

Mohrschladt, Hannes; Siedhoff, Susanne

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HANNES MOHRSCHLADT AND SUSANNE SIEDHOFF

The Valuation of Loss Firms: A Stock Market Perspective

The proportion of exchange-listed firms with negative earnings has increased to over 40% in recent years. Previous research shows that the valuation of these loss firms is comparably difficult due to their uncertain future earnings path. Given these valuation issues, we argue that the stocks of loss firms should be particularly prone to mispricing such that simple firm value proxies might allow the prediction of subsequent stock returns. Supporting this hypothesis empirically, we find that book-to-market and revenue-to-price positively predict the cross-section of loss firms' stock returns. In particular, these value effects are significantly stronger compared to gain firms. Our further analyses support a behavioural mechanism for the empirical observations as the return predictability is disproportionately strong around earnings announcements and as analysts are too optimistic for loss firms with low values of book-to-market and revenue-to-price. Our analyses on short selling and option trading indicate that sophisticated investors are aware of the documented return predictability, but limits to arbitrage prevent an immediate correction of mispricing.

Key words: Firm valuation; Loss firms; Stock mispricing; Value effect.

Prior research has found it difficult to use fundamental accounting figures to explain the market values of firms with negative earnings compared to the market values of firms with positive earnings (Darrough and Ye, 2007; Balakrishnan *et al.*, 2010; Jan and Ou, 2012). This 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). As researchers find it comparably difficult to value loss firms, investors presumably face a similar challenge. Thus, observable market prices of loss firms may not only be more difficult to reconcile with accounting-based valuation models, they may also substantially deviate from their fundamental values. We examine this hypothesis and test whether simple book equity, revenue, and

HANNES MOHRSCHLADT (hannes.mohrschladt@wiwi.uni-muenster.de) and SUSANNE SIEDHOFF are with the School of Business & Economics, University of Münster.

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earnings information is adequately reflected in loss firms' stock prices. If this was not the case, these accounting figures should allow prediction of the loss firms' subsequent stock returns.

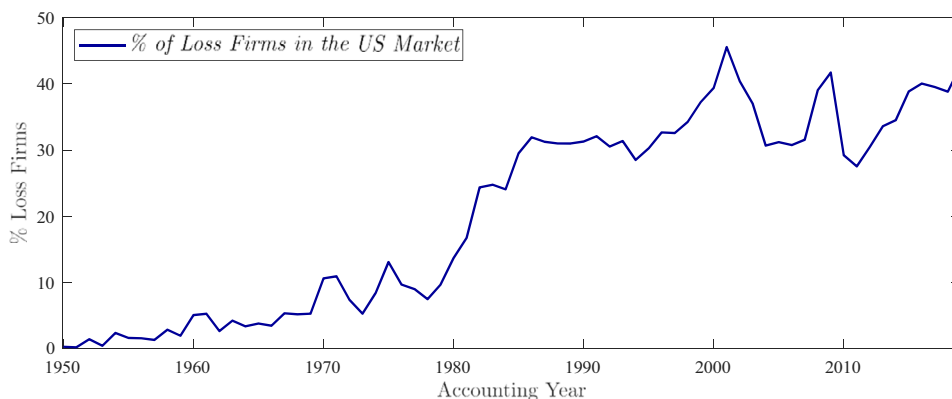
The potential mispricing of loss firms is particularly relevant for the functioning of financial markets as loss firms represent an increasingly large share of the overall market (Collins *et al.*, 1999; Joos and Plesko, 2005). Figure 1 illustrates this, and shows that the proportion of exchange-listed US firms with negative earnings has increased to more than 40% in recent years. Hence, systematic mispricing among these firms implies that capital might not be allocated efficiently causing a loss of economic welfare. For loss firms, such inefficiencies could be particularly problematic since their dependence on external financing is often comparably strong due to their weak operating performance.

We start our analysis by examining the relationship between 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, we find that loss firms with accounting figures that are comparably high in relation to their market values earn significantly higher subsequent stock returns on average. For example, the quintile portfolio of high- BM (high- RP) loss firms outperforms the quintile portfolio of low- BM (low- RP) loss firms by 1.04% (1.16%) per month. Hence, our portfolio sort analyses imply a

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 with common ordinary shares trading on the NYSE, AMEX, or NASDAQ.

significant value effect in the cross-section of loss firm stocks. Moreover, these value effects are substantially stronger compared to gain firms and remain significant after controlling for several asset pricing factors. Beyond this univariate evidence from portfolio sorts, we run Fama-MacBeth-regressions to control for other known cross-sectional return predictors. We find that both *BM* and *RP* predict subsequent returns with a positive sign and that these effects are significantly stronger among loss firms. Thus, our observations are consistent with the hypothesis that loss firms are particularly difficult to value and that accounting figures can be used to partly identify the resulting mispricing.

Our subsequent analyses provide further support for this hypothesis. We find that financial analysts are too optimistic with respect to growth (low-*RP* and low-*BM*) loss firms. In line with analysts contributing to mispricing (Engelberg *et al.*, 2020), 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. Hence, the severe overvaluation of growth loss firms is consistent with over-optimistic beliefs that potentially result from an over-extrapolation of high expected growth rates to the far future (Lakonishok *et al.*, 1994; Barberis *et al.*, 1998). Beyond biased beliefs, we show that investor preferences for positive return skewness (Kahneman and Tversky, 1979; Barberis and Huang, 2008) could further increase the overvaluation of growth loss firms since these firms have the most positive return skewness (Zhang, 2013).

Further aligned with severe mispricing among loss firms, our examination of short interest and option-implied volatility spreads indicates that sophisticated investors in shorting and options markets 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. Consistent 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 significant body of literature arguing that loss firm values are difficult to explain by means of accounting figures (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 consistent 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). Moreover, our findings are consistent with those of Baker and Wurgler (2006) and Riedl *et al.* (2021), who show that loss firms are more strongly influenced by investor sentiment than gain firms. Further, our evidence extends the work of Balakrishnan *et al.* (2010) and Li (2011). Their stock return analyses indicate that investors process loss persistence and information of low-earnings firms in a biased way, but they do not explicitly examine value effects among loss firms.

In addition, we add to 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, although 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), Barberis *et al.* (1998), Hirshleifer (2001), and Zhang (2013), our further analyses support a behavioural 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 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.

DATA AND VARIABLES

Our sample consists of common ordinary US stocks traded on the 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

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

option trading. Daily and monthly return factors are obtained from the homepages of Kenneth R. French and Lin Sun. 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.²

The main value proxies of interest are *BM*, *RP*, and *EP*. The numerator of the underlying 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 the denominator. Following Fama and French (1992) and Barbee *et al.* (1996), *BM* and *RP* correspond to the natural logarithm of the underlying ratios. The book value of equity is defined as in Fama and French (1993), that is, the book value of shareholder's equity is 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.

In our regression analyses, we consider further control variables that have been shown to predict the cross-section of stock returns. *BETA* is a stock's market beta estimated based on daily returns of the previous year with the CRSP value-weighted market return as market proxy. *SIZE* is the natural logarithm of the stock's market capitalization and *MOM* the stock's momentum return, that is, the stock return of the previous year skipping the most recent month. Following Fama and French (2015), we consider operating profitability *OP* and firm investments *INV*. In addition, *ACC*, *NOA*, and *EDR* refer to accruals (Sloan, 1996), net operating assets (Hirshleifer *et al.*, 2004), and earnings downside risk (Konchitchki *et al.*, 2016), respectively.

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.³ Referring to the entire sample that includes all firms, as expected, firms with higher book

² 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%).

³ We provide rank correlations as these are not strongly influenced by extreme outliers. In line with this notion, untubulated Pearson correlation coefficients provide qualitatively the same picture but tend to be smaller in magnitude.

TABLE 1
SUMMARY STATISTICS AND RANK CORRELATION COEFFICIENTS

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

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.

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—consistent 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 low correlation of earnings with market capitalization for the subsample of loss firms. The negative correlation is in line with Burgstahler and Dichev (1997) and Collins *et al.* (1999) and reflects the economic intuition that the earnings of large firms vary more in absolute dollar terms such that the potential loss magnitude is higher compared to small companies. As earnings seems 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 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.

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 might 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.

VALUE EFFECTS AMONG LOSS FIRMS

Loss firms are considered difficult 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. Hence, we expect mispricing to be larger among loss firms and value effects to be stronger. To compare value effects in loss versus gain firms, we conduct monthly portfolio sorts based on *BM*, *RP*, and *EP* separately for loss and gain firms. Following the standard procedure in the empirical asset pricing literature, 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. Portfolio weights are given by the firm's market capitalization in order to avoid micro-caps having a disproportionate impact on our findings (Hou *et al.*, 2020). We calculate simple average portfolio raw returns and return metrics that are adjusted for the portfolios' exposure to popular asset pricing factors. More specifically, we

adjust the returns for their exposure with respect to the market factor, the four-factor model of Carhart (1997), the six-factor model of Fama and French (2018), and the behavioural factor model of Daniel *et al.* (2020). Table 2 presents both raw and risk-adjusted portfolio returns. In addition, the difference portfolios (5–1) reflect the return spreads between value and growth portfolios. Moreover, we provide *t*-statistics in parentheses that are corrected for heteroscedasticity and autocorrelation.

To start with the return predictability associated with *BM* and *RP*, monthly return spreads are positive in each specification, supporting the corresponding seminal evidence on value effects in Rosenberg *et al.* (1985) and Barbee *et al.* (1996). 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. Moreover, we find particularly strong evidence on value effects among loss firms with significant return spreads in each specification. However, for gain firms, the return spreads are substantially smaller and not consistently significant. For example, *BM* induces a raw return spread of 1.04% per month among loss firms and only 0.35% among gain firms.⁴

The last rows of Table 2 show a very different picture for *EP*. Consistent with Table 1, *EP* can serve as a value proxy for gain firms such that it predicts subsequent returns with a positive sign (though not significant in all specifications). However, as also indicated by Table 1, *EP* does not seem to be a valid value proxy for loss firms. Supporting this conjecture, *EP* is no significant return predictor among loss firms in any specification. Consequently, we drop *EP* in the following analyses and further examine the value indicators *BM* and *RP* only.

Beyond this univariate evidence on the return predictability associated with *BM* and *RP*, we also run regression analyses to test whether our findings are subsumed by other well-known cross-sectional return predictors. To do so, we follow the standard in empirical asset pricing and run Fama-MacBeth-regressions (Fama and MacBeth, 1973). More specifically, for each month *t* in our sample, we estimate the cross-sectional regression

$$R_{i,t} = \beta_{0,t} + \beta_{1,t}VP_{i,t-1} + \beta_{2,t}LOSS_{i,t-1} + \beta_{3,t}VP_{i,t-1}LOSS_{i,t-1} + \beta_{4,t}CTRL_{i,t-1} + \epsilon_{i,t} \quad (1)$$

with monthly stock returns $R_{i,t}$ as the dependent variable. The key independent variables are *BM* or *RP* as value proxy *VP*, the loss dummy *LOSS*, and the interaction between *VP* and *LOSS*. Moreover, we include several control variables in *CTRL*. The corresponding slope coefficients are $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$, and $\beta_{4,t}$, respectively. $\beta_{0,t}$ denotes the intercept and $\epsilon_{i,t}$ the error term. Our coefficient of interest is $\beta_{3,t}$ as it reflects the extent to which value effects are stronger among loss firms compared to gain firms.

⁴ 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 substantially stronger compared to gain firms.

TABLE 2

RETURN PREDICTABILITY IN PORTFOLIO SORTS

Sorts Based on <i>BM</i>										
	Loss Firms					Gain Firms				
	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}
low	0.74	-0.56	-0.54	-0.30	-0.12	0.91	-0.08	-0.01	-0.06	-0.13
2	0.72	-0.46	-0.40	-0.29	0.03	1.00	0.07	0.07	-0.05	-0.04
3	0.99	-0.19	-0.21	-0.22	0.15	1.07	0.15	0.08	-0.03	0.07
4	0.92	-0.22	-0.10	0.00	0.35	1.08	0.19	0.17	0.11	0.19
high	1.78	0.54	0.90	0.91	1.39	1.26	0.35	0.36	0.30	0.43
5-1	1.04	1.09	1.44	1.20	1.50	0.35	0.43	0.36	0.36	0.56
<i>t</i> (5-1)	(2.69)	(2.82)	(4.55)	(3.71)	(3.64)	(1.59)	(1.87)	(3.71)	(3.66)	(2.54)
Sorts Based on <i>RP</i>										
	Loss Firms					Gain Firms				
	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}
low	0.19	-1.11	-0.94	-0.59	-0.35	0.90	-0.08	-0.00	-0.01	-0.10
2	1.07	-0.11	-0.08	0.00	0.28	1.00	0.10	0.10	0.03	0.04
3	0.82	-0.34	-0.35	-0.34	-0.05	1.10	0.17	0.14	-0.02	0.12
4	1.31	0.17	0.23	0.12	0.59	1.16	0.20	0.18	0.02	0.16
high	1.34	0.12	0.19	0.04	0.62	1.31	0.28	0.27	0.16	0.39
5-1	1.16	1.22	1.13	0.63	0.97	0.41	0.35	0.27	0.16	0.49
<i>t</i> (5-1)	(2.65)	(2.64)	(3.69)	(2.10)	(2.26)	(1.99)	(1.57)	(2.48)	(1.38)	(2.07)
Sorts Based on <i>EP</i>										
	Loss Firms					Gain Firms				
	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}
low	0.92	-0.44	-0.09	0.03	0.63	1.00	-0.06	-0.02	-0.00	-0.03
2	1.13	-0.14	0.15	0.29	0.71	0.87	-0.06	-0.07	-0.20	-0.21
3	0.87	-0.39	-0.24	-0.11	0.26	1.02	0.12	0.12	-0.02	0.01
4	0.93	-0.25	-0.20	-0.02	0.22	1.22	0.33	0.37	0.25	0.35
high	0.85	-0.32	-0.30	-0.14	0.04	1.30	0.32	0.40	0.39	0.51
5-1	-0.06	0.12	-0.21	-0.17	-0.58	0.30	0.38	0.42	0.39	0.54
<i>t</i> (5-1)	(-0.16)	(0.30)	(-0.63)	(-0.46)	(-1.21)	(1.39)	(1.72)	(4.32)	(3.68)	(2.57)

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 portfolio returns) and portfolio returns that are adjusted for their exposure with respect to the market excess return (α_{MKT}), the Carhart (1997) four-factor model (α_{FFC}), the Fama and French (2018) six-factor model (α_{FF6}), and the Daniel *et al.* (2020) behavioural factor model (α_{DHS}). These alphas correspond to the intercepts in regressions of monthly portfolio returns on the respective return factors. 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 12 lags.

TABLE 3

RETURN PREDICTABILITY IN FAMA-MACBETH-REGRESSIONS

	BM as Value Proxy VP			RP as Value Proxy VP		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>intercept</i>	1.4038 (6.07)	3.4300 (3.93)	3.8215 (4.36)	1.1929 (5.52)	3.4931 (3.91)	3.8240 (4.19)
<i>VP</i>	0.3110 (3.57)	0.3043 (4.23)	0.3687 (5.13)	0.2415 (3.41)	0.1621 (2.75)	0.1532 (2.69)
<i>VPxLOSS</i>	0.3630 (4.70)	0.4121 (5.49)	0.3231 (3.94)	0.1041 (2.21)	0.1715 (4.11)	0.1584 (3.82)
<i>LOSS</i>	0.0265 (0.14)	-0.0291 (-0.21)	-0.0292 (-0.26)	-0.0562 (-0.29)	-0.2351 (-1.86)	-0.2292 (-2.17)
<i>BETA</i>		0.0289 (0.20)	0.0404 (0.29)		-0.0268 (-0.18)	-0.0112 (-0.08)
<i>SIZE</i>		-0.1162 (-2.76)	-0.1172 (-2.92)		-0.1264 (-2.93)	-0.1315 (-3.13)
<i>MOM</i>		0.9544 (6.08)	0.8903 (5.97)		0.7626 (4.90)	0.6726 (4.47)
<i>OP</i>			0.5390 (3.85)			0.3357 (3.00)
<i>INV</i>			-0.1829 (-1.66)			-0.3641 (-2.83)
<i>ACC</i>			-0.6198 (-2.06)			-0.7596 (-2.49)
<i>NOA</i>			-0.7087 (-4.96)			-0.4686 (-2.98)
<i>EDR</i>			-0.1454 (-0.23)			-0.9519 (-1.54)

This table presents time-series averages of monthly cross-sectional regression estimates. The dependent variable is the stock return of the subsequent month. The explanatory variables are given in the first column. The value proxy *VP* corresponds to the book-to-market ratio *BM* in columns (1) to (3) and to the revenue-to-price ratio *RP* in columns (4) to (6). The loss dummy *LOSS* equals one if annual earnings are negative and zero otherwise. *BETA* is the stock's market beta estimated based on daily returns of the previous year, *SIZE* the stock's log market capitalization, and *MOM* the stock return over the previous year skipping the most recent month. *OP* and *INV* denote operating profitability and investments following Fama and French (2015), respectively. *ACC*, *NOA*, and *EDR* refer to accruals (Sloan, 1996), net operating assets (Hirshleifer *et al.*, 2004), and earnings downside risk (Konchitchki *et al.*, 2016), respectively. The *t*-statistics in parentheses are based on standard errors following Newey and West (1987) using 12 lags. The sample period covers July 1972 to December 2020.

Table 3 reports time-series averages of the regression coefficients from equation (1). The first three columns examine the return predictability associated with the book-to-market ratio, the last three columns refer to the revenue-to-price ratio. In each regression specification, these value proxies significantly predict subsequent returns with positive sign. In addition, this effect is significantly stronger among loss firms. The *VPxLOSS*-coefficients show a similar magnitude as the *VP*-coefficients, indicating that *BM* and *RP* predict subsequent returns twice as strong among loss firms as among gain firms. These results hold after controlling for market beta, size, and momentum in columns (2) and (5) and also after controlling for further

accounting figures such as operating profitability, investments, accruals, net operating assets, and earnings downside risk in columns (3) and (6).

Controlling for economic downside risk *EDR* is of particular interest as it shows a high correlation of 32% with the loss dummy *LOSS* (see full correlation matrix for the variables from Table 3 in the Online Appendix). This positive correlation is in line with the straightforward intuition that loss firms tend to be distressed, volatile, and unprofitable, implying a higher level of risk. Hence, *LOSS* might not only proxy for valuation uncertainty resulting in more severe mispricing and value effects; *LOSS* might also proxy for fundamental risks that are associated with risk premiums in the cross-section of stock returns. Given this potential double role of *LOSS*, we consider long-term stock returns, nominal share price, idiosyncratic return volatility, cash flow volatility, tail risk, the distress proxy O-score, and financial leverage as additional control variables in the Online Appendix. All of these variables are correlated with *LOSS* and might proxy for fundamental sources of risk. After adding these controls, we find that the regression coefficients for *VPxLOSS* remain statistically significant and qualitatively the same as in Table 3. Hence, the documented return premiums do not seem to be a compensation for the potential risks captured by these control variables.

EVIDENCE ON THE UNDERLYING MECHANISM

In this section, we further investigate the underlying mechanism of the return predictability. First, given the low subsequent stock returns of low-*BM* and low-*RP* loss firms, we explore potential behavioural mechanisms that imply an overvaluation of these firms. Afterwards, we present empirical evidence in favour of behavioural explanations since sophisticated investors seem to exploit the documented return spreads and since the return spreads are largest among the stocks with the most severe limits to arbitrage.

Investors' Beliefs and Preferences

As a belief-based explanation for the empirical observations in Tables 2 and 3, the market's beliefs might be too optimistic (pessimistic) with respect to low-*BM* and low-*RP* (high-*BM* and high-*RP*) firms such that the overvaluation (undervaluation) is corrected later when investors revise their biased expectations. Lakonishok *et al.* (1994) and Barberis *et al.* (1998) argue that investors' excessive optimism with respect to growth stocks might result from naively extrapolating growth expectations too far into the future. These beliefs can result from investors' application of representativeness heuristics (Tversky and Kahneman, 1974): if they consider a small sample of positive growth rates as representative for a firm's growth path in subsequent decades, their beliefs are likely to be overly optimistic. These behavioural patterns should be particularly strong among loss firms, when compared to gain firms, as the former are more difficult to value, implying that the potential for biased beliefs is substantially larger (see analysts' comparably high forecast errors for loss firms as documented by Brown (2001)). In addition, the

TABLE 4

ANALYST RECOMMENDATIONS AND EARNINGS ANNOUNCEMENT RETURNS

	Analyst Recommendations				Earnings Announcement Returns			
	Sorts Based on <i>BM</i>		Sorts Based on <i>RP</i>		Sorts Based on <i>BM</i>		Sorts Based on <i>RP</i>	
	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
<i>t</i> (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	
<i>t</i> (Δ)	(6.08)		(19.14)		(-0.91)		(-6.09)	

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 12 lags.

overvaluation of low-*BM* and low-*RP* loss firms can be intensified by the post loss/profit announcement drift (Balakrishnan *et al.*, 2010)—if investors do not fully respond to the negative information contained in loss announcements, their beliefs are too optimistic, resulting in low subsequent stock returns.

Based on these arguments, we analyze how biased beliefs relate to *BM*, *RP*, and the firms' loss status. In this context, Engelberg *et al.* (2020) argue that systematic analyst biases can shape market beliefs and contribute to mispricing. Vice versa, market-wide excessive optimism with respect to specific stocks could be reflected in analyst recommendations to some extent. Table 4 reports separately the average monthly analyst recommendation for each quintile portfolio formed on the basis of *BM* and *RP* 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. Consistent with Drake *et al.* (2011) and Engelberg *et al.* (2020), Table 4 shows that the average analyst recommendation is significantly more favourable for growth compared to value stocks, although value stocks outperform growth stocks on average. Hence, given the return patterns we document in Table 2, analysts' 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 beliefs among loss firms and could rationalize the stronger return spreads among loss firms compared to gain firms.

Analysts' beliefs seem to be particularly upward biased for growth stocks with negative earnings. Motivated by this finding, we hypothesize that investors will particularly correct their biased beliefs when new fundamental information on the fair stock value is obtained. Although investors continuously receive and process information such that the correction of mispricing is not exclusively confined to specific days, the revision of biased beliefs should be most pronounced around earnings announcements when value-relevant information is published. We provide the corresponding empirical evidence in the right part of Table 4. Consistent with investors revising their biased beliefs, both *BM* and *RP* positively predict stock returns in a symmetric 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 in Table 2, a major proportion of the return predictability is realized when fundamental earnings information is published.⁵ 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.

Beyond biased beliefs, the overvaluation of low-*BM* and low-*RP* loss firms could also result from investor preferences that do not comply with the rational benchmark of expected utility maximization. In this context, (cumulative) prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) is the most popular descriptive theory for decision making under risk. Among other components, prospect theory implies that individuals over-weight small probabilities when evaluating different investment opportunities. Consequently, prospect theory predicts that investors exhibit a preference for assets with positive return skewness such that these assets tend to be overvalued (see corresponding arguments in Barberis and Huang (2008), Boyer and Vorkink (2014), An *et al.* (2020)). In particular, Zhang (2013) shows that the return spreads between value and growth stocks are partly driven by investors' preferences for positive return skewness—since the return distributions of growth stocks have comparably large right tails, these stocks are attractive to investors, become overvalued, and earn low subsequent returns. Since distress firms have comparably high return skewness (An *et al.*, 2020), we conjecture that this observation also holds for loss firms.

⁵ While our evidence shows that mispricing tends to be corrected around earnings announcements, this does not imply that information is always processed in a perfectly unbiased way on these days. Indeed, our Online Appendix analyses support previous evidence on substantial post-earnings announcement drift (see, among many others, Ball and Brown (1968), Bernard and Thomas (1989)). Moreover, we find that post-earnings announcement drift is significantly stronger among loss compared to gain firms lending further support to our hypothesis that loss firm valuation is challenging for investors resulting in more pronounced mispricing among these firms.

TABLE 5

RETURN SKEWNESS AND IDIOSYNCRATIC RETURN SKEWNESS

	Return Skewness				Idiosyncratic Return Skewness			
	Sorts Based on <i>BM</i>		Sorts Based on <i>RP</i>		Sorts Based on <i>BM</i>		Sorts Based on <i>RP</i>	
	loss	gain	loss	gain	loss	gain	loss	gain
low	0.34	0.22	0.33	0.21	0.28	0.19	0.27	0.18
2	0.31	0.20	0.28	0.18	0.26	0.17	0.23	0.15
3	0.28	0.19	0.28	0.18	0.23	0.16	0.23	0.16
4	0.25	0.17	0.26	0.18	0.20	0.14	0.20	0.15
high	0.20	0.15	0.23	0.18	0.14	0.11	0.17	0.14
5–1	−0.14	−0.07	−0.10	−0.03	−0.14	−0.08	−0.10	−0.05
<i>t</i> (5–1)	(−8.85)	(−7.35)	(−8.12)	(−3.79)	(−9.69)	(−9.19)	(−8.83)	(−6.49)
Δ	0.07		0.07		0.06		0.05	
<i>t</i> (Δ)	(5.65)		(6.93)		(5.38)		(5.89)	

This table presents return skewness and idiosyncratic return skewness 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 shows the skewness of daily stock returns in the previous month. In the right part of the table, the skewness is based on the residuals from regressing daily excess returns on the market excess return. 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 12 lags. The sample period covers July 1972 to December 2020.

Combining these two arguments, we expect growth loss firms to have the highest level of return skewness resulting in the strongest degree of overvaluation.

Table 5 shows the skewness of daily stock returns for quintile portfolios sorted by *BM* and *RP*, separately for loss and gain firms. In the left part of the table, return skewness is calculated based on a stock's daily unadjusted returns of the month prior to portfolio formation. In the right part, we report the skewness of market-model adjusted daily returns of the prior month (Bali *et al.*, 2016). Consistent across both specifications, and consistent with the previous arguments, we find that growth stocks (low *BM* and low *RP*) have higher return skewness than value stocks (high *BM* and high *RP*) and loss firms have higher return skewness than gain firms. In addition, the skewness difference between growth and value stocks is always significantly larger among loss than among gain firms. Hence, to the extent that value effects are driven by investors' skewness preferences (Zhang, 2013), the evidence from Table 5 can explain why value effects are disproportionately strong among loss firms.

Informed Trading on Value Effects Among Loss Firms

The previous analyses suggest that mispricing leads 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, in particular, value effects are driven by unsophisticated investors.

TABLE 6

SOPHISTICATED TRADING AMONG LOSS FIRMS

	Sorts Based on <i>BM</i>				Sorts Based on <i>RP</i>			
	<i>RSI</i>	<i>VS_{BH}</i>	<i>VS_{CW}</i>	<i>O/S</i>	<i>RSI</i>	<i>VS_{BH}</i>	<i>VS_{CW}</i>	<i>O/S</i>
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
<i>t</i> (5-1)	(-5.44)	(6.15)	(7.06)	(-19.08)	(-4.18)	(6.17)	(5.33)	(-14.50)

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 12 lags.

Therefore, we examine whether more sophisticated investors are able to identify over- and under-pricing 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), which suggests that short-sellers can identify mispricing and profit from its exploitation.

Moreover, rational investors might trade on mispricing in the options 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 6 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.

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 options 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 6 shows that both VS_{BH} and VS_{CW} are substantially more negative for growth compared to value stocks. Hence, sophisticated investors in the options 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. Consistent with the previous findings, Table 6 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.

Limits to Arbitrage

Our analyses indicate that low-*BM* and low-*RP* loss firms are overvalued. 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 of 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.

To analyze 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), illiquidity (see, Amihud, 2002), 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 7 reports average returns of the subsequent month for each of the resulting 25 portfolios.

Table 7 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 *BM* and *RP*. For example, the return spread associated with *BM* amounts to 0.42% among stocks with low idiosyncratic return volatility while it is 1.74% among stocks with high idiosyncratic return volatility. Hence, in line with a behavioural explanation, the mispricing is strongest among volatile and illiquid stocks.⁶ Vice versa, if limits to arbitrage are low, the combined evidence from Tables 6 and 7 suggests that sophisticated investors can substantially reduce the magnitude of value effects among loss firms.

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 a 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.

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} .

⁶ In the Online Appendix, we provide qualitatively the same evidence when using equal-weighted portfolios instead of the value-weighted approach applied in Table 7.

VALUATION OF LOSS FIRMS

TABLE 7

LIMITS TO ARBITRAGE AMONG LOSS FIRMS

Panel A: Idiosyncratic volatility

	low	2	3	4	high		low	2	3	4	high
low <i>BM</i>	1.16	0.85	0.51	0.26	-0.87	low <i>RP</i>	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 <i>BM</i>	1.58	1.75	1.61	1.08	0.87	high <i>RP</i>	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
<i>t</i> (5-1)	(1.13)	(1.81)	(2.62)	(1.57)	(2.36)	<i>t</i> (5-1)	(0.98)	(2.14)	(2.34)	(2.01)	(1.51)

Panel B: Illiquidity (Amihud, 2002)

	low	2	3	4	high		low	2	3	4	high
low <i>BM</i>	0.97	0.61	0.49	0.14	-0.12	low <i>RP</i>	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 <i>BM</i>	1.19	1.48	1.52	1.63	2.60	high <i>RP</i>	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
<i>t</i> (5-1)	(0.52)	(2.38)	(2.76)	(3.28)	(8.30)	<i>t</i> (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 <i>BM</i>	1.46	0.65	0.94	0.42	-0.69	low <i>RP</i>	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 <i>BM</i>	0.73	0.90	1.82	1.48	2.17	high <i>RP</i>	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
<i>t</i> (5-1)	(-1.41)	(0.59)	(1.40)	(1.77)	(5.59)	<i>t</i> (5-1)	(0.67)	(1.12)	(1.80)	(2.03)	(3.43)

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 illiquidity measure (Amihud, 2002) 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 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 12 lags.

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.

TABLE 8

SUMMARY STATISTICS AND RANK CORRELATION COEFFICIENTS—ALTERNATIVE VALUATION MEASURES

Summary Statistics									
	All Firms			Loss Firms			Gain Firms		
	<i>MVE</i>	<i>VP_{IREV}</i>	<i>VP_{MM}</i>	<i>MVE</i>	<i>VP_{IREV}</i>	<i>VP_{MM}</i>	<i>MVE</i>	<i>VP_{IREV}</i>	<i>VP_{MM}</i>
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		
	<i>MVE</i>	<i>VP_{IREV}</i>	<i>VP_{MM}</i>	<i>MVE</i>	<i>VP_{IREV}</i>	<i>VP_{MM}</i>	<i>MVE</i>	<i>VP_{IREV}</i>	<i>VP_{MM}</i>
<i>MVE</i>	1.00			1.00			1.00		
<i>VP_{IREV}</i>	0.83	1.00		0.58	1.00		0.86	1.00	
<i>VP_{MM}</i>	0.81	0.97	1.00	0.52	0.91	1.00	0.84	0.97	1.00

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 at 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.

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}*.

Summary Statistics of Alternative Valuation Measures

Summary statistics on the market value of equity, *VP_{IREV}* and *VP_{MM}* can be obtained from Table 8. 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 8 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 8 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

TABLE 9

RETURN PREDICTABILITY OF ALTERNATIVE VALUATION MEASURES

Sorts Based on VP_{IREV}/MVE

	Loss Firms					Gain Firms				
	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}
low	0.23	-1.11	-0.92	-0.53	-0.42	0.89	-0.11	-0.03	-0.03	-0.12
2	0.67	-0.50	-0.48	-0.36	-0.07	1.00	0.12	0.10	-0.00	0.01
3	1.08	-0.04	-0.10	-0.12	0.25	1.02	0.12	0.10	0.01	0.04
4	1.35	0.16	0.28	0.24	0.64	1.09	0.19	0.18	0.09	0.17
high	1.38	0.13	0.20	0.13	0.68	1.28	0.27	0.24	0.11	0.35
5-1	1.15	1.24	1.12	0.66	1.10	0.39	0.38	0.27	0.13	0.48
$t(5-1)$	(2.63)	(2.76)	(3.51)	(2.26)	(3.28)	(2.08)	(1.88)	(2.29)	(1.08)	(3.18)

Sorts Based on VP_{MM}/MVE

	Loss Firms					Gain Firms				
	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}	raw	α_{MKT}	α_{FFC}	α_{FF6}	α_{DHS}
low	0.32	-1.01	-0.85	-0.54	-0.33	0.90	-0.09	-0.04	-0.06	-0.14
2	0.70	-0.46	-0.42	-0.29	-0.02	0.97	0.09	0.09	-0.02	-0.01
3	1.00	-0.13	-0.21	-0.28	0.06	0.93	0.06	0.01	-0.10	-0.07
4	1.23	0.05	0.13	0.06	0.51	1.21	0.28	0.28	0.20	0.29
high	1.30	0.10	0.12	0.06	0.57	1.24	0.24	0.20	0.07	0.33
5-1	0.98	1.11	0.97	0.60	0.90	0.34	0.33	0.24	0.13	0.47
$t(5-1)$	(2.48)	(2.62)	(3.18)	(1.98)	(2.74)	(1.98)	(1.75)	(2.08)	(1.08)	(3.21)

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 at 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 and portfolio returns that are adjusted for their exposure with respect to the market excess return (α_{MKT}), the Carhart (1997) four-factor model (α_{FFC}), the Fama and French (2018) six-factor model (α_{FF6}), and the Daniel *et al.* (2020) behavioural factor model (α_{DHS}). 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 12 lags.

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} .

Return Predictability Based on Alternative Valuation Measures

The summary statistics in Table 8 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 9 shows value-weighted portfolio returns of month t . In line with our previous methodology, these returns are either presented on a raw basis or adjusted for their exposure with respect to several factor models.

Table 9 shows that both value proxies predict subsequent returns with a positive sign. Hence, the documented value effects support our conjecture that both VP_{IREV} and VP_{MM} allow the identification of mispricing. From an economic and statistical point of view, these effects are strong among loss firms and less pronounced among gain firms. Hence, Table 9 lends additional support to our hypothesis that value effects and the underlying magnitude of mispricing are larger among loss firms compared to gain firms. In the Online Appendix, we show that the return spreads are even larger for equal-weighted portfolios and again stronger for loss firms.

The findings from Table 9 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. 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 mispricing.

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 fair 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.

Our findings highlight 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 where continued existence is at stake.

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Appendix S1: Supplementary Appendix