-shortest
24. Kargar, M., Lester, B., Lindsay, D., Liu, S. Weill, P.-O., & Zúñiga, D. (2021). Corporate bond liquidity during the COVID-19 crisis. *The Review of Financial Studies, 34*(11), 5352–5401. https://doi.org/10.1093/rfs/hhab063
25. Li, K., Liu, X., Mai, F., & Zhang, T. (2021). The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis, 56*(7), 2545–2583. https://doi.org/10.1017/S0022109021000326
26. Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the March 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters, 38*, 101690. https://doi.org/10.1016/j.frl.2020.101690
27. O'Hara, M., & Zhou, X. (2021). Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. *Journal of Financial Economics, 142*(1), 46–68. https://doi.org/10.1016/j.jfineco.2021.05.052
28. Ohlson, J. (1995). Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Research, 11*(2), 661–687. https://doi.org/10.1111/j.1911-3846.1995.tb00461.x
29. Pástor, L. & Vorsatz, B. (2020). Mutual fund performance and flows during the COVID-19 crisis. *The Review of Asset Pricing Studies, 10*(4), 791–833. https://doi.org/10.1093/rapstu/raaa015
30. Ramelli, S., & Wagner, A. (2020). Feverish stock price reactions to COVID-19. *The Review of Corporate Finance Studies, 9*(3), 622–655. https://doi.org/10.1093/rcfs/cfaa012
31. Schrimpf, A., Shin, H., & Sushko, V. (2020). *Leverage and margin spirals in fixed income markets during the COVID-19 crisis* (BIS Bulletin No. 2). Bank for International Settlements. https://doi.org/10.2139/ssrn.3761873
32. Skinner, D., & Soltes, E. (2011). What do dividends tell us about earnings quality? *Review of Accounting Studies, 16*(1), 1–28. https://doi.org/10.1007/s11142-009-9113-8

APPENDIX A. DEFINITION OF VARIABLES

Variable	*Description and computation*
ACC_t	Accruals, measured as net income minus cash flow from operations scaled by lagged total assets = $(NI_t - OANCF_t)/AT_{t-1}$
BVE_t	Book value of equity scaled by lagged total assets (CEQ_t/AT_{t-1})
$Cash_t$	Cash scaled by lagged total assets, measured as CH_t/AT_{t-1}
CFO_t	Cash flow from operations scaled by lagged total assets = $OANCF_t/AT_{t-1}$
$DbtIss_t$	New long-term debt issuance in year *t* scaled by lagged total assets, measured as $DLTIS_t/AT_{t-1}$
$DivDum_t$	A dummy variable equal to 1 if a firm pays dividends in year *t*, and 0 otherwise.
$DivDec_t$	A dummy variable equal to 1 if the amount of a firm's dividend payment in year *t* is lower than that in year *t–1*, and 0 otherwise
$FirstLoss_t$	A dummy variable equal to 1 if the current year's loss is the first in a sequence, and 0 otherwise
IB_t	Income before extraordinary items from Compustat
$Loss_t$	If $IB_t < 0$ then $Loss_t = 1$; otherwise $Loss_t = 0$
$LossSEQ_t$	Number of sequential losses over the past five years before the current loss
MVE_t	Market value of equity scaled by lagged total assets ($PRCC\_F_t$ x $CSHO_t/AT_{t-1}$)
$NegSGR_t$	Equals $SaleGR_t$ if $SaleGR_t < 0$; otherwise $NegSGR_t = 0$
$Past\_ACC_t$	Average *ACC* over the past five years (i.e., *t–5* through *t–1*)
$Past\_CFO_t$	Average *CFO* over the past five years (i.e., *t–5* through *t–1*)
$Past\_ROA_t$	Average *ROA* over the past five years (i.e., *t–5* through *t–1*)
RD_t	Research and development expenses scaled by lagged total assets = XRD_t/AT_{t-1}
$Reversal_{t+1}$	Equals 1 if the loss firm becomes profitable in the next year (*t+1*), and 0 otherwise
ROA_t	Return on assets; calculated as IB_t/AT_{t-1}
$SaleGR_t$	Growth in sales, measured as $SALE_t/SALE_{t-1} - 1$
$SPIW_t$	Absolute value of special items scaled by lagged total assets (SPI_t/AT_{t-1})
$Size_t$	Natural log of market capitalization (*price close ($PRCC\_F_t$) x common shares outstanding ($CSHO_t$)*)
$StkIss_t$	New stock issues in year *t* scaled by lagged total assets ($SSTK_t/AT_{t-1}$)

APPENDIX B. LOGISTIC REGRESSIONS OF LOSS REVERSAL BASED ON MODEL II

Variable	*Estimates (p-value)*			
	Expected sign	*Whole sample period*	*Global Financial Crisis*	*COVID-19 crisis*
CFO_t	+	2.050*** (<0.0001)	1.372** (0.033)	1.825*** (<0.0001)
ACC_t	+	0.275* (0.051)	0.072 (0.791)	-0.367* (0.063)
$Past\_CFO_t$	+	0.574*** (<0.0001)	0.179*** (0.002)	0.524* (0.086)
$Past\_ACC_t$	+	0.254 (0.101)	0.236*** (0.001)	0.233 (0.449)
$Size_t$	+	0.081*** (<0.0001)	0.161* (0.091)	0.028 (0.255)
$SaleGR_t$	?	0.060*** (0.004)	0.104 (0.178)	0.045 (0.572)
$Firstloss_t$	+	0.093** (0.035)	0.393 (0.114)	0.295* (0.079)
$LossSEQ_t$	-	-0.148*** (<0.0001)	-0.163 (0.141)	-0.216*** (<0.0001)
$DIVDUM_t$	+	0.472*** (<0.0001)	0.411** (0.015)	0.689*** (<0.0001)
$DIVDEC_t$	-	-0.133*** (<0.0001)	-0.105 (0.243)	0.105 (0.510)
N of observations		46,932	4,511	1,974
Average pseudo R-square		0.187	0.232	0.309
Average likelihood ratio (LR)		219.946	402.604	503.531
Average LR p-value		<0.0001	<0.0001	<0.0001

*Note: This table presents the results from the annual logistic regressions of loss reversals based on Model II over the whole sample period (1976–2021), the Global Financial Crisis (2008–2009), and the COVID-19 crisis (2020). The dependent variable $Reversal_{t+1}$ equals 1 if a loss firm becomes profitable one year later. The definitions of the independent variables are provided in Appendix A. The coefficients are the mean of the coefficients from annual regressions, and the p-value (in parentheses) are calculated using the Fama–MacBeth method, adjusted for autocorrelation using the Newey-West method. ***, **, * indicates statistical significance at the 1, 5, and 10 percent levels, respectively, using two-sided t-tests.*