The Valuation of Loss Firms: A Stock Market Perspective

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Abstract: The proportion of exchange-listed firms with negative earnings has increased to over 40% in recent years. Given that the fundamental value of these loss firms is difficult to determine, we expect particularly strong value effects among these firms. We find that the return predictability associated with book-to-market and revenue-to-price is indeed significantly stronger compared to gain firms. Our further analyses on financial analysts, earnings announcement returns, short selling activities, option trading, and limits to arbitrage support a behavioral mechanism for our main finding.

Keywords: Loss Firms, Firm Valuation, Value Effect, Stock Mispricing

JEL: G02, G12, G14, M41

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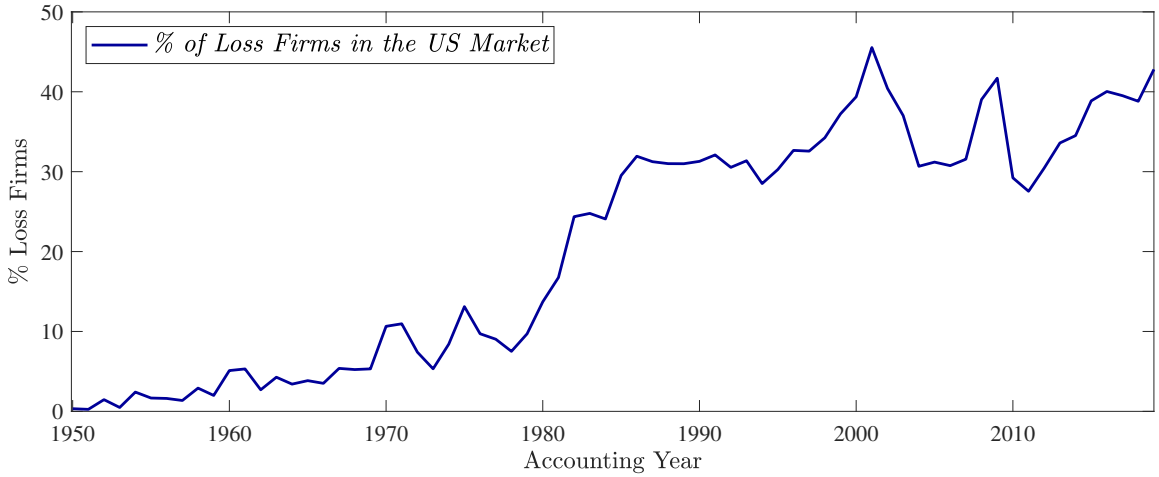
1. Introduction

The consensus in the literature is that valuing firms with negative earnings is more difficult than valuing firms with positive earnings (Darrough and Ye, 2007; Balakrishnan et al., 2010; Jan and Ou, 2012; Riedl et al., 2021). This notion is frequently attributed to the fact that the reported earnings of loss firms are less indicative of future earnings or cash flows than those of gain firms (Hayn, 1995; Collins et al., 1999; Joos and Plesko, 2005). These difficulties in loss firm valuation are particularly relevant for the functioning of financial markets and the efficient allocation of capital as loss firms represent an increasingly large share of the overall market (Collins et al., 1999; Joos and Plesko, 2005). Figure 1 illustrates this and shows that the proportion of exchange-listed US firms with negative earnings has increased to more than 40% in recent years.

Figure 1. Proportion of Loss Firms in US Market
This figure shows the proportion of firms with negative earnings in a given accounting year. The sample contains all US firms whose common ordinary shares trade on NYSE, AMEX, or NASDAQ.



As academia finds it comparably difficult to explain loss firms' market values by means of the firms' accounting figures, investors presumably face a similar challenge. Thus, observable market prices of loss firms might not only be more difficult to reconcile with

accounting-based valuation models, they might also substantially deviate from their fundamental values. Therefore, we test whether simple book equity, revenue, and earnings information is adequately reflected in loss firms' stock prices. If this was not the case, these accounting figures should allow to predict the stocks' subsequent returns.

We start our analysis by examining the relationship between the firms' stock market valuations and their accounting figures. We find that loss firms with higher book equity and higher revenue also have higher market values. However, earnings show a negative correlation with the market capitalization among loss firms (see similar evidence in Collins et al., 1999; Kothari, 2001; Darrough and Ye, 2007). Based on this evidence, we consider book equity and revenue as value indicators for loss firms. If their relevance is not sufficiently acknowledged by the market, book-to-market ratio BM and revenue-to-price ratio RP should predict subsequent stock returns among loss firms.

In line with this conjecture about loss firms' stock returns, we find that both BM and RP are associated with substantial return spreads of more than 1% per month: Stocks with accounting figures that are comparably high in relation to their market values earn significantly higher subsequent returns on average. Hence, our portfolio sort analyses imply a significant value effect in the cross-section of loss firm stocks. Moreover, these value effects are significantly stronger compared to gain firms. This observation is in line with our hypothesis that loss firms are particularly difficult to value and that accounting figures can be used to partly identify this mispricing.

Our subsequent analyses provide further support for this hypothesis. We find that financial analysts are too optimistic with respect to low-RP and low-BM stocks. These biased expectations could rationalize the indicated overvaluation and the low subsequent returns of these stocks. Moreover, a disproportionate percentage of the return premiums

is earned on earnings announcement dates when investors seem to adjust their biased expectations. These effects are stronger among loss firms compared to gain firms. Further in line with severe mispricing among loss firms, our examination of short interest and option-implied volatility spreads indicates that sophisticated investors consider low-RP and low-BM firms as overvalued on average. However, this subgroup of sophisticated investors seems unable to correct the apparent stock mispricing due to limits to arbitrage. In line with this conjecture, the return premiums are largest among the stocks with the most severe limits to arbitrage, that is, the return predictability is most pronounced among illiquid and volatile stocks where mispricing is most likely to persist (Shleifer and Vishny, 1997). Finally, we show that our findings remain qualitatively the same if we apply more sophisticated firm valuation measures beyond book equity and simple revenue to identify value effects among loss firms. More specifically, we use industry-adjusted revenue, account for the firm's level of debt, and apply the Merton (1974) option framework to estimate the fair value of equity.

Our overall findings support the huge strand of literature arguing that loss firms are difficult to value (Joos and Plesko, 2005; Darrough and Ye, 2007). We extend this evidence by providing a market perspective. More specifically, we do not only use a firm's market capitalization as a benchmark and try to explain it via accounting figures, but we question whether the market capitalization adequately reflects the fundamental equity value. Our analyses show that this is not always the case as the simplest accounting figures are sufficient to identify mispricing and predict subsequent returns. The high mispricing propensity of loss firms compared to gain firms is in line with previous evidence that earnings expectations are more biased and analyst forecasts more dispersed for loss firms (Hwang et al., 1996; Das et al., 1998; Gu and Wu, 2003; Liu and Natarajan, 2012).

In addition, we extend the large literature on the predictive power of accounting figures for the cross-section of stock returns. In particular, we examine the value effects associated with BM and RP. While Rosenberg et al. (1985) and Barbee et al. (1996) show that both ratios predict the broad cross-section of stock returns, we focus on the subgroup of loss firms where we find value effects to be stronger. Moreover, albeit the proportion of loss firms has increased over time, the overall magnitude of value effects has been prone to a substantial decay (McLean and Pontiff, 2016; Park, 2019). This observation is in line with a general increase in market efficiency which can, for example, be rationalized by a faster availability of information and lower transaction costs (Busse and Green, 2002). In line with overall declining value effects, we find that BM and RP are indeed comparably weak return predictors among gain firms. However, we find value effects to be highly significant among loss firms. In addition, supporting the empirical and theoretical evidence of Lakonishok et al. (1994), Daniel et al. (1998), Hirshleifer (2001), and Zhang (2013), our further analyses support a behavioral mechanism for the documented value effects, that is, an irrational high demand for growth stocks (low-BM and low-RP stocks). If this demand moves prices, the resulting overvaluation implies that BM and RP can predict subsequent returns. While this line of argument can naturally be applied to both loss and gain firms, the effect magnitude should be stronger among loss firms due to their hard-to-value nature. Our empirical analyses strongly support this hypothesis.

The remainder of this paper is structured as follows. Section 2 introduces the data set and the main variables. Section 3 provides evidence on the return predictability associated with book equity, revenue, and earnings. The underlying mechanisms of the documented value effects are examined in Section 4. In Section 5, we investigate alternative revenue-based value measures. Finally, we conclude in Section 6.

2. Data and Variables

Our sample consists of common ordinary US stocks traded on NYSE, AMEX, or NASDAQ. The sample period of our main analyses is July 1972 to December 2020.[1] The main data sources are COMPUSTAT for accounting data, short interest data, and industry classification codes and the Center for Research in Security Prices (CRSP) for daily and monthly stock returns, market capitalization, and trading volume. Analyst recommendations are retrieved from IBES and individual stock option data from Optionmetrics is used to examine informed option trading. Daily and monthly return factors are obtained from Kenneth R. French's homepage[2]. We use annual balance sheet data at the earliest at the end of June of the following year in line with Fama and French (1993). Any stock-month observation is included in our sample if the main variables of interest, market value of equity MVE, book-to-market ratio (BM), revenue-to-price ratio (RP), earnings-to-price ratio (EP), and loss firm dummy, are available. Further, only observations with positive revenue are included in our study and we exclude financial firms (SIC-code 6000-6999). This leads to our final sample of 2,064,998 stock-month observations.[3]

The main value proxies of interest are BM, RP, and EP. The numerator of these ratios is updated on an annual basis at the end of each June based on annual accounting data (book value of equity, revenue, and earnings, respectively) from the preceding calendar year. The end-of-month market value of equity is used as denominator. The book value of equity is defined as in Fama and French (1993), that is, the book value of shareholder's equity is

[1]The sample period starts in July 1972 since quarterly earnings announcement returns are not sufficiently available for earlier periods.

[2]See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[3]These 2,064,998 observations split up into 588,061 observations on loss firms (28.5%) and 1,476,937 observations on gain firms (71.5%).

adjusted by adding deferred tax and investment tax credit and subtracting the book value of preferred stock. For revenues, we use the 'Revenue - Total' figure from COMPUSTAT and earnings is defined as COMPUSTAT item 'Income Before Extraordinary Items'. The loss dummy is also based on this earnings figure and takes a value of one if earnings are negative and zero otherwise.

2.1. Summary Statistics

Table 1 shows summary statistics on the market value of equity, book value of equity, revenue, and earnings for all sample observations as well as separate summary statistics for loss and gain firms. The figures comprise mean, 10%-, 50%-, and 90%-quintile. In addition, we provide rank correlation coefficients.[4] Referring to the entire sample that includes all firms, as expected, firms with higher book equity, revenue, and earnings have higher market capitalization. The respective cross-sectional rank correlation coefficients are all above 65%. Hence, all three accounting figures seem relevant to explain a firm's market value.

Referring to loss firms, the average equity value is smaller in this subsample – in line with the weak earnings. Further, we expect that equity valuation based on earnings is difficult for these firms as current earnings do not represent a strong predictor for the magnitude of future earnings. This expectation is supported by the negative correlation of earnings with market capitalization for the subsample of loss firms (see similar findings in Burgstahler and Dichev, 1997 and Collins et al., 1999). As earnings seem to be a weak value proxy for loss firms, we take a closer look at the book values of equity and revenues. According to Table 1, both measures show relatively high correlations with the loss firms' market

[4]We provide rank correlations throughout all of our analyses as these are not strongly influenced by extreme outliers. In line with this notion, untabulated Pearson correlation coefficients provide qualitatively the same picture but tend to be smaller in magnitude.

capitalizations. Consequently, a large proportion of equity value can be rationalized via book equity and revenue. Given that these two figures are comparably good proxies for the market capitalization of loss firms, we obtain a negative correlation of earnings with these two measures.

Table 1. Summary Statistics and Rank Correlation Coefficients
This table reports time-series averages of cross-sectional sample mean, 0.1-quantile, median, 0.9-quantile, and rank correlation coefficients on an annual basis. Summary statistics (in million USD) and rank correlation coefficients are separately provided for all firms, loss firms (negative earnings), and gain firms (non-negative earnings). MVE is the market value of equity at the end of June of year t. BVE, REV, and $EARN$ denote the firm's annual book values of equity, revenues, and earnings for year $t-1$, respectively. The sample period covers July 1972 to December 2020.

Summary Statistics

	All Firms				Loss Firms				Gain Firms			
	MVE	BVE	REV	$EARN$	MVE	BVE	REV	$EARN$	MVE	BVE	REV	$EARN$
mean	2438.96	958.93	1831.22	104.58	490.21	227.77	513.18	-54.92	3548.56	1355.00	2546.77	193.60
$q_{0.1}$	16.08	5.61	10.99	-24.36	8.15	0.84	2.37	-83.55	36.56	16.31	39.92	1.60
$q_{0.5}$	258.75	108.95	227.10	5.14	75.12	29.35	47.84	-9.36	507.53	209.83	438.96	24.08
$q_{0.9}$	4081.40	1578.40	3323.77	192.44	867.75	366.62	818.91	-1.06	6487.36	2415.58	4777.85	339.09

Rank Correlation Coefficients

	All Firms				Loss Firms				Gain Firms			
	MVE	BVE	REV	$EARN$	MVE	BVE	REV	$EARN$	MVE	BVE	REV	$EARN$
MVE	1.00				1.00				1.00			
BVE	0.85	1.00			0.61	1.00			0.87	1.00		
REV	0.79	0.84	1.00		0.49	0.61	1.00		0.82	0.87	1.00	
$EARN$	0.68	0.69	0.68	1.00	-0.53	-0.39	-0.45	1.00	0.90	0.87	0.86	1.00

So far, the literature examining the valuation of loss firms has strongly focused on the relationship between accounting figures and market values as reflected by Table 1. The conclusion that loss firms are more difficult to value triggers the following question: Do loss firm values show a systematically stronger deviation from their fundamental values compared to gain firm values? Unfortunately, this mispricing cannot be observed directly. However, such deviations between market value and fundamental value imply that proxies for a firm's fundamental value predict subsequent stock returns when the mispricing vanishes. Given the difficulty to value loss firms, this return predictability should be

particularly pronounced among loss firms. We examine this central hypothesis in the following section.

3. Value Effects Among Loss Firms

Loss firms are considered hard to value (Darrough and Ye, 2007; Jan and Ou, 2012; Riedl et al., 2021) as these firms show a high uncertainty with respect to their future earnings path (Lakonishok et al., 1994; Billings and Morton, 2001). Hence, we expect mispricing to be larger among loss firms and value effects to be stronger. In order to compare value effects in loss versus gain firms, we conduct monthly portfolio sorts based on BM, RP, and EP. To this end, we sort stocks into quintile portfolios based on BM, RP and EP at the end of each month and calculate the portfolio return of the subsequent month as well as the market risk adjusted portfolio return. Portfolio weights are given by the firm's market capitalization in order to avoid that micro-caps have a disproportionate impact on our findings (Hou et al., 2020). The average raw and market risk adjusted portfolio returns are provided in Table 2. The difference portfolios (5-1) reflect the average return spread between value and growth portfolios; the difference-in-differences portfolio (Δ) shows to which extent the return spreads differ between loss and gain firms.

To start with the return predictability associated with BM and RP, average monthly return spreads among loss firms exceed 1% in each specification. Hence, we find strong evidence on value effects among loss firms. Firms with comparably high (low) levels of BM and RP seem to be undervalued (overvalued) leading to high (low) returns upon the correction of this mispricing. On the contrary, for gain firms, the return spreads are substantially smaller and not consistently significant. The difference-in-differences

Table 2. Return Predictability
This table reports subsequent value-weighted portfolio returns of quintile portfolios. Stocks are allocated to quintile portfolios at the end of each month $t-1$ based on the book-to-market ratio BM, the revenue-to-price ratio RP, or the earnings-to-price ratio EP. Portfolio returns for month t are calculated on a value-weighted basis. The table presents portfolio raw returns (i.e., the time-series average of these monthly value-weighted portfolio returns) and market risk adjusted returns (α_{MKT}). α_{MKT} is the intercept in a regression of monthly value-weighted portfolio returns on the excess market return. The portfolio sorts are conducted separately for loss firms (negative earnings) and gain firms (non-negative earnings). The sample period covers July 1972 to December 2020. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Sorts Based on BM				Sorts Based on RP				Sorts Based on EP			
	raw		α_{MKT}		raw		α_{MKT}		raw		α_{MKT}	
	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain
low	0.74	0.91	-0.56	-0.08	0.19	0.90	-1.11	-0.08	0.92	1.00	-0.44	-0.06
2	0.72	1.00	-0.46	0.07	1.07	1.00	-0.11	0.10	1.13	0.87	-0.14	-0.06
3	0.99	1.07	-0.19	0.15	0.82	1.10	-0.34	0.17	0.87	1.02	-0.39	0.12
4	0.92	1.08	-0.22	0.19	1.31	1.16	0.17	0.20	0.93	1.22	-0.25	0.33
high	1.78	1.26	0.54	0.35	1.34	1.31	0.12	0.28	0.85	1.30	-0.32	0.32
5-1	1.04	0.35	1.09	0.43	1.16	0.41	1.22	0.35	-0.06	0.30	0.12	0.38
t(5-1)	(2.69)	(1.59)	(2.82)	(1.87)	(2.65)	(1.99)	(2.64)	(1.57)	(-0.16)	(1.39)	(0.30)	(1.72)
Δ	-0.68		-0.66		-0.74		-0.87		0.36		0.26	
t(Δ)	(-2.34)		(-2.25)		(-2.16)		(-2.47)		(0.72)		(0.49)	

portfolios imply that the return predictability is indeed significantly stronger among loss firms. These observations apply to raw as well as to market risk adjusted returns.[5]

The overall positive value premium is in line with seminal studies on BM and RP (see, for example, Rosenberg et al., 1985 and Barbee et al., 1996, respectively). Moreover, its low magnitude among gain stocks fits more recent evidence by McLean and Pontiff (2016) who show that anomaly return spreads substantially decline after publication of the initial findings, for example, because informed investors exploit the return predictability (Collins et al., 2003). Notwithstanding, we document significant value effects among loss firms. This

[5]In the Online Appendix, we also adjust the returns for their exposure with respect to the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. In both specifications, for both BM and RP, the value effects are stronger for loss compared to gain firms. Notably, the Fama and French (1993) three-factor model is explicitly designed to capture the return predictability associated with BM. Indeed, it does so for gain firms, but BM still induces a significant quintile return spread of 0.69% among loss firms. Beyond additional factor models, the Online Appendix also presents the analyses from Table 2 applying equal-weighted instead of value-weighted portfolio returns. Again, RP and BM significantly predict subsequent stock returns among loss firms and the effect magnitude is significantly stronger compared to gain firms.

observation is in line with previous findings that loss firms are difficult to value such that mispricing is less likely to be eliminated by informed investors and thus more likely to persist.

The last columns of Table 2 show that EP is no significant predictor of returns, neither for loss nor for gain firms. First, this is in line with the deteriorating magnitude of value effects in general (McLean and Pontiff, 2016). Second, based on Table 1, we should not expect EP to predict subsequent returns in the loss domain as it is no valid value indicator for loss firms. Consequently, we drop EP in the following analyses and further examine the value indicators BM and RP.

4. Underlying Mechanism

4.1. Biased Expectations About Loss Firms

Our arguments imply that loss firms are particularly prone to mispricing as the fair value of these firms is difficult to determine. We conjecture that such mispricing is partly identified by the value measures BM and RP resulting in the return spreads documented in Table 2. This conjecture with respect to the return predictability's underlying mechanism suggests that the market is too optimistic (pessimistic) with respect to low-BM and low-RP (high-BM and high-RP) firms such that the overvaluation (undervaluation) is corrected when investors revise their biased expectations. Moreover, these effects should be particularly strong among loss compared to gain firms as the former are more difficult to value. For example, Hwang et al. (1996) and Brown (2001) find that earnings forecasts by financial analysts are too high for loss firms and that forecast errors are substantially higher compared to gain firms.

Based on these arguments, we analyze how analyst recommendations relate to BM and RP. To do so, in Table 3, we report the average monthly analyst recommendation for each quintile portfolio formed on the basis of BM and RP, separately for loss and gain firms. Following Engelberg et al. (2020) and Guo et al. (2020), we investigate consensus analyst recommendations, which range from 1 to 5, where 1 reflects a 'strong sell' recommendation and 5 a 'strong buy' recommendation. In line with Drake et al. (2011) and Engelberg et al. (2020), Table 3 shows that the average analyst recommendation is significantly more favorable for growth compared to value stocks, although value stocks are known to outperform growth stocks. Hence, analyst's recommendations are too optimistic with respect to the future development of growth stocks. In addition, the analysts' tendency to recommend growth stocks more than value stocks is significantly more pronounced among loss firms. This observation indicates more strongly biased expectations among loss firms and could rationalize the disproportionate return predictability documented in Table 2.

Analysts' expectations seem to be particularly upward-biased for growth stocks with negative earnings. Motivated by this finding, we hypothesize that investors will correct their biased expectations when new fundamental information on the fair stock value is published. To test this conjecture, we examine the stock returns around quarterly earnings announcements. The corresponding evidence is provided in the right panel of Table 3. Consistent with investors revising their biased expectations, both BM and RP positively predict stock returns in a three-day window around the next quarterly earnings announcement date. The return spreads are significantly positive in each specification (also see empirical evidence on the correction of mispricing around earnings announcement dates in Pincus, 1983, La Porta, 1996, and Engelberg et al., 2018). Comparing the return spreads based on the three-day earnings announcement window with the monthly return spreads

Table 3. Analyst Recommendations and Earnings Announcement Returns
This table presents analyst recommendations and earnings announcement returns for *BM*-based and *RP*-based quintile portfolios. For each month, separately for loss and gain firms, stocks are allocated to quintile portfolios based on book-to-market ratio *BM* or revenue-to-price ratio *RP*. The left part of the table (sample period January 1994 to December 2020) shows the consensus analyst recommendation of the stocks in each portfolio (5 reflects 'strong buy' and 1 reflects 'strong sell'). The right part of the table (sample period July 1972 to December 2020) shows the return around the stocks' next earnings announcement (plus/minus one trading day) in percent. In both panels, the table presents time-series averages of the corresponding cross-sectional means. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	Analyst Recommendations				Earnings Announcement Returns			
	Sorts Based on *BM*		Sorts Based on *RP*		Sorts Based on *BM*		Sorts Based on *RP*	
	loss	gain	loss	gain	loss	gain	loss	gain
low	3.96	3.91	4.05	3.93	0.10	0.22	-0.59	0.17
2	3.98	3.88	3.92	3.81	-0.14	0.31	-0.00	0.27
3	3.82	3.82	3.76	3.78	0.52	0.40	0.42	0.33
4	3.66	3.71	3.64	3.74	0.63	0.43	0.71	0.45
high	3.41	3.53	3.44	3.62	0.52	0.47	0.91	0.62
5-1	-0.54	-0.37	-0.61	-0.31	0.42	0.25	1.50	0.45
t(5-1)	(-20.78)	(-8.70)	(-26.79)	(-11.09)	(2.49)	(3.10)	(7.99)	(5.25)
Δ	0.17		0.30		-0.17		-1.05	
t(Δ)	(6.08)		(19.14)		(-0.91)		(-6.09)	

in Table 2, a major proportion of the return predictability is realized when fundamental earnings information is published: the *BM*-induced return spreads around quarterly earnings announcements amount to more than one third of its monthly premium while the *RP*-induced return premium around quarterly earnings announcements is even larger compared to its average monthly effect magnitude. Finally, the difference-in-differences portfolios again suggest, that the biases in expectations and the resulting correction of mispricing have a higher magnitude among loss firms than among gain firms.

Concluding Table 3, we provide evidence for excessively optimistic expectations with respect to growth stocks. This effect is particularly strong among loss firms as the high valuation uncertainty seemingly allows for a higher magnitude in market participants' judgment biases. In line with these biased expectations, low-*BM* and low-*RP* stocks can

become overvalued leading to the return patterns documented in Table 2 which are further amplified around earnings announcements when investors adjust their biased expectations.

4.2. Informed Trading on Value Effects among Loss Firms

The previous analyses suggest that biased expectations and mispricing lead to the value effects among loss firms. However, market participants are not homogeneous such that there might also exist sophisticated investors who are aware of the mispricing (Shleifer and Vishny, 1997). For example, the analyses in Ali et al. (2003) suggest that value effects are driven by unsophisticated investors in particular. Therefore, we examine whether more sophisticated investors are able to identify over- and underpricing within loss firms. To this end, we use relative short interest data as well as option measures to identify informed trading in value versus growth stocks. This procedure is supported by the empirical evidence in Cohen et al. (2007b) suggesting that short-sellers can identify mispricing and profit from its exploitation. Moreover, rational investors might trade on mispricing in the option market if they face short-sell constraints or because they want to trade on their beliefs in a levered way (Black, 1975; Easley et al., 1998; Lin and Lu, 2016). Hence, option prices might reflect this informed demand before the mispricing is eliminated in stock prices (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010).

Table 4 examines these hypotheses with respect to value effects in the subsample of loss firms. Relative short interest RSI is the number of shorted stocks over the total number of outstanding stocks. Thus, a high level of RSI indicates a pessimistic opinion of sophisticated short-sellers. We provide the average level of RSI for each BM- and RP-based quintile portfolio. Our findings are similar across the two value indicators: RSI is significantly

higher for growth firms than for value firms indicating that a subgroup of sophisticated investors indeed recognizes the documented mispricing.

Table 4. Sophisticated Trading among Loss Firms
This table presents indicators for sophisticated trading in BM-based and RP-based quintile portfolios. For each month, the stocks of loss firms are allocated to quintile portfolios based on book-to-market ratio BM or revenue-to-price ratio RP. The table presents time-series averages of the cross-sectional mean of the following variables. Relative short interest RSI is the ratio of shorted stocks to outstanding stocks. VS_{BH} and VS_{CW} denote the difference between call and put option-implied volatilities following the methodology of Bali and Hovakimian (2009) and Cremers and Weinbaum (2010), respectively; daily observations are averaged to obtain monthly estimates. The option-to-stock trading volume ratio O/S follows Roll et al. (2010)) and is the number of options traded in a given month over the number of shares traded in a given month. The sample period is January 1973 to December 2020 for the RSI-analysis while the option-based analyses refer to a truncated sample period that starts in January 1996. All four measures are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Sorts Based on BM				Sorts Based on RP			
	RSI	VS_{BH}	VS_{CW}	O/S	RSI	VS_{BH}	VS_{CW}	O/S
low	2.50	-2.02	-2.04	5.67	2.54	-2.00	-1.99	5.58
2	2.21	-1.42	-1.41	4.05	2.05	-1.36	-1.26	4.03
3	1.78	-1.14	-1.04	2.84	1.63	-0.96	-0.83	2.60
4	1.52	-0.94	-0.71	2.16	1.50	-0.84	-0.67	2.13
high	1.42	-0.99	-0.72	1.49	1.71	-1.35	-1.17	1.87
5-1	-1.08	1.04	1.32	-4.18	-0.83	0.65	0.83	-3.71
t(5-1)	(-5.44)	(6.15)	(7.06)	(-19.08)	(-4.18)	(6.17)	(5.33)	(-14.50)

Next, we turn to the option measures VS_{BH} and VS_{CW}. They reflect option-implied volatility spreads and their estimation is based on Bali and Hovakimian (2009) and Cremers and Weinbaum (2010), respectively. More specifically, VS_{BH} is the difference between the implied volatilities of calls and puts averaged across near-the-money options with a short time to maturity. VS_{CW} is the open-interest-weighted spread between call- and put-implied volatilities. If sophisticated investors express their negative stock return expectations in the option market, put options receive disproportionate demand compared to call options. This asymmetric demand pressure leads to comparably high put prices and, thus, high put-implied volatilities (Bollen and Whaley, 2004). Consequently, low levels of VS_{BH} and VS_{CW} indicate investors' pessimism with respect to the underlying stock and have been

shown to predict low subsequent stock returns (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010). Table 4 shows that both VS_{BH} and VS_{CW} are substantially more negative for growth compared to value stocks. Hence, sophisticated investors in the option market seem to be more pessimistic for growth compared to value stocks. Consequently, this subgroup of investors correctly anticipates that high-BM and high-RP stocks outperform their low-BM and low-RP counterparts on average.

Finally, we consider the option-to-stock trading volume ratio O/S as introduced by Roll et al. (2010). Johnson and So (2012) argue that, if short-sell constraints are binding, sophisticated investors can express their positive opinion in the stock market, but not their negative opinion. Following this argument, options are disproportionately used to trade on negative return expectations such that a high option-to-stock trading volume ratio can be interpreted as an indicator for pessimistic sophisticated investors. In line with the previous findings, Table 4 shows that O/S is indeed higher for growth than for value stocks. In conclusion, the empirical evidence suggests that sophisticated market participants partly identify the mispricing associated with BM and RP among loss firms.

4.3. Limits to Arbitrage

Our analyses indicate that low-BM and low-RP loss firms are overvalued due to overly optimistic market expectations. Nonetheless, the previous subsection also shows that some market participants seemingly recognize the mispricing and try to exploit it via shorting or option trading. This insight raises the question why the stock mispricing can persist and is not eliminated by sophisticated investors immediately. A potential explanation follows the arguments of Shleifer and Vishny (1997), Cohen et al. (2007a) and Xue and Zhang (2011): if limits to arbitrage are sufficiently high, mispricing may persist even in the presence of

sophisticated arbitrageurs. Consequently, we hypothesize that the documented value effects are particularly pronounced among stocks with arbitrage constraints.

Table 5. Limits to Arbitrage among Loss Firms
This table reports market risk adjusted value-weighted returns from conditional portfolio double sorts. First, in each month $t-1$, each stock is allocated to a quintile portfolio based on a limits to arbitrage proxy. In Panel A, the idiosyncratic return volatility is calculated as the volatility of daily stock return residuals with respect to the three Fama and French (1993) factors in the previous month (Ang et al., 2006). In Panel B, the Amihud (2002) illiquidity measure is the ratio of daily absolute stock return to daily dollar trading volume averaged over the previous year. In Panel C, the stock's average closing bid-ask-spread over the previous year is employed (Goyenko et al., 2009). Second, within each quintile portfolio, each stock is allocated to a quintile portfolio based on the book-to-market ratio *BM* or the revenue-to-price ratio *RP*. The subsequent returns in month *t* are adjusted for their market risk exposure, i.e., the table presents the intercepts from a regression of monthly value-weighted portfolio returns on the excess market return. The analyses consider loss firms only. The sample period is July 1972 to December 2020 in Panels A and B and January 1993 to December 2020 in Panel C. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

Panel A: Idiosyncratic Volatility

	low	2	3	4	high		low	2	3	4	high
low *BM*	0.04	-0.48	-0.93	-1.16	-2.22	low *RP*	-0.25	-0.83	-1.19	-1.34	-2.29
2	0.04	-0.22	-0.63	-1.37	-2.32	2	0.13	-0.07	-0.32	-1.09	-1.69
3	0.15	-0.56	-0.19	-0.91	-1.30	3	0.34	0.02	-0.63	-0.71	-1.29
4	0.09	-0.03	-0.54	-0.65	-1.10	4	-0.02	-0.32	-0.14	-0.89	-1.19
high *BM*	0.54	0.51	0.24	-0.38	-0.58	high *RP*	0.28	0.28	0.11	-0.21	-1.17
5-1	0.49	1.00	1.17	0.78	1.65	5-1	0.54	1.11	1.30	1.13	1.12
t(5-1)	(1.35)	(1.94)	(2.74)	(1.50)	(2.29)	t(5-1)	(1.18)	(2.21)	(2.41)	(2.06)	(1.55)

Panel B: Amihud (2002) Illiquidity

	low	2	3	4	high		low	2	3	4	high
low *BM*	-0.29	-0.62	-0.77	-0.97	-1.18	low *RP*	-0.92	-0.46	-0.75	-1.42	-0.91
2	-0.39	-0.42	-0.22	-0.82	-0.58	2	-0.29	-0.51	-0.22	-0.60	-0.35
3	-0.24	-0.32	-0.25	-0.05	0.25	3	-0.13	-0.32	-0.08	0.09	-0.35
4	-0.33	-0.21	0.06	0.40	0.60	4	-0.16	-0.05	0.09	0.35	0.65
high *BM*	-0.01	0.15	0.24	0.48	1.53	high *RP*	0.00	-0.01	-0.01	0.53	0.77
5-1	0.28	0.78	1.01	1.45	2.70	5-1	0.93	0.45	0.75	1.95	1.68
t(5-1)	(0.68)	(2.15)	(2.70)	(3.23)	(8.65)	t(5-1)	(1.75)	(1.16)	(1.52)	(4.53)	(3.96)

Panel C: Bid-Ask-Spread

	low	2	3	4	high		low	2	3	4	high
low *BM*	0.13	-0.70	-0.45	-0.75	-1.68	low *RP*	-0.77	-0.94	-0.72	-1.23	-1.64
2	-0.22	-0.66	-0.71	-0.48	-0.73	2	-0.06	-0.84	-0.14	-0.75	-0.22
3	-0.29	-0.55	-0.01	-0.45	0.44	3	-0.28	-0.82	-0.28	-0.06	0.27
4	-0.66	-0.32	0.11	0.15	1.16	4	-0.50	-0.43	0.09	0.53	0.73
high *BM*	-0.50	-0.54	0.27	0.29	0.99	high *RP*	-0.14	-0.32	0.38	0.20	0.00
5-1	-0.63	0.16	0.72	1.04	2.66	5-1	0.63	0.62	1.10	1.43	1.64
t(5-1)	(-1.21)	(0.36)	(1.17)	(1.79)	(5.42)	t(5-1)	(0.83)	(0.90)	(1.56)	(2.26)	(3.35)

In order to analyze in how far value effects among loss firms depend on limits to arbitrage, we conduct dependent portfolio double sorts within the subsample of loss firms. As proxies for limits to arbitrage, we use idiosyncratic return volatility (see Ang et al., 2006), Amihud (2002) illiquidity, and bid-ask-spreads (see Goyenko et al., 2009). The choice of these variables reflects the notion that arbitrageurs might not eliminate mispricing if such strategies are risky and expensive to implement (Stambaugh et al., 2015). For each of the three measures, higher values indicate higher limits to arbitrage and hence less arbitrage capital to correct mispricing. First, we sort loss firms into quintile portfolios based on each of the three measures for each month. Second, within each quintile portfolio, we sort stocks into quintile portfolios based on BM and RP. Table 5 reports the average market risk adjusted returns in the subsequent month for each of the resulting 25 portfolios.

Table 5 shows that value effects among loss firms are substantially stronger for stocks with high limits to arbitrage. This observation applies to all three limits to arbitrage proxies and to both value measures. For example, the return spread associated with BM amounts to 0.49% among stocks with low idiosyncratic return volatility while it is 1.65% among stocks with high idiosyncratic return volatility. Hence, in line with a behavioral explanation, the mispricing is strongest among volatile and illiquid stocks.[6] Vice versa, if limits to arbitrage are low, the combined evidence from Tables 4 and 5 suggests that sophisticated investors can substantially reduce the magnitude of value effects among loss firms.

[6] In the Online Appendix, we provide qualitatively the same evidence when applying equal-weighted portfolios and raw returns instead of the value-weighted approach using market adjusted returns in Table 5.

5. Alternative Valuation Measures

Standard valuation models imply that a stock's fair value is equal to its discounted future cash flows. As a consequence, accounting figures such as revenue, book equity, and earnings can only serve as proxy for a stock's fundamental value. Among loss firms, we find that revenue and book equity are sufficiently good value proxies to predict subsequent stock returns. Nonetheless, more sophisticated firm value proxies exist and might result in more pronounced return predictability. First, a specific level of revenue frequently goes along with different firm values dependent on the specific industry, for example because of different profit margins across sectors (for industry effects in firm valuation, see Alford, 1992 and Liu et al., 2002). Second, the relationship between revenue magnitude and firm value should depend on the firm's leverage. If the debt-to-equity ratio is high, a large proportion of operating profits is allocated to debt instead of equity investors. This latter aspect should be of particular relevance for loss firms as their poor earnings situation frequently goes along with a high level of leverage. Consequently, in the following, we investigate two additional value proxies that take these arguments into account.

5.1. Construction of Alternative Valuation Measures

The first value proxy is based on simple industry-specific revenue multiples as similar approaches are frequently used in practice (Davis, 2002; Foster et al., 2012; Plenborg and Pimentel, 2016; Pinto et al., 2019). More specifically, we assign each stock-month observation to an industry based on its two-digit SIC code. Next, requiring at least five stocks within each industry, we calculate the median revenue multiple (i.e. MVE/REV) for each industry

and month. Finally, the product of industry-specific revenue multiple and a firm's actual revenue is used as value proxy VP_{IREV}.

The second proxy takes the firm's leverage into account. We calculate the enterprise market value for each firm as market value of equity plus market value of debt. The latter is estimated based on the Merton (1974) model implemented as in Bharath and Shumway (2008), that is, we use balance sheet debt in current liabilities plus half of long-term debt as the face value of debt and the stock return volatility over the previous year to obtain the market value of debt. Next, we obtain the median revenue multiple for each industry and month by using the enterprise market value of the firm as numerator and revenue as denominator. Then, we use the product of industry-specific revenue multiple and a firm's actual revenue as enterprise value proxy. Finally, upon subtracting the firm's market value of debt, we obtain the equity value proxy VP_{MM}.

5.2. Summary Statistics of Alternative Valuation Measures

Summary statistics on the market value of equity, VP_{IREV}, and VP_{MM} can be obtained from Table 6. The average level of the two revenue-based value proxies is by construction close to the mean actual market capitalization. The rank correlations between actual market value of equity on the one hand side and VP_{IREV} and VP_{MM} on the other hand side are 83% and 81%, respectively. In addition, Table 6 provides summary statistics separately for the subsample of loss and gain firms. As expected, the market values of gain firms are easier to predict such that their correlation with the value proxies is higher compared to loss firms. Nonetheless, both VP_{IREV} and VP_{MM} show a substantially positive correlation with MVE even for loss firms justifying their use as value proxies. Comparing Table 6 with Table 1, the alternative valuation measures VP_{IREV} and VP_{MM} show a slightly stronger correlation with

MVE compared to simple revenue for both loss firms and gain firms. Hence, in line with the previous literature, industry adjustments can improve the performance of multiples in firm valuation. However, the additional consideration of a firm's leverage via the Merton (1974) model does not add explanatory power in this context as VP_{MM} does not correlate more strongly with MVE compared to VP_{IREV}.

Table 6. Summary Statistics and Rank Correlation Coefficients – Alternative Valuation Measures
This table reports time-series averages of cross-sectional sample mean, 0.1-quantile, median, 0.9-quantile, and rank correlation coefficients on an annual basis. Summary statistics (in million USD) and rank correlation coefficients are separately provided for all firms, loss firms (negative earnings), and gain firms (non-negative earnings). VP_{IREV} denotes the firm's equity value proxy based on an industry-adjusted revenue multiple and VP_{MM} the firm's equity value proxy based on an industry-adjusted revenue multiple which is applied on the enterprise level where the market value of debt is based on a Merton (1974) model estimation. The sample period covers July 1972 to December 2020.

Summary Statistics

	All Firms			Loss Firms			Gain Firms		
	MVE	VP_{IREV}	VP_{MM}	MVE	VP_{IREV}	VP_{MM}	MVE	VP_{IREV}	VP_{MM}
mean	2438.96	2328.40	2461.26	490.21	590.59	631.22	3548.56	3302.27	3385.13
$q_{0.1}$	16.08	16.35	16.84	8.15	3.92	1.86	36.56	50.50	56.28
$q_{0.5}$	258.75	265.44	315.04	75.12	75.24	82.04	507.53	490.34	575.19
$q_{0.9}$	4081.40	3981.31	4583.03	867.75	978.60	1129.79	6487.36	6235.81	6862.26

Rank Correlation Coefficients

	All Firms			Loss Firms			Gain Firms		
	MVE	VP_{IREV}	VP_{MM}	MVE	VP_{IREV}	VP_{MM}	MVE	VP_{IREV}	VP_{MM}
MVE	1.00			1.00			1.00		
VP_{IREV}	0.83	1.00		0.58	1.00		0.86	1.00	
VP_{MM}	0.81	0.97	1.00	0.52	0.91	1.00	0.84	0.97	1.00

5.3. Return Predictability Based on Alternative Valuation Measures

The summary statistics in Table 6 suggest that VP_{IREV} and VP_{MM} can be used as value proxies for both loss and gain firms. To follow up on our previous analyses, we test to which extent these two proxies allow to predict the cross-section of stock returns. To this end, we sort stocks into quintile portfolios based on the ratio of firm value proxy to actual market value of equity in month $t-1$. Hence, a high ratio indicates comparably high

fundamentals such that we expect these firms to be undervalued resulting in comparably high subsequent returns. Table 7 shows value-weighted average portfolio returns of month t averaged over the entire sample period. In line with our previous methodology, these returns are either presented on a raw basis or adjusted for their market risk exposure.

Table 7 shows that both value proxies predict subsequent returns with positive sign. Hence, the documented value effects support our conjecture that both VP_{IREV} and VP_{MM} allow to identify mispricing. From an economic and statistical point of view, these effects are strong among loss firms and less pronounced among gain firms. In particular, our analysis of difference-in-differences emphasizes that the magnitude of mispricing is larger among loss firms presumably because these firms are more difficult to value.

Table 7. Return Predictability – Alternative Valuation Measures
This table reports subsequent value-weighted portfolio returns of quintile portfolios. Stocks are allocated to quintile portfolios at the end of each month $t-1$ based on VP_{IREV}/MVE or VP_{MM}/MVE. VP_{IREV} denotes the firm's equity value proxy based on an industry-adjusted revenue multiple and VP_{MM} the firm's equity value proxy based on an industry-adjusted revenue multiple which is applied on the enterprise level where the market value of debt is based on a Merton (1974) model estimation.MVE is the actual market value of equity. Portfolio returns for month t are calculated on a value-weighted basis. The table presents portfolio raw returns (i.e., the time-series average of these monthly value-weighted portfolio returns) and market risk adjusted returns (α_{MKT}). α_{MKT} is the intercept in a regression of monthly value-weighted portfolio returns on the excess market return. The portfolio sorts are conducted separately for loss firms (negative earnings) and gain firms (non-negative earnings). The sample period covers July 1972 to December 2020. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Sorts Based on VP_{IREV}/MVE				Sorts Based on VP_{MM}/MVE			
	raw		α_{MKT}		raw		α_{MKT}	
	loss	gain	loss	gain	loss	gain	loss	gain
low	0.23	0.89	-1.11	-0.11	0.32	0.90	-1.01	-0.09
2	0.67	1.00	-0.50	0.12	0.70	0.97	-0.46	0.09
3	1.08	1.02	-0.04	0.12	1.00	0.93	-0.13	0.06
4	1.35	1.09	0.16	0.19	1.23	1.21	0.05	0.28
high	1.38	1.28	0.13	0.27	1.30	1.24	0.10	0.24
5-1	1.15	0.39	1.24	0.38	0.98	0.34	1.11	0.33
t(5-1)	(2.63)	(2.08)	(2.76)	(1.88)	(2.48)	(1.98)	(2.62)	(1.75)
Δ	-0.76		-0.86		-0.64		-0.78	
$t(\Delta)$	(-2.18)		(-2.44)		(-1.83)		(-2.16)	

These findings from Table 7 qualitatively match our baseline analysis in Table 2. In line with the revenue-based construction of VP_{IREV} and VP_{MM}, these two sophisticated value measures induce similar return spreads as the simple unadjusted revenue proxy. Hence, while VP_{IREV} and VP_{MM} might be more suitable to explain actual market values, this ability does not translate to their return predictability in a significant way.[7] In conclusion, we document that several value proxies induce significant return predictability and that the specific return patterns support the notion that loss firms are particularly prone to the underlying mispricing.

6. Conclusion

Loss firms are difficult to value as the future earnings path is highly uncertain. Thus, the probability that corresponding stock market prices deviate from their fundamental values should be comparably high. We support this hypothesis and show that the simple firm value indicators book equity and revenues can be used to identify mispriced loss firms. More specifically, we find that both book-to-market ratio and revenue-to-price ratio positively predict the cross-section of stock returns among loss firms with monthly return spreads of more than 1% and high statistical significance. On the contrary, the documented value effects are substantially smaller among gain firms. Our further analyses indicate that beliefs about loss firms indeed seem to be particularly biased such that the mispricing is comparably large. While some sophisticated investors apparently identify overvalued versus undervalued loss firms correctly, our analyses suggest that limits to arbitrage prevent the timely correction of the documented stock mispricing.

[7] As the estimation of the sophisticated trading measures requires additional data beyond simple revenue, the sample decreases from 2,064,998 observations in Table 2 to 1,798,186 observations in Table 7. However, the magnitude of return predictability remains very similar if we apply the analyses from Table 2 to the restricted sample from Table 7 (see Online Appendix).

Our findings point out that loss firms are not only more difficult to value, but also more prone to mispricing. While the efficient pricing of assets is of relevance for economic welfare in general, it is particularly important for loss firms which frequently have to acquire additional capital due to the weak earnings situation. The documented mispricing might imply that capital and resources are not efficiently allocated among loss firms whose continued existence is at stake.

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Online Appendix for

"The Valuation of Loss Firms: A Stock Market Perspective"

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Table A1. Return Predictability – Further Factor Models
This table reports subsequent value-weighted portfolio returns of quintile portfolios. Stocks are allocated to quintile portfolios at the end of each month $t-1$ based on the book-to-market ratio BM, the revenue-to-price ratio RP, or the earnings-to-price ratio EP. Portfolio returns for month t are calculated on a value-weighted basis. The table presents average portfolio returns that are adjusted for their exposure with respect to the three Fama and French (1993) factors (α_{FF3}) or the four Carhart (1997) factors (α_{C4}). The portfolio sorts are conducted separately for loss firms (negative earnings) and gain firms (non-negative earnings). The sample period covers July 1972 to December 2020. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Sorts Based on BM				Sorts Based on RP				Sorts Based on EP			
	α_{FF3}		α_{C4}		α_{FF3}		α_{C4}		α_{FF3}		α_{C4}	
	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain
low	-0.43	0.07	-0.54	-0.01	-0.88	0.06	-0.94	-0.00	-0.70	0.12	-0.09	-0.02
2	-0.36	0.06	-0.40	0.07	-0.08	0.09	-0.08	0.10	-0.26	-0.02	0.15	-0.07
3	-0.34	0.07	-0.21	0.08	-0.47	0.06	-0.35	0.14	-0.53	0.07	-0.24	0.12
4	-0.44	0.02	-0.10	0.17	-0.10	0.04	0.23	0.18	-0.27	0.21	-0.20	0.37
high	0.26	0.10	0.90	0.36	-0.28	0.04	0.19	0.27	-0.24	0.12	-0.30	0.40
5-1	0.69	0.03	1.44	0.36	0.60	-0.03	1.13	0.27	0.45	0.00	-0.21	0.42
t(5-1)	(2.07)	(0.25)	(4.55)	(3.71)	(1.84)	(-0.23)	(3.69)	(2.48)	(1.50)	(0.01)	(-0.63)	(4.32)
Δ	-0.66		-1.07		-0.63		-0.86		-0.45		0.63	
t(Δ)	(-2.06)		(-3.37)		(-1.98)		(-2.70)		(-1.37)		(1.83)	

Table A2. Return Predictability – Equal-Weighted Portfolios
This table reports subsequent equal-weighted portfolio returns of quintile portfolios. Stocks are allocated to quintile portfolios at the end of each month $t-1$ based on the book-to-market ratio BM, the revenue-to-price ratio RP, or the earnings-to-price ratio EP. Portfolio returns for month t are calculated on an equal-weighted basis. The table presents portfolio raw returns (i.e., the time-series average of these monthly equal-weighted portfolio returns) and market risk adjusted returns (α_{MKT}). α_{MKT} is the intercept in a regression of monthly equal-weighted portfolio returns on the excess market return. The portfolio sorts are conducted separately for loss firms (negative earnings) and gain firms (non-negative earnings). The sample period covers July 1972 to December 2020. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Sorts Based on BM				Sorts Based on RP				Sorts Based on EP			
	raw		α_{MKT}		raw		α_{MKT}		raw		α_{MKT}	
	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain
low	0.47	1.00	-0.78	-0.10	0.27	0.96	-0.99	-0.11	2.09	1.02	0.83	-0.08
2	0.54	1.09	-0.66	0.05	0.90	1.08	-0.30	0.09	1.32	1.10	0.14	0.09
3	0.89	1.19	-0.27	0.19	1.30	1.22	0.12	0.23	0.98	1.19	-0.19	0.21
4	1.48	1.31	0.37	0.34	1.55	1.37	0.40	0.36	0.81	1.42	-0.34	0.44
high	2.66	1.71	1.45	0.68	2.02	1.67	0.87	0.60	0.83	1.57	-0.33	0.50
5-1	2.19	0.71	2.24	0.78	1.75	0.71	1.86	0.70	-1.26	0.55	-1.15	0.58
t(5-1)	(7.77)	(3.33)	(8.11)	(3.74)	(5.09)	(3.01)	(5.40)	(2.97)	(-3.36)	(2.68)	(-3.10)	(2.91)
Δ	-1.48		-1.46		-1.04		-1.16		1.81		1.74	
t(Δ)	(-7.63)		(-7.66)		(-4.89)		(-5.55)		(3.58)		(3.50)	

Table A3. Limits to Arbitrage among Loss Firms – Equal-Weighted Portfolios
This table reports market risk adjusted equal-weighted returns from conditional portfolio double sorts. First, in each month $t-1$, each stock is allocated to a quintile portfolio based on a limits to arbitrage proxy. In Panel A, the idiosyncratic return volatility is calculated as the volatility of daily stock return residuals with respect to the three Fama and French (1993) factors in the previous month (Ang et al., 2006). In Panel B, the Amihud (2002) illiquidity measure is the ratio of daily absolute stock return to daily dollar trading volume averaged over the previous year. In Panel C, the stock's average closing bid-ask-spread over the previous year is employed (Goyenko et al., 2009). Second, within each quintile portfolio, each stock is allocated to a quintile portfolio based on the book-to-market ratio *BM* or the revenue-to-price ratio *RP*. The subsequent returns in month t are adjusted for their market risk exposure, i.e., the table presents the intercepts from a regression of monthly equal-weighted portfolio returns on the excess market return. The analyses consider loss firms only. The sample period is July 1972 to December 2020 in Panels A and B and January 1993 to December 2020 in Panel C. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

Panel A: Idiosyncratic Volatility

	low	2	3	4	high		low	2	3	4	high
low *BM*	-0.23	-0.24	-0.53	-0.90	-1.56	low *RP*	-0.29	-0.74	-0.75	-1.00	-1.48
2	-0.02	-0.23	-0.43	-1.07	-1.52	2	0.04	-0.24	-0.17	-0.82	-0.90
3	0.27	-0.24	0.01	-0.38	-0.89	3	0.51	0.45	0.03	0.00	-0.05
4	0.23	0.46	0.25	0.49	0.35	4	0.28	0.56	0.49	0.51	0.10
high *BM*	0.72	0.78	1.28	1.55	2.43	high *RP*	0.42	0.52	0.95	0.98	1.13
5-1	0.95	1.02	1.81	2.45	3.99	5-1	0.71	1.26	1.70	1.97	2.61
t(5-1)	(3.32)	(3.49)	(7.35)	(6.52)	(8.01)	t(5-1)	(2.19)	(3.16)	(5.29)	(5.44)	(4.39)

Panel B: Amihud (2002) Illiquidity

	low	2	3	4	high		low	2	3	4	high
low *BM*	-0.97	-0.73	-0.86	-0.79	-0.22	low *RP*	-1.04	-0.62	-0.78	-0.97	0.27
2	-0.70	-0.54	-0.41	-0.75	-0.11	2	-0.75	-0.49	-0.33	-0.34	0.35
3	-0.65	-0.44	-0.21	-0.19	0.51	3	-0.34	-0.54	-0.01	0.11	0.66
4	-0.28	-0.28	0.06	0.55	1.55	4	-0.25	-0.21	0.10	0.20	1.62
high *BM*	-0.08	-0.08	0.42	0.68	3.62	high *RP*	-0.32	-0.22	-0.01	0.49	2.40
5-1	0.89	0.65	1.29	1.47	3.84	5-1	0.72	0.40	0.77	1.45	2.13
t(5-1)	(2.35)	(1.75)	(3.49)	(3.80)	(10.64)	t(5-1)	(1.59)	(1.11)	(1.86)	(3.28)	(4.81)

Panel C: Bid-Ask-Spread

	low	2	3	4	high		low	2	3	4	high
low *BM*	-0.35	-0.83	-0.78	-1.02	-0.84	low *RP*	-0.78	-1.05	-0.97	-1.05	-0.41
2	-0.62	-0.77	-0.46	-0.77	-0.71	2	-0.39	-0.70	0.08	-0.74	0.53
3	-0.62	-0.57	-0.11	-0.50	0.82	3	-0.48	-0.41	-0.16	0.11	0.74
4	-0.66	-0.26	0.14	0.57	1.86	4	-0.51	-0.23	0.10	0.31	1.89
high *BM*	-0.44	-0.40	-0.12	0.42	3.17	high *RP*	-0.54	-0.46	-0.38	0.05	1.56
5-1	-0.10	0.42	0.66	1.44	4.00	5-1	0.24	0.59	0.58	1.10	1.97
t(5-1)	(-0.24)	(0.95)	(1.42)	(3.15)	(7.28)	t(5-1)	(0.41)	(0.94)	(0.96)	(2.23)	(3.38)

Table A4. Limits to Arbitrage among Loss Firms – Raw Portfolio Returns
This table reports value-weighted raw returns from conditional portfolio double sorts. First, in each month $t-1$, each stock is allocated to a quintile portfolio based on a limits to arbitrage proxy. In Panel A, the idiosyncratic return volatility is calculated as the volatility of daily stock return residuals with respect to the three Fama and French (1993) factors in the previous month (Ang et al., 2006). In Panel B, the Amihud (2002) illiquidity measure is the ratio of daily absolute stock return to daily dollar trading volume averaged over the previous year. In Panel C, the stock's average closing bid-ask-spread over the previous year is employed (Goyenko et al., 2009). Second, within each quintile portfolio, each stock is allocated to a quintile portfolio based on the book-to-market ratio *BM* or the revenue-to-price ratio *RP*. The subsequent value-weighted portfolio returns in month *t* are presented on a raw basis. The analyses consider loss firms only. The sample period is July 1972 to December 2020 in Panels A and B and January 1993 to December 2020 in Panel C. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

Panel A: Idiosyncratic Volatility

	low	2	3	4	high		low	2	3	4	high
low *BM*	1.16	0.85	0.51	0.26	-0.87	low *RP*	0.88	0.47	0.20	0.06	-0.97
2	1.15	1.05	0.67	-0.02	-1.09	2	1.20	1.18	1.01	0.32	-0.35
3	1.15	0.74	1.17	0.42	0.03	3	1.37	1.32	0.74	0.58	0.01
4	1.14	1.23	0.84	0.67	0.19	4	1.03	0.99	1.23	0.53	0.17
high *BM*	1.58	1.75	1.61	1.08	0.87	high *RP*	1.32	1.48	1.44	1.12	0.09
5-1	0.42	0.90	1.11	0.82	1.74	5-1	0.44	1.00	1.24	1.05	1.07
t(5-1)	(1.13)	(1.81)	(2.62)	(1.57)	(2.36)	t(5-1)	(0.98)	(2.14)	(2.34)	(2.01)	(1.51)

Panel B: Amihud (2002) Illiquidity

	low	2	3	4	high		low	2	3	4	high
low *BM*	0.97	0.61	0.49	0.14	-0.12	low *RP*	0.37	0.79	0.51	-0.25	0.12
2	0.84	0.80	1.03	0.32	0.40	2	0.92	0.77	0.95	0.48	0.63
3	0.90	0.87	0.89	1.01	1.16	3	1.05	0.87	1.13	1.14	0.70
4	0.82	1.03	1.25	1.46	1.67	4	1.01	1.19	1.30	1.45	1.58
high *BM*	1.19	1.48	1.52	1.63	2.60	high *RP*	1.17	1.26	1.24	1.66	1.83
5-1	0.22	0.87	1.04	1.49	2.72	5-1	0.79	0.47	0.73	1.92	1.70
t(5-1)	(0.52)	(2.38)	(2.76)	(3.28)	(8.30)	t(5-1)	(1.56)	(1.18)	(1.40)	(4.26)	(4.06)

Panel C: Bid-Ask-Spread

	low	2	3	4	high		low	2	3	4	high
low *BM*	1.46	0.65	0.94	0.42	-0.69	low *RP*	0.59	0.43	0.58	-0.04	-0.61
2	1.04	0.66	0.43	0.69	0.23	2	1.26	0.48	1.03	0.43	0.66
3	0.92	0.68	1.19	0.66	1.30	3	1.00	0.44	0.99	1.02	1.25
4	0.59	0.96	1.36	1.23	2.12	4	0.69	0.82	1.41	1.63	1.63
high *BM*	0.73	0.90	1.82	1.48	2.17	high *RP*	1.07	1.18	1.92	1.31	1.14
5-1	-0.73	0.25	0.87	1.06	2.86	5-1	0.48	0.75	1.34	1.35	1.75
t(5-1)	(-1.41)	(0.59)	(1.40)	(1.77)	(5.59)	t(5-1)	(0.67)	(1.12)	(1.80)	(2.03)	(3.43)

Table A5. Return Predictability – Restricted Sample
This table reports subsequent value-weighted portfolio returns of quintile portfolios. Stocks are allocated to quintile portfolios at the end of each month $t-1$ based on the book-to-market ratio BM, the revenue-to-price ratio RP, or the earnings-to-price ratio EP. Portfolio returns for month t are calculated on a value-weighted basis. The table presents portfolio raw returns (i.e., the time-series average of these monthly value-weighted portfolio returns) and market risk adjusted returns (α_{MKT}). α_{MKT} is the intercept in a regression of monthly value-weighted portfolio returns on the excess market return. The portfolio sorts are conducted separately for loss firms (negative earnings) and gain firms (non-negative earnings). The sample is restricted to those 1,798,186 stock-month-observations for which VP_{IREV} and VP_{MM} are available. The sample period covers July 1972 to December 2020. Subsequent returns are stated in percent. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags.

	Sorts Based on BM				Sorts Based on RP				Sorts Based on EP			
	raw		α_{MKT}		raw		α_{MKT}		raw		α_{MKT}	
	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain	loss	gain
low	0.75	0.90	-0.52	-0.08	0.23	0.88	-1.02	-0.07	0.91	0.96	-0.44	-0.07
2	0.73	1.01	-0.45	0.07	1.09	0.97	-0.08	0.08	1.21	0.87	-0.07	-0.06
3	0.93	1.07	-0.24	0.16	0.77	1.13	-0.37	0.20	0.82	1.00	-0.43	0.10
4	0.92	1.07	-0.22	0.18	1.38	1.16	0.22	0.20	0.95	1.22	-0.23	0.32
high	1.85	1.27	0.61	0.35	1.29	1.30	0.05	0.26	0.85	1.29	-0.30	0.32
5-1	1.10	0.37	1.13	0.43	1.06	0.42	1.08	0.33	-0.06	0.34	0.14	0.39
t(5-1)	(2.81)	(1.74)	(2.86)	(1.92)	(2.47)	(2.06)	(2.32)	(1.49)	(-0.15)	(1.64)	(0.35)	(1.87)
Δ	-0.73		-0.70		-0.64		-0.74		0.40		0.25	
$t(\Delta)$	(-2.41)		(-2.31)		(-1.90)		(-2.13)		(0.80)		(0.49)	