Distress Risk, Expected Shareholder Losses, and the Cross-Section of Expected Returns*

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Abstract

We analyse the impact of financial distress on expected stock returns accounting for the severity of default. Whereas shareholders' average losses amount to 32% of equity value from the day before to the day after a bankruptcy filing, outcomes differ substantially among firms. We specify and estimate a model that predicts these losses for individual firms. When sorting stocks into portfolios according to their predicted bankruptcy losses, we find that a long-short strategy buying stocks with high predicted bankruptcy losses and selling stocks with low predicted bankruptcy losses earns a monthly premium of 0.5%. We also sort stocks independently into quintiles according to predicted bankruptcy loss and failure probability. We find that the distress-risk puzzle is not present among stocks in the highest quintile of predicted bankruptcy loss. On the contrary, the long-short returns of stocks sorted by predicted bankruptcy losses are strongest for stocks in the highest quintile of failure probability.

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1 Introduction

The idea that equities bear a distinct premium for risk of financial distress has been an important conceptual premise of asset pricing for over two decades. Chan and Chen (1991) and Fama and French (1996) speculate that failures of the CAPM may be due to the pricing of comovement of the returns on financially distressed firms. The question of whether this hypothesis has empirical support has been studied in many papers[1]. Most directly related to our study, Campbell, Hilscher, and Szilagyi (2008) specify and estimate a distress prediction model. The authors find that when the fitted model is used to predict whether a firm will become distressed in the next twelve months, that those firms with high distress probability earn low average returns relative to firms with low distress probability using standard factor benchmark models. Since economic theory predicts a positive premium for distress risk, this empirical result has posed a challenge to the asset pricing literature.

In this paper, we investigate an additional dimension to financial distress; the risk of loss given default. In standard bond pricing frameworks, there are two components to default risk; the probability that the firm will default on its obligations, and the amount that creditors stand to lose in case of default. In the Merton (1974) credit modeling framework, this loss given default is a concern only to bondholders, as equity investors put the firm to the creditors and endure a 100% loss in case of default. However, in reality, losses to equity holders are frequently not 100%; the studies of Franks and Torous (1994, 1989), Eberhart, Moore, and Roenfeldt (1990), Weiss (1990), and Betker (1995) find that equity on average receives 7.6% of reorganized firm value in Chapter 11 bankruptcy. Clark and Weinstein (1983) show that of 162 bankrupt firms in their sample, 83 of the firms' equity retained value after the bankruptcy proceedings. The authors also show that firms lose on average 47% of their value in the three days surrounding the bankruptcy filing. These results

[1] Among the papers that examine whether distress risk is linked to average returns are Dichev (1998) and Griffin and Lemmon (2002), who find that firms with high bankruptcy probabilities earn lower average returns. Vassalou and Xing (2004) show that the size and book-to-market effects of Fama and French (1992) are present only in high default-risk firms and that the Fama and French (1993) size and book-to-market factors contain information about default risk. Chava and Jarrow (2004) find that implied expected return estimates suggest that high default risk firms have high expected returns and that investors were surprised by low returns on distressed firms during the 1980s.

suggest that, even in the case of reorganization, equity holders assign some positive probability to the event that their shares will have value after emergence from bankruptcy.[2]

In examining the contribution of loss given default, we proceed in two steps. We first specify and estimate a loss given default model for equity holders in the same spirit as Campbell, Hilscher, and Szilagyi (2008). We measure the loss to shareholders as the cumulative abnormal return in the day before, day of, and day after bankruptcy filing, following Clark and Weinstein (1983) and Li (2013). The model regresses loss rates on equities on a number of firm characteristics that we speculate may be related to equityholders' losses in case of bankruptcy. Fitted values of this regression are used to calculate individual firm expected loss rates upon bankruptcy filing.

We next sort firms into quintiles on the basis of expected loss rates as forecast by our prediction model and form portfolios on the basis of these quintiles. We find that firms in the highest equity loss rate quintile earn statistically significant average excess returns of 50 basis points per month relative to firms in the lowest quintile, adjusted for the factors in Fama and French (2015). We then sort stocks independently into quintiles on the basis of both equity loss rate and probability of default. We find evidence to suggest an independent premium for equity loss rates and discount for probability of default. We find that high probability of default firms continue to earn statistically significantly lower average returns than low probability of default firms in the first four quintiles of equity loss rate, consistent with the results in Campbell, Hilscher, and Szilagyi (2008). However, for the highest equity loss rate quintile, high probability of default firms earn average returns that are not statistically significantly different than those of low probability of default firms. Thus, when equity holders expect large losses on their holdings, the puzzling discount for probability of default is no longer present.

Finally, we estimate parameters of cross-sectional regressions of returns on failure probability and equity loss rates, using the methodology of Fama and MacBeth (1973). Controlling for a number of firm characteristics, we find that equity loss rate is a robust positive and statistically significant

[2]Bharath, Panchapegesan, and Werner (2010) document that the frequency of absolute priority deviations has fallen sharply from approximately 75% in the 1980s to 22% in the 1991-2005 period. Our evidence suggests that losses associated with bankruptcy filings, measured using the window in Clark and Weinstein (1983), have risen in magnitude over time, but that these losses are still substantially less than 100% on average.

predictor of cross-sectional variation in returns. We also find that including a profitability factors weakens the influence of failure probability. Since profitability is documented to be positively related to average returns in Hou, Xue, and Zhang (2014) and Fama and French (2015), our results suggest, consistent with Hou, Xue, and Zhang (2015), that the profitability factor contains information on probability of failure. We also find that using failure probability based on Campbell, Hilscher, and Szilagyi (2008) in a cross-sectional regression for stock returns requires controlling for the short-term reversal effect.

The results presented in this paper complement extant results that examine the distress premium puzzle. Chava and Purnanandam (2010) show that implied costs of capital indicate that investors expect higher returns on high probability of default firms than on low probability of default firms. The authors suggest that much of the distress premium puzzle arises from the experience of investors in the 1980s, who realized substantially lower-than-expected returns on high default probability securities. Our results complement theirs in showing that the puzzle is concentrated in firms with low expected loss rates, implying that at least some of the puzzle can be attributed to expectations of relatively positive returns upon bankruptcy announcement. Similarly, Conrad, Kapadia, and Xing (2014) show that high distress firms also exhibit positive skewness, implying that investors are expecting relatively high returns on some of these distressed stocks.

2 Expected Returns and Distress Risk

When assessing the risk of extending credit to a borrower, there are two primary considerations that drive the price of credit; the probability that the borrower will default and the loss of principal that the lender will incur in case of the default. For example, Duffie and Singleton (1999) propose that the value of a zero-coupon security that promises to pay X_{t+m} at date $t+m$ is given by

$$V_t = q_t e^{-r_t} E_t^Q \left[D_{t+1} \right] + \left(1 - q_t\right) e^{-r_t} E_t^Q \left[V_{t+1} \right], \tag{1}$$

where q_t is the risk-neutral probability that the borrower defaults at time $t+1$, r_t is the risk-free rate of return from time t to time $t+1$, and D_{t+1} $(< X_{t+m})$ is the amount recovered upon default in $t+1$. The superscript Q denotes the fact that probabilities are being measured using the risk neutral probability measure. Iterating forward, and assuming that recovery can be expressed as a fraction of the market value of the claim at time s, $(1-L_s)\, E_s^Q [V_{s+1}]$, with $L_s \leq 1$, the value of the claim can be expressed as

$$\begin{aligned} V_t &= E_t^Q \left[e^{-\sum_{j=0}^{m-1} R_{t+j}} X_{t+m} \right], \\ R_t &\approx r_t + q_t L_t. \end{aligned} \tag{2}$$

Equation (2) shows that there are two components to the spread over the risk free rate of the security; the risk neutral probability of default, q_t, and the risk neutral loss given default, L_t.

While this framework applies to the pricing of debt, similar concepts can be applied to the pricing of equity. As discussed above, given the evidence that equity emerges from bankruptcy holding some positive fraction of the firm's value on average, we assume that there is some risk-neutral expected loss rate at t, L_t^E, that equity holders suffer in case of default or bankruptcy. The cum-cash flow value of equity's claim, V_t^E, is given by

$$V_t^E = e^{-r_t} \left(q_t \left(1 - L_t^E\right) E_t^Q \left[V_{t+1}^E\right] + (1 - q_t)\, E_t^Q \left[V_{t+1}^E\right] \right) + C_t^E, \tag{3}$$

where C_t^E is the payment of cash flow to shareholders. Expression (3) suggests that the value of the claim is composed of two parts. The first is given by the present value of the continuation value of the firm conditional on default or bankruptcy, which occurs with risk neutral probability q_t, $\left(1 - L_t^E\right) E_t^Q \left[V_{t+1}^E\right]$. The second is the present value of the continuation value of the firm if there is no default, which occurs with probability $1 - q_t$. As is clear from expression (3), the loss on equity given default and the probability of default both potentially affect the value of an equity claim.

Expression (3) is meant to simply illustrate how probability of default and loss given default might impact firm value. It is assumed to generate an expected return-risk relationship where the risk premium on an equity claim can be expressed as

$$E[R_i] - R_f = \sum_{k=1}^{K} \beta_{i,k}\lambda_k + \beta_{i,d}\lambda_d, \tag{4}$$

where $\beta_{i,k}$ is the exposure of asset i to risk factor k, λ_k is the premium for this risk, $\beta_{i,d}$ is the exposure of asset i to a default risk factor, and λ_d is the price of this risk. Although this representation is not explicitly expressed in Campbell, Hilscher, and Szilagyi (2008), it is consistent with the framework that the authors discuss. Implicit in their analysis is the idea that the physical probability of default, $p_{i,t}$ as measured by their default prediction model, summarizes exposure to default risk, $\beta_{i,d}$. The puzzle in their empirical results is that the empirical estimate of the risk premium appears to be negative.

The focus of our work is to suggest that there are two components to this default risk; the probability of default as estimated in Campbell, Hilscher, and Szilagyi (2008) and loss in case of default. This two-faceted component of default risk could manifest itself in at least two ways. One possibility is that $p_{i,t}$ is not a sufficient statistic for exposure to default risk and, instead, default risk should be measured by considering both the probability of default and loss given default (under the physical measure), l_{it}^E. In this case, to an approximation, we could think of the compensation for distress risk as

$$\beta_{i,d}\lambda_d \approx f\left(p_i, l_i^E\right)\lambda_d, \tag{5}$$

where $f(\cdot)$ is some functional form translating probability of default and loss given default into a risk exposure, $\beta_{i,d}$. This expression implicitly assumes that there is a common distress factor, but that there are cross-sectional differences in the exposure to the distress factor due to different probabilities of default and expected losses given default.

Alternatively, there might be separate compensations for the risk of default and the risk of loss given default. In this case, the risk premium associated with distress can be written as

$$\beta_{i,d}\lambda_d = \beta_{i,p}\lambda_p + \beta_{i,l^E}\lambda_{l^E}, \tag{6}$$

where $\beta_{i,p}$ represents exposure to risks that cause firms' probabilities of default to covary and β_{i,l^E} represents exposure to risks that cause the amount that equityholders recover in case of default to covary. The assumption here is that there are different factors governing probability of default and loss given default, and each bears a separate price of risk.

The existing evidence on probability of default and recovery rates suggests that the former explanation, as represented in equation (5) is more likely than the latter, as expressed in equation (6). Altman, Brady, Resti, and Sironi (2005) show that aggregate default rates and loss rates are 75% correlated in time series over 1982-2001, suggesting that a common factor drives the magnitude of default probabilities and credit losses. However, the study does not speak to cross-sectional covariation in default probability and recovery rates. Further, the evidence pertains to the correlation between debt recovery rates and probability of default. Thus, independent cross-sectional variation in loss given default and rates of loss on equity remains an open empirical question.

3 Measuring Bankruptcy Probabilities and Expected Loss Rates

3.1 Measurement Framework

A number of approaches have been proposed in the literature to gauge the ex ante probability that a firm will default or file for bankruptcy. Beaver (1966), Altman (1968), Ohlson (1980), and Zmijewski (1984) are all examples of models that relate the likelihood of bankruptcy to accounting variables. Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008) estimate dynamic logit models with both accounting and market variables as predictors of bankruptcy. We are not aware of any study that forecasts the losses that shareholders suffer when firms file bankruptcy. In this section, we discuss a framework for this estimation.

A first challenge in capturing expected loss rates is the measurement of the loss on equity given default. In the case of fixed income securities, losses can be measured relative to the cash flows promised by the security contract. Duffie and Singleton (1999) adopt a recovery of market value convention, where the bondholder recovers some fraction of the value of the security had it survived. The recovery of market value concept can be extended to equity. The definition then requires measurement of the pre-default equity value that serves as reference. We adopt the approach of Li (2013), who measures these losses as the losses associated with bankruptcy filing. Clark and Weinstein (1983) document that most of the losses attributed to the news of a bankruptcy filing are captured by cumulative abnormal returns over the period one day prior through one day after the bankruptcy filing,

$$ELR_{i,t} = 1 - \prod_{j=-1}^{1} \left(1 + AR_{i,t+j}\right), \tag{7}$$

where $AR_{i,t+j}$ is the return on stock i in excess of the market return.

In order to predict this expected loss rate, we utilize a set of firm-specific variables in a linear regression specification,

$$ELR_{i,t} = a + \mathbf{b}'\mathbf{x}_{i,t-j} + e_{i,t}, \tag{8}$$

where $\mathbf{x}_{i,t-j}$ are firm-specific characteristics measured at month $t-j$ relative to the loss for $j = \{1, 3, 6, 12\}$. We utilize the lasso procedure of Tibsharanit (1996) to select firm specific characteristics from the following candidates:

R&D expenditure ($RDEXPAVG$). Firms with higher research and development expenses are more vulnerable to liquidity shortages in a financially distressed state (Opler and Titman (1994)). In case of a bankruptcy, cash-flow-based covenants put creditors in charge and prevent a successful debt renegotiation, thereby reducing the bargaining power of shareholders (Garlappi, Shu, and Yan (2008)). Furthermore, high research and development expenses increase bankruptcy losses for shareholders as profitable growth opportunities no longer receive the required funding and liquidation values of those assets are low (Alderson and Betker (1996) and Lyandres and Zhidanov

(2013)). We therefore expect shareholder losses to rise with research and development expenses.

Insider Holdings ($INSIDER$). If the senior management holds a large equity share, the incentive to distribute value from creditors to shareholders during a bankruptcy increases and principal agency conflicts are diminished. Betker (1995) shows that shareholders receive payments from insolvent firms more frequently if the CEO owns a large equity share.

Liquidation value ($TANG$). Higher liquidation values lower the incentive of creditors to reach an agreement with shareholders (see Bergman and Callen (1991)) and therefore increase the losses that occur to shareholders (see also Garlappi, Shu, and Yan (2008) and Hackbarth, Haselmann, and Schoenherr (2013)).

Industry concentration (HHI). Acharya, Bharath, and Srinivasan (2007) show that bond recovery rates are significantly lower if the respective industry is in distress due to fire-sales effects (Shleifer and Vishny (1992)). The effect is stronger for industries with specific assets as these can not be easily redistributed in case of a default. We follow Garlappi, Shu, and Yan (2008) and use the concentration of the industry as a proxy for asset-specificity. Higher asset-specificity should therefore lower bankruptcy losses for shareholders as their bargaining position is strengthened.

Industry constraints ($ILLIQ$). Industry constraints lower liquidation values due to fire-sale effects (see HHI) and therefore improve the bargaining position of stockholders as creditors have a higher incentive to negotiate with shareholders and avoid liquidation. We therefore expect higher equity values in default if industry constraints are in place.

Industry distress ($DIST$). Following Acharya, Bharath, and Srinivasan (2007), we expect larger losses for creditors if the industry in general is in a state of distress and assets are intended to be liquidated. As a consequence, creditors have a higher incentive to avoid liquidation which improves the bargaining position of shareholders.

Firm size ($RSIZE$). Garlappi, Shu, and Yan (2008) argue that in larger firms, shareholders are in a better position, because information asymmetries between creditors and shareholders are less pronounced and, because creditors have more problems of coordination. Both effects lead to a better bargaining position of shareholders and therefore we would expect lower losses for shareholders in case of a default event.

Short term Debt ($STDEBT$). Davydenko and Strebulaev (2013) use the proportion of debt that is short term to proxy for negotiation frictions. The proxy is based on Gertner and Scharfstein (1991) and Berglöf and von Thadden (1994), suggesting that short term debt holders are less willing to renegotiate than long term creditors, since they are unwilling to make concessions to effectively less senior long-term creditors.

We utilize information on each variable available at time $t - j$; a detailed description of the construction of each variable is provided in the Appendix.

3.2 Data

Bankruptcy filings are obtained from the comprehensive database in Chava and Jarrow (2004) (subsequently updated in Chava (2014) and Alanis, Chava, and Kumar (2014)) that contains the bankruptcy filing dates of 2,991 stocks in CRSP between 1964 and 2014. We use only the earliest default event for each stock if a stock has more than one default event. As in Campbell, Hilscher, and Szilagyi (2008), we use a broader definition of failure that includes bankruptcy filings, performance-related delistings, and credit defaults.[3] After merging all default databases, we are left with 6,882 default events for which we observe returns.

We follow Campbell, Hilscher, and Szilagyi (2008) in estimating failure probability using a set of accounting and market-based variables. Similarly, the loss rate prediction model uses both accounting and market-based variables to forecast expected loss rate. Accounting variables are obtained from Compustat and market variables are obtained from CRSP. Details of variable construction are provided in the Appendix.

Our ELR measure is calculated using returns obtained from CRSP for firms with formal

[3] Performance-related delistings are obtained from CRSP. Following Shumway (1997); we include a delisting if the delisting codes are 500 or between 520 and 584. A credit default is defined as a downgrade in the Standard & Poor's Rating to 'D' (default) or 'SD' (selective default).

bankruptcy filings under either Chapter 7 or Chapter 11.[4] We include bankruptcies if return data is available and trading volume is positive (and not missing) for all three days around the bankruptcy filing and use the return of the S&P's 500 index as the market return. After applying these criteria, we are left with information on 637 default events for which we observe post-default trading data. Summary statistics for these equity loss rates are presented in Table **??**. As shown in the Table, the average (median) abnormal return on the bankruptcy filing date is -15.21% (-7.57%), with significant negative abnormal returns the day prior to and day subsequent to the filing. The average (median) firm in our sample experiences a cumulative abnormal loss of 31.60% (33.65%).

Importantly for our study, there is considerable variation in the degree to which investors earn abnormal returns around the filing of bankruptcy. The table shows that the standard deviation of expected loss rate is 31.13%, compared to a mean of 31.60%, suggesting large variation in the degree of loss suffered by investors. Interestingly, the results suggest that bankruptcy filing can sometimes be *good* news for shareholders. The minimum expected loss rate in our sample is -49.59%, indicating that upon bankruptcy filing shareholders experienced a 50% abnormal gain in the value of shares in the three days surrounding the bankruptcy event. At the other extreme, the worst performance of a firm filing for bankruptcy was a loss of 95.64% over the three days surrounding the filing.

3.3 Estimating Failure Probability and Expected Loss Rate

We estimate probability of failure following Campbell, Hilscher, and Szilagyi (2008), who specify a logit failure probability model,

$$\begin{aligned} FAIL_{i,t+\tau} = \quad & b_0 + b_1 NIMTAAVG_{i,t} + b_2 TLMTA_{i,t} + b_3 EXRETAVG_{i,t} + b_4 SIGMA_{i,t} \\ & + b_5 RSIZE_{i,t} + b_6 CASHMTA_{i,t} + b_7 MB_{i,t} + b_8 PRICE_{i,t} + e_{i,t+\tau}. \end{aligned} \tag{9}$$

In this specification, $FAIL_{i,t+\tau}$ is an indicator variable that takes the value 1 if the firm fails in month $t+\tau$ and zero otherwise. The independent variables are $NIMTAAVG_{i,t}$, a moving average

[4] In a few bankruptcies that occur on a non-trading date, we use the next trading day as the bankruptcy filing day.

of the ratio of net income to market value of total assets, $TLMTA_{i,t}$, the ratio of total liabilities to total assets, $EXRETAVG_{i,t}$, the moving average of the excess return on the firm's stock over the S&P 500 index, $SIGMA_{i,t}$, the standard deviation of the firm's daily stock return over the preceding three months, $RSIZE_{i,t}$, the log ratio of the firm's market capitalization to that of the S&P 500 index, $CASHMTA_{i,t}$, the ratio of cash and equivalents to market value of total assets, and $PRICE_{i,t}$, the maximum of the firm's log share price or the log of \$15. Detailed variable descriptions are again provided in the Appendix.

Our procedure for estimating expected loss rates is similar. We regress equity loss rates, as defined in equation (7) on the predictor variables discussed above,

$$\begin{aligned} ELR_{i,t+\tau} = \quad & c_0 + c_1 RDEXPAVG_{i,t} + c_2 INSIDER_{i,t} + c_3 TANG_{i,t} + c_4 RSIZE_{i,t} \\ & + c_5 STDEBT_{i,t} + c_6 DIST_{i,t} + c_7 ILLIQ_{i,t} + c_8 HHI_{i,t} + u_{i,t+\tau}. \end{aligned} \tag{10}$$

In both the equity loss and probability of failure specifications, we utilize a prediction length of twelve months; $\tau = 12$. We select a model for predicting loss rates using the least absolute shrinkage and selection operator (LASSO) approach of Tibsharanit (1996).

Summary statistics for the explanatory variables are presented in Table **??**. Of greatest interest is a comparison of those firms that default and for which we can compute equity loss rate and the sample as a whole. The table generally suggests that defaulting firms do not appear to be substantially different than those of the population as a whole. The defaulted firms have somewhat lower R&D expenditures and insider shareholdings than the full sample, and somewhat higher short term debt and industry illiquidity. The Herfindahl index and tangibility measures of both sets of firms appear quite similar. Perhaps not surprisingly, a larger fraction of the defaulted firms are in industries that are deemed distressed than in the population as a whole.

4 Empirical Results

4.1 Failure and Loss Rate Prediction

We first examine the power of the failure probability and loss rate models to predict subsequent failures and losses on equity. The failure probability model is extensively examined in Campbell, Hilscher, and Szilagyi (2008); here we simply compare results using slightly different data. Results of the estimation are presented in Table **??**. As shown in the table, the results in our sample are qualitatively quite similar to those presented in Campbell, Hilscher, and Szilagyi (2008). Profitability, excess return, relative size, cash holdings, and price all have negative marginal effects on failure probability, while leverage, market-to-book, and volatility exert negative influences. Our results suggest that price is a statistically significant predictor of failure probability, whereas the earlier results suggest no effect using a twelve months lag. Finally, the pseudo-R^2 suggests that we are capturing variation in failure probability in our data of similar magnitude to that reported in Campbell, Hilscher, and Szilagyi (2008).

In Table **??**, we present results of the estimation of parameters in the equity loss prediction model. Similar to Campbell, Hilscher, and Szilagyi (2008), we examine the forecasting power of the model at various horizons, but focus on the twelve month horizon in the remainder of our empirical work. The LASSO procedure of Tibsharanit (1996) selects five predictor variables; $RDEXPAVG$, the ratio of R&D expenditure to book value of assets, $INSIDER$, the fraction of shares owned by insiders, $TANG$, the asset tangibility measure from Berger, Ofek, and Swary (1996), $RSIZE$, the market capitalization of the firm relative to that of the S&P 500, and $ILLIQ$, the measure of industry financial constraints. The number of firms generally drops with the horizon; this decrease is due to the more limited ability of data for firms at longer lags relative to the bankruptcy filing date.

Results of the estimation are similar at all horizons, with predictive power as measured by the regression R^2 falling slightly at the 12 and 24 month horizons. Research and development expenditures are positively associated with expected loss rates, consistent with the rationales discussed above. Firms with higher R&D expenditures are more vulnerable to liquidity shortages in distress as suggested by Opler and Titman (1994), growth opportunities no longer receive required funding, and liquidation values are low, as suggested by Alderson and Betker (1996) and Lyandres and Zhidanov (2013). Insider holdings are negatively related to expected loss rates. As suggested in Davydenko and Strebulaev (2013), higher insider holdings suggest greater bargaining power on the part of shareholders, and are therefore associated with lower equity loss rates. Consistent with our prediction that higher liquidation values imply better outside options for creditors, the asset tangibility measure from Berger, Ofek, and Swary (1996) is positively related to expected loss rates. A similar argument has been made for the illiquidity measure of the industry which is negatively related to expected shareholder losses (even though not statistically significantly for the overall sample).

In summary, the results reported in Table **??** suggest that variables hypothesized to affect the degree of losses that shareholders experience upon declaration of bankruptcy consistently predict the magnitude of these losses. At the twelve-month horizon, the model explains approximately 7% of the variation in loss rates. We proceed using this preferred model to calculate predicted loss rates in case of bankruptcy in the remainder of the paper.

4.2 Loss Rates and Equity Returns

Each month, we calculate predicted 12-month equity loss rates using the results of Section 4.1 for firms with available data. We calculate predicted equity loss rates at the end of December each year and sort firms into quintiles on the basis of this measure. The ranking is then used to form value-weighted portfolios, holding the quintiles constant until the end of the next calendar year. Portfolios are re-formed based on updated predicted equity loss rates, and the procedure is repeated until the end of the sample. Returns are sampled at the monthly frequency over the period January, 1981 through December, 2014, for 408 monthly observations.

Summary statistics for the results of this procedure are presented in Table **??**. In the table, we present average raw excess returns for each of the quintile portfolios, alphas with respect to the

Fama and French (2015) five-factor model, and factor loadings for the factor model. The table shows that the excess returns on the quintile portfolios increase monotonically across expected loss rate quintiles, suggesting that investors demand higher average returns for firms that are expected to have larger losses in case of bankruptcy. Firms in the highest expected loss quintile earn an average return of 89 basis points per month compared 57 basis points per month for firms in the lowest quintile. This difference of 32 basis points, representing an average premium of approximately 3.6% per annum is economically fairly large, but is not statistically different than zero at conventional critical thresholds. Thus, the data suggests an economically relevant, but statistically insignificant premium for bearing expected loss risk.

In the second row of the table, we present excess returns on the loss rate-sorted portfolios relative to adjustment for the five factors explored in Fama and French (2015). In contrast to the raw returns, the results indicate that adjusting for risk present in these five factors, bearing expected loss risk is compensated with both an economically large and statistically significant average risk premium. Like the raw returns, excess returns on the quintile portfolios increase monotonically across quintiles and are statistically significantly different than zero for the fourth and fifth quantile of expected equity loss rate. The top quintile portfolio earns an average excess return of 47 basis points per month (t-value=2.98), while the bottom quintile portfolio earns an average excess return that is indistinguishable from zero (t-value=-0.56). These excess returns combine to suggest that a portfolio long high equity loss rate firms and short low equity loss rate firms earns an average excess return of 50 basis points per month (t-value=2.81).

In order to get some insight into the sources of covariation that dominate the equity loss rate portfolios, we present loadings on the five risk factors in Panel B of Table **??**. The table indicates that the portfolios exhibit significant covariation with all of the factors with the exception of the investment factor, CMA, for which only the bottom equity loss rate portfolio bears a statistically significant loading. Loadings also tend to move in a near-monotonic pattern across quintiles; high equity loss rate firms load more strongly positively on the market risk premium and size factors, and more negatively on the value and profitability factors. These results are intuitively sensible; firms with lower continuation values are likely to appear riskier in exposure to aggregate market movements, have lower market capitalizations, and less profitable. The difference in loadings between the high equity loss rate and low equity loss rate portfolios indicate that the differences are statistically significant for all of the factors, with the exception of the investment factor.

As a final point of interest, in Panel C we summarize means of three characteristics of the quintile portfolios; market capitalization, probability of failure implied by our estimates of Campbell, Hilscher, and Szilagyi (2008) failure model, and the equity loss rate predicted by our model. By construction, equity loss rates increase across quintiles; the average firm in the bottom quintile is expected to lose 20.31% of its equity value upon declaration of bankruptcy, while the average firm in the top quintile is expected to lose 43.77% of its value. While nowhere near as extreme as the variation in actual losses shown in the data, this difference of more than 23% in anticipated losses seems to us to be economically quite significantly different. As suggested by the factor loadings, firms in the high expected loss rate portfolio are on average considerably smaller than those in the low expected loss rate portfolio. Finally, the statistics suggest a strong correlation between probability of failure equity loss rate. Firms in the bottom quintile have on average a predicted rate of failure of 0.10%, while those in the top quintile have a predicted failure rate of 0.42%. These results suggest that the effect of failure probability and equity loss rate are positively correlated, and we next examine the degree to which we can disentangle these effects.

4.3 Equity Loss, Probability of Failure and Average Returns

In order to explore the links between equity loss rate and probability of failure, we first conduct an analysis similar to that in Campbell, Hilscher, and Szilagyi (2008) and document that in our sample firms with high probabilities of failure have low average returns relative to those with a low probability of failure. Similarly to our procedure for equity loss rate, we sort firms into quintiles on the basis of predicted probability of failure at the end of each calendar year, and hold the firms in value-weighted portfolios. Summary statistics for these portfolios are presented in Table

??. Raw returns decrease monotonically across quintiles from 63 basis points per month for the lowest probability of failure quintile to 7 basis points per month for the highest probability of default quintile; the difference of 55 basis points per month is marginally statistically significant. Adjusting for the Fama and French (2015) factors, a strategy long the lowest probability of default quintile and short the highest probability of default quintile earns an excess return of 53 basis points per month, statistically significant at the 1% critical threshold. This difference is of comparable magnitude to, but of opposite sign of the results for firms sorted on equity loss rates.

Factor loadings suggest that high probability of default firms tend to have higher market betas and covary more with small and less profitable firms than firms with low probability of default. Again, these results are similar to those documented for portfolios sorted on equity loss rates. One difference in the results for probability of default relative to expected loss rates is the fact that firms with low probabilities of default appear to covary more with growth firms, while high probability of default firms exhibit no significant loading on the HML factor. The difference between the high probability of default and low probability of default firms' loading is statistically significantly positive, whereas the difference for equity loss rate is statistically significantly negative. Like the results for equity loss rates, the investment factor does not seem to statistically significantly distinguish between low probability of default and high probability of default firms.

Last, Panel C of the table documents similar characteristics of firms sorted on probability of default as those of firms sorted on equity loss rates. Market capitalizations of firms decrease across probability of default quintile, with the difference in the sizes of low probability of default firms and high probability of default firms more pronounced than those of differences in those of low and high equity loss rate firms. Probabilities of default increase more steeply across default probability quintiles than equity loss rate quintiles, ranging from 0.02% on average for the lowest quintile firms to 0.92% for the highest quintile firms. Finally, loss rates also increase across quintiles, though less steeply than those for portfolios sorted on predicted equity loss rates. These loss rates increase from 25.17% for the bottom quintile of default probability firms to 36.00% for the highest quintile. Thus, as suggested above, there are strong commonalities in probability of default and equity loss rates in terms of factor loadings, market capitalization, and the link between default probability and expected loss rates.

To try to tease out differences in probability of default and equity loss rates, we proceed sorting firms independently into quintiles of equity loss rate and probability of failure. We form 25 (value-weighted) portfolios on the basis of the intersection of these quintiles. Given our results thus far, there is some concern that there is insufficient independent variation in probability of failure and equity loss rate to generate a complete set of portfolios based on independent sorts. However, in each month of our sample, we are able to find intersections in quintiles. Not surprisingly, there are on average fewer firms at the intersection of low equity loss rate and high probability of default quintiles and high equity loss rate and low probability of default quintiles. The extreme portfolios in these categories each average 32 firms in the portfolio. Firms have a much higher propensity to be low equity loss rate and low probability of default or high equity loss rate and high probability of default.

The table also presents excess returns on each portfolio relative to the Fama and French (2015) five-factor model. The patterns across quintiles of probability of failure and equity loss rate documented in univariate sorts remain the same, but are generally more extreme than those reported above. At the extreme, for firms with low equity loss rates, the difference in the excess return on high probability of failure and low probability of failure firms is -1.26% per month, statistically different than zero at the 1% critical level. Firms with high probabilities of failure exhibit a difference across high and low equity loss rate quintiles of 1.76% per month, also statistically significantly different than zero at the 1% critical level. Across equity loss rate quintiles, differences in average excess returns of high and low probability of failure firms increase monotonically, while differences in average excess returns of high and low equity loss rate firms also increase across probability of failure quintiles, except for the second quintile of probability of failure.

Of particular interest is the pattern of excess returns for firms with high equity loss rates. As shown in the table, the difference in excess returns between high probability of failure and low probability of failure firms is -0.28% per month, which is not statistically distinguishable from zero at conventional levels. This result suggests that when investors expect to lose a large fraction of their investment upon announcement of bankruptcy, that they do not require average returns that are statistically different for firms with high probability of default than low probability of default. That is, the anomalous pattern documented in Campbell, Hilscher, and Szilagyi (2008) is no longer statistically present. For these firms, the issue of the loss expected to be suffered appears to dominate to probability that loss will in fact be suffered. In contrast, the pattern documented in Campbell, Hilscher, and Szilagyi (2008) appears to be most severe if investors expect relatively low losses upon declaration of bankruptcy.

The results documented in this section suggest that there is some independent variation and interaction in the premium that investors require for the probability of failure and the losses that they expect to bear upon the declaration of bankruptcy. When firms have high expected equity loss rates, the discount for probability of failure documented in Campbell, Hilscher, and Szilagyi (2008) is no longer present, and the discount is most pronounced for firms for which losses on equity are expected to be relatively low. These results do not indicate that accounting for equity loss rates is a solution to the puzzle of low expected returns on firms with high probabilities of default. In the first four equity loss rate quintiles, a statistically significant discount for probability of failure remains. However, the attenuation of the discount, accounting for equity loss rates suggests that the relation between probability of failure and average returns is more nuanced than one might otherwise think. That is, other factors beyond the physical probability of failure affect the premium that investors demand for bearing failure risk.

4.4 Equity Loss, Probability of Failure, and the Cross-Section of Expected Returns

The evidence in the preceding section suggests that expected equity loss rate and probability of failure are both important for understanding cross-sectional variation in average returns related to failure risk. To a certain extent, these variables are interrelated, but there appears to be independent variation in expected returns related to these variables. In this section, we examine these links more formally using Fama and MacBeth (1973) regressions to estimate risk premia associated with probability of failure and equity loss rate risks. In each month $t+1$, we regress excess returns on a set of firm characteristics, predicted probability of failure, and predicted equity loss rate,

$$R_{i,t+1} - R_{f,t} = \gamma_{0,t} + \sum_{k} \gamma_{k,t} X_{i,k,t} + \gamma_{FAIL,t} FAIL_{i,t} + \gamma_{ELR,t} ELR_{i,t} + u_{i,t+1}. \tag{11}$$

The variables $\mathbf{X}_{i,t}$ are a set of firm-specific characteristics that have been documented to be related to average returns. We report average point estimates of the coefficients, as well as t-statistics calculated using autocorrelation and heteroskedasticity-consistent standard errors.

One issue that demands consideration is which firm-specific characteristics, $\mathbf{X}_{i,t}$ to include in the regression. Harvey, Liu, and Zhu (2015) document that 313 different firm-specific variables have been used in the literature to predict cross-sectional variation in returns, and that this number likely understates the actual number of variables considered. Lewellen (2015) examines 15 different variables that have either theoretical or empirical rationales for predicting cross-sectional variation in average returns. His results suggest that ten of the variables have statistically significant slopes in Fama and MacBeth (1973) regressions using all stocks, eight variables, which are not a proper subset of the original ten, have statistically significant power for explaining cross-sectional variation in the set of all but tiny stocks, and that seven have statistically significant power for explaining cross-sectional variation in the set of large stocks. When considering only seven variables, he finds that all seven are reliably statistically significant in multiple regressions using all stocks, all but tiny stocks, and large stocks.

We use all seven variables from Lewellen (2015) in our cross-sectional regressions in addition to probability of failure and equity loss rate. In particular, we include profitability (ROA_{Y-1}), log size ($LogSize_{t-1}$), log book-to-market ($LogB/M_{t-1}$), momentum ($Ret_{t-2,t-12}$), share issuance ($LogIssues_{t-1,t-36}$), accruals ($Accruals_{Y-1}$) and log asset growth ($LogAG_{Y-1}$). We additionally add the stock return of the prior month (Ret_{t-1}) to control for short-term reversal documented by Jegadeesh (1990) and Lehman (1990). We include the short-term reversal factor as Huang, Liu, Rhee, and Zhang (2010) show that its omission can lead to biased results in a Fama and MacBeth

(1973) regression using individual stock characteristics. The factors that we use comprise those of the four factor model of Hou, Xue, and Zhang (2014) and the five-factor model of Fama and French (2015).

Estimation results are presented in Table **??**. The first column of the table presents results including just the firm-specific characteristics, restricting $\gamma_{FAIL,t} = \gamma_{ELR,t} = 0$. As shown in the table, seven of the eight characteristics have significant predictive power for explaining cross-sectional variation in average returns. All factors have coefficient signs that correspond to their expectations based on the literature. As predicted by Lehman (1990) and Jegadeesh (1990), the previous month's stock return is negatively correlated with average returns. Profitability is positively related to average returns as shown in Fama and French (2015), among others. Consistent with Fama and French (1992), the market-to-book ratio is positively and significantly related to average returns, while the coefficient for size has the expected sign, but is statistically insignificant at conventional levels. Past returns are positively related to average returns as in Jegadeesh and Titman (1993) and stock issuance is negatively related to average returns as shown in Daniel and Titman (2006). Accruals are negatively related to average returns consistent with Sloan (1996) and asset growth is negatively related to average returns as in Cooper, Gulen, and Schill (2008).

In the second and third columns of the table, we independently include probability of failure ($FAIL$) and equity loss rate (ELR) as explanatory variables. The results for failure probability are consistent with the finding of Campbell, Hilscher, and Szilagyi (2008) that higher default likelihood is related to lower average returns. When we include the equity loss rate as an independent variable, we find a strong statistically significant effect on average stock returns similar to our portfolio sort results. The magnitude of the slope coefficients of the profitability and momentum factor increase slightly after including equity loss rate. In the fourth column, we present results of the unrestricted regression. The overall results are qualitatively identical to those of the second and third column. Including failure probability and equity loss rate, the slope coefficients of both variables decrease slightly, leading to a drop in the statistical significance of probability of failure to the 5%-level. The result suggests that even though the failure probability and equity loss rate are (partially) related, both factors exhibit an independent statistically and economically significant influence on average stock returns.

Hou, Xue, and Zhang (2014) show that the distress anomaly is related to the profitability factor. We therefore exclude the profitability factor to compare the results for equity loss rate and failure probability with and without the profitability factor. The results for excluding the profitability factor are shown in the fifth column. Comparing columns four and five shows that inclusion of the profitability factor reduces the influence of failure probability by roughly one third, but slightly increases the effect of equity loss rate on average stock returns. These findings are consistent with the univariate portfolio sort results in which default probability has a positive and equity loss has a negative loading on the profitability factor from Fama and French (2015).

Huang, Liu, Rhee, and Zhang (2010) show that omitting the short-term reversal factor can lead to biased results in a Fama and MacBeth (1973) regression using idiosyncratic risk variables. To check whether the previous month's stock return has an impact on failure probability and equity loss rate, we restrict its coefficient to zero and report the results in the last column. Surprisingly, the effect of failure probability loses its statistical significance if one excludes the short-term reversal factor and the coefficient of the book-to-market factor decreases in magnitude. One possible explanation for the first finding is that the excess stock return measured at the prior month enters as predictive variable in the estimation of failure probability and then interacts with the short-term reversal effect. This explanation is supported by cross-sectional regression results of Campbell, Hilscher, and Szilagyi (2008) showing that while prior month's excess stock returns do not forecast stock returns, but those used at higher lags do. In unreported results, we use a time-lag of two months for the failure probability finding it forecasts stock returns irrespective of including the short-term reversal factor which supports the former explanation.

The results in this section suggest several interesting findings. First, there appears to be a robust positive premium associated with expected equity loss rates. Investors seem to demand compensation for the risk of bankruptcy through the amount that they expect to lose on filing if the firm files for bankruptcy. This premium is robust to the inclusion of probability of failure and eight firm characteristics documented to be related to cross-sectional variation in average returns in the literature. Second, the effect of probability of failure on average stock returns is weakened by the inclusion of the profitability factor. Third, using failure probability predicted by the model of Campbell, Hilscher, and Szilagyi (2008) requires to control for the short-term reversal effect in Fama and MacBeth (1973) regressions that lag individual characteristics by one month.

5 Conclusion

The literature has long speculated equity holders demand independent compensation for the risk of distress beyond risks captured by the return on the aggregate market portfolio. Campbell, Hilscher, and Szilagyi (2008) measure this risk directly as the probability that a firm will experience a failure event, and document a negative relation between the probability of this failure and future average returns. This finding has puzzled the literature, as rational pricing would suggest that the greater the likelihood of failure, the greater the premium that investors should demand for holding the firm's equity.

We speculate that like debt, there are two considerations in assessing the risks inherent in failure; the probability that the firm fails and the losses that equity holders experience conditional upon that failure. The question that we address is whether there are separate premia for bearing these two risks. To address this question, we specify a model for the prediction of the amount that a firm loses upon filing bankruptcy, and analyze the relation between this expected loss and future returns. We find that firms with high expected losses earn higher average returns than firms with low expected losses, and that this premium is present independently of the probability of failure. Additionally, we find that the probability of failure discount documented in Campbell, Hilscher, and Szilagyi (2008) is most pronounced in firms in which equity loss rates are expected to be relatively low, and statistically indistinguishable from zero for firms in which equity loss rates are expected to be high. While this evidence does not resolve the failure probability discount puzzle, it suggests that distress risk is more multi-faceted than probability of default alone.

Finally, we show in Fama and MacBeth (1973) regressions that while the premium for equity loss rate is robustly positive controlling for other cross-sectional return predictors, the influence of the probability of failure is partially subsumed by including a profitability factor. Moreover, we show that controlling for short-term reversal effects is necessary to identify the influence of failure probability in cross-sectional regressions of stock returns.

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A Equity Loss Rate Prediction Variables

Table A.1: Description of Equity Loss Rate Prediction Candidate Variables

The table describes the variables used in the initial equity loss rate prediction model. Compustat mnemonics are given in parentheses. *NIMTAAVG* and *RDEXPAVG* are a geometric weighted averages over the previous accounting year where missing lag values are replaced with cross-sectional means, following Campbell, Hilscher, and Szilagyi (2008).

Variable	Definition
RDEXPAVG	Ratio of quarterly research and development expenses (XRDQ) divided by the book value of assets. Book value of assets is adjusted following the procedure by Cohen, Polk, and Vuolteenaho (2003); we adjust the book value of assets by adding 10% of the difference between the market value of equity and the book value of equity. Missing quarterly research and development expenses are augmented using the yearly item (XRD), where we assume a linear distribution of expenses across the year. If the item is still not available, it is set to zero following Berger, Ofek, and Swary (1996).
INSIDESHARE	Ratio of shares owned by executives (SHROWN_EXCL_OPTS) from Standard & Poor's ExecuComp and common shares outstanding (CSHO) for the respective year.
TANG	Following Berger, Ofek, and Swary (1996), we define the liquidation value of the company as $TANG =$ (0.715 $\cdot$ total receivables (RECTQ) $+$ 0.547 $\cdot$ total inventories (INVTQ) $+$ 0.535 $\cdot$ net property, plant and equipment (PPENTQ) $+$ cash and short-term investments (CHEQ)) / book value of equity. where book value of equity is again adjusted following Cohen, Polk, and Vuolteenaho (2003).
RSIZE	Logarithm of the ratio of the market value of equity (PRC * SHROUT) and the market capitalization of all S&P500 firms (TOTVAL).
STDEBT	Ratio of debt in current liabilities (DLCQ) and the book value of total liabilities (LTQ).
DIST	Measure for the state of the industry using a dummy variable that equals one if the median of the rolling 12 months stock return in the three digit SIC industry is below -30%.
ILLIQ	Measure for the financial constraints of all firms in the three digit SIC industry. Defined as the inverse of the median industry quick ratio. The interest coverage ratio is calculated as the ratio of current assets (ACTQ) - inventories (INVTQ) divided by current liabilities (LCTQ). We set a few cases where the current liabilities equal zero to missing.
HHI	A measure for the concentration of the industry based on the normalized Herfindahl-Hirschmann index. The index is calculated as $HHI = \begin{cases} \frac{\sum_{i=1}^{N} s^2 - \frac{1}{N}}{1-\frac{1}{N}} & \text{for } N > 1, \\ 1 & \text{for } N = 1. \end{cases}$ s is the amount of quarterly sales of firm i (SALEQ) in a three digit SIC industry which consists of N firms.

B Variable Selection Procedure

We use the LASSO (least absolute shrinkage and selection operator) procedure of Tibsharanit (1996) to select among the potential variables predicting shareholder bankruptcy losses. The LASSO procedure chooses a sparse set of variables in a regression setup by setting some of the regression coefficients to zero. Coefficient values are determined in the LASSO procedure by minimizing an objective function that includes the sum of the absolute coefficient values. As we model equity loss rates as a linear function of the predictor variables, the objective function of the LASSO procedure is:

$$\min_{a,b} \frac{1}{2N} \sum_{i=1}^{N} (ELR_{i,t} - a - b' x_{i,t-j})^2 + \lambda \, ||b||_1 \tag{12}$$

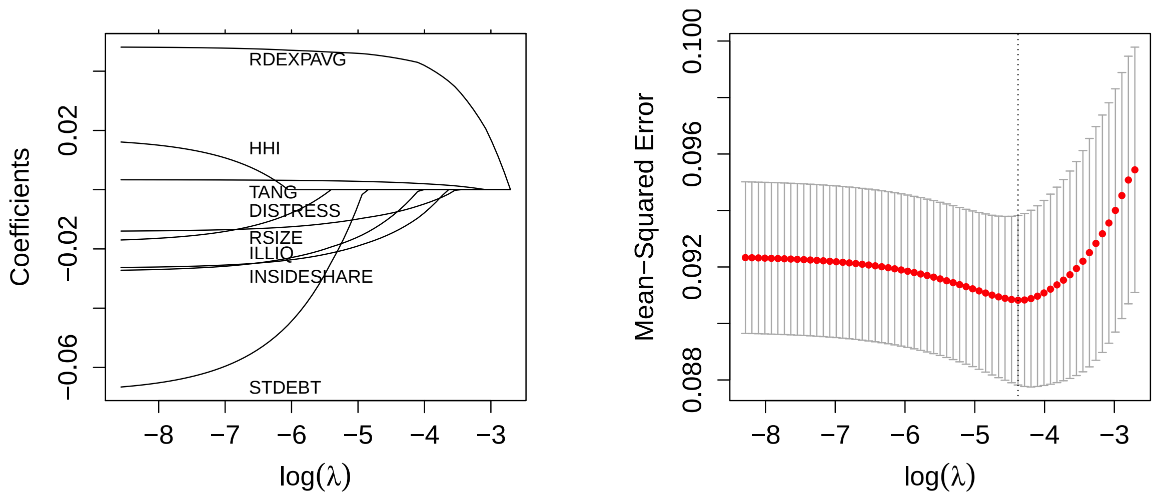
where $x_{i,t-j}$ are the firm-specific predictor variables described in Appendix A.1, measured 12 months before the equity loss rate $ELR_{i,t}$. λ is the penalty parameter of the LASSO procedure (for the L_1-norm of b). We apply the LASSO procedure to the predictor variables using all 396 bankruptcies where we have information about the equity loss rate and all predictor variables. For this purpose, we employ the R software package glmnet based on Friedman, Hastie, and Tibshirani (2010). We choose the penalty parameter by applying a five-fold cross-validation with the mean-squared error as the selection criterion. We then employ the penalty parameter that is suggested by the lowest mean-squared error in the cross-validation which results in the following choice of variables: $RDEXPAVG$, the ratio of R&D expenditure to book value of assets, $INSIDER$, the fraction of shares owned by insiders, $TANG$, the asset tangibility measure from Berger, Ofek, and Swary (1996), $RSIZE$, the market capitalization of the firm relative to that of the S&P 500, and $ILLIQ$, the measure of industry financial constraints.

The left plot in Figure **??** shows the regression coefficients for different penalty parameter values. Higher values of the penalty parameter lead to an increasing number of coefficients that are set to zero. The right plot illustrates the average mean-squared error and its standard-error (indicated in grey lines around the average) for different choices of the penalty parameter in the cross-validation.

The vertical line refers to the penalty parameter with the lowest mean-squared error.

Figure B.1: Results of LASSO Selection Procedure for Equity Loss Rate Forecast Model.

The left figure shows the relationship between the logarithm of the penalty parameter λ and the size of each coefficient using a lag of 12 months for the predictor variables. The variables $RDEXPAVG$, $INSIDESHARE$ and $TANG$ are used as percentage values for this figure. The right figure shows the relationship between the logarithm of the penalty parameter and the mean-squared error of the resulting deviation between the forecast model and the realized equity loss rate based on a five-fold cross-validation.



C Default Probability Forecast Model

Table C.1: Default Probability Prediction Variables

The table describes the variables used in predicting probability of failure. We follow Campbell, Hilscher, and Szilagyi (2008) in constructing variables. Compustat and CRSP mnemonics are given in parentheses.

Variable	Definition
NIMTAAVG	Moving average of profitability over the previous fiscal year with geometrically declining weights. Profitability is defined as net income (NIQ) divided by the market value of total assets. Market value of total assets is calculated as the sum of the market value of equity (PRC * SHROUT) plus the book value of total liabilities (LTQ).
TLMTA	Total liabilities (LTQ) divided by the market value of total assets (for the definition of the latter item see NIMTAAVG) .
EXRETAVG	Moving average of the logarithmic excess stock return (with respect to the value-weighted market return VWRETD) over the previous 12 months using geometrically declining weights.
SIGMA	Standard deviation of the daily stock returns over the previous three months (calculated if at least five stock returns are available).
RSIZE	Logarithm of the ratio of the market value of equity (PRC * SHROUT) and the market capitalization of all S&P500 firms (TOTVAL).
CASHMTA	Ratio of cash and short-term investments (CHEQ) and the market value of total assets (see NIMTAAVG)
MB	Ratio of the market value of equity (PRC * SHROUT) and the adjusted book value of assets. Following Campbell, Hilscher, and Szilagyi (2008), the adjusted book value of equity is the sum of the book value of equity plus 10% of the difference between the market value of equity and the book value of equity (if the adjusted book value of equity is negative, we replace it with a value of USD 1). The latter item is calculated following Davis, Fama, and French (2000) and Cohen, Polk, and Vuolteenaho (2003) as stockholder's equity (SEQQ) plus deferred taxes and investment tax credit (TXDITCQ) minus the book value of preferred stock (PSTKQ). If stockholder's equity is missing, the sum of the book value of common equity (CEQQ) and the par value of preferred stock (PSTKQ) is used. If the later item is also missing, stockholder's equity is calculated as the difference between total assets (ATQ) and total book value of liabilities (LTQ).
PRICE	Logarithm of the stock price (PRC), where the stock price is winsorized at USD 15.

Table 1: Summary Statistics for Abnormal Stock Returns and Equity Loss Rates.

The table shows summary statistics for the abnormal stock return one day before (AR_{t-1}), on (AR_t) and one day after the bankruptcy filing date (AR_{t+1}) in percent. Abnormal returns are calculated as the difference between the stock return and the return of the Standard & Poor's 500 index. ELR is the equity loss rate of Equation (7). We winsorize positive abnormal stock returns and negative equity loss rates (shareholder gains) at the 1%-level. N is the number of observations. *t-value* is the value of a simple t-test with the null hypothesis that the realized value equals zero.

	Mean	Median	Std.Dev.	Min	Max	t-value	N
Abnormal stock returns							
AR_{t-1}	− 3.30	− 0.86	16.37	−84.00	44.79	− 4.49	495
AR_t	−15.21	− 7.57	27.64	−96.60	63.33	−12.25	495
AR_{t+1}	−13.41	− 8.77	29.44	−93.65	66.20	−10.13	495
Equity loss rate							
ELR	31.60	33.65	31.13	− 49.59	95.64	22.59	495

Table 2: Descriptive statistics of equity loss predictor candidates. This table shows summary statistics of the candidate factors for predicting the equity loss rate. The sample ranges from 1972 to 2014 and is based on monthly CRSP and Compustat data. Panel A shows summary statistics for the full sample. Panel B is a subset that shows summary statistics for stocks that defaulted. Panel C further restricts this subsample to those firms that have information on equity loss rates. N is the number of firm-months. All variables are winsorized at the 5%/95%-level.

	Min	1st Qu.	Median	Mean	Std.	3rd Qu.	Max
Panel A: Non-defaulted stocks (N = 1,064,179)							
RDEXPAVG	0.000	0.000	0.001	0.006	0.009	0.008	0.032
INSIDER	0.000	0.000	0.000	0.004	0.009	0.000	0.036
TANG	0.239	0.420	0.514	0.498	0.125	0.580	0.726
RSIZE	-13.724	-11.558	-10.298	-10.231	1.807	-8.961	-6.851
STDEBT	0.000	0.002	0.033	0.082	0.115	0.111	0.444
DIST	0.000	0.000	0.000	0.106	0.308	0.000	1.000
ILLIQ	0.412	0.489	0.690	0.769	0.370	0.909	2.060
HHI	0.051	0.081	0.124	0.177	0.155	0.221	1.000
Panel B: Defaulted stocks (N = 377,789)							
RDEXPAVG	0.000	0.000	0.000	0.006	0.009	0.007	0.032
INSIDER	0.000	0.000	0.000	0.001	0.005	0.000	0.036
TANG	0.239	0.425	0.519	0.503	0.129	0.585	0.726
RSIZE	-13.724	-13.133	-12.075	-11.859	1.532	-10.902	-6.851
STDEBT	0.000	0.012	0.081	0.146	0.155	0.255	0.444
DIST	0.000	0.000	0.000	0.147	0.354	0.000	1.000
ILLIQ	0.412	0.519	0.721	0.794	0.371	0.924	2.060
HHI	0.051	0.084	0.138	0.206	0.192	0.251	1.000
Panel C: Defaulted stocks with equity loss rate (N = 39,643)							
RDEXPAVG	0.000	0.000	0.000	0.005	0.009	0.005	0.032
INSIDER	0.000	0.000	0.000	0.002	0.008	0.000	0.036
TANG	0.239	0.440	0.519	0.502	0.110	0.569	0.726
RSIZE	-13.724	-11.622	-10.490	-10.429	1.705	-9.249	-6.851
STDEBT	0.000	0.014	0.059	0.114	0.132	0.167	0.444
DIST	0.000	0.000	0.000	0.131	0.337	0.000	1.000
ILLIQ	0.412	0.608	0.823	0.929	0.460	1.071	2.060
HHI	0.051	0.082	0.127	0.187	0.166	0.232	1.000

Table 3: Default Probability Prediction Results

Table **??** estimates parameters of the failure probability model examined in Campbell, Hilscher, and Szilagyi (2008),

$$\begin{aligned} FAIL_{i,t+\tau} = \quad & b_0 + b_1 NIMTAAVG_{i,t} + b_2 TLMTA_{i,t} + b_3 EXRETAVG_{i,t} + b_4 SIGMA_{i,t} \\ & + b_5 RSIZE_{i,t} + b_6 CASHMTA_{i,t} + b_7 MB_{i,t} + b_8 PRICE_{i,t} + e_{i,t+\tau}, \end{aligned}$$

where $FAIL_{i,t+\tau}$ is an indicator variable that takes the value 1 if the firm fails in month $t+\tau$ and zero otherwise. The independent variables are $NIMTAAVG_{i,t}$, a moving average of the ratio of net income to market value of total assets, $TLMTA_{i,t}$, the ratio of total liabilities to total assets, $EXRETAVG_{i,t}$, the moving average of the excess return on the firm's stock over the S&P 500 index, $SIGMA_{i,t}$, the standard deviation of the firm's daily stock return over the preceding three months, $RSIZE_{i,t}$, the log ratio of the firm's market capitalization to that of the S&P 500 index, $CASHMTA_{i,t}$, the ratio of cash and equivalents to market value of total assets, and $PRICE_{i,t}$, the maximum of the firm's log share price or the log of \$15. We set $\tau = 12$ and present results from Campbell, Hilscher, and Szilagyi (2008) in the first column and results using our data in the second column. Data are obtained from Compustat and CRSP and, for our sample, cover the period 1973-2014. Statistical significance at the 10%, 5%, and 1% levels are denoted by one, two, and three asterisks, respectively.

	CHS (2008)	1973-2014
Intercept	-9.16^{***}	-10.88^{***}
	(30.89)	(47.37)
NIMTAAVG	-20.26^{***}	-15.67^{***}
	(18.09)	(25.12)
TLMTA	1.42^{***}	0.89^{***}
	(16.23)	(14.25)
EXRETAVG	-7.13^{***}	-4.53^{***}
	(14.15)	(14.81)
RSIZE	-0.04^{**}	-0.39^{***}
	(2.09)	(23.10)
CASHMTA	-2.13^{***}	-1.86^{***}
	(8.53)	(12.48)
MB	0.08^{***}	0.13^{***}
	(6.33)	(17.30)
PRICE	-0.06	-0.36^{***}
	(1.40)	(14.13)
SIGMA	1.41^{***}	0.38^{***}
	(16.49)	(8.34)
Num. obs.	1,565,634	1,393,923
Failures	1,968	4,729
Pseudo-R^2	11.40	15.97

Table 4: Equity Loss Rate Prediction

The table shows the results of the equity loss rate forecast model of Equation (10) using predictors that have been identified by the least absolute shrinkage and selection operator (LASSO) introduced by Tibsharanit (1996). The prediction model is specified as

$$\begin{aligned} ELR_{i,t+\tau} = \quad & c_0 + c_1 RDEXPAVG_{i,t} + c_2 INSIDER_{i,t} + c_3 TANG_{i,t} + c_4 RSIZE_{i,t} \\ & + c_5 STDEBT_{i,t} + c_6 DIST_{i,t} + c_7 ILLIQ_{i,t} + c_8 HHI_{i,t} + u_{i,t+\tau}, \end{aligned}$$

where $ELR_{i,t+\tau}$ is the loss rate on equity in τ months, $RDEXPAVG$ is expenditure on research and development, $INSIDER$ is the percentage of insider holdings, $TANG$ is the measure of asset tangibility from Berger, Ofek, and Swary (1996), $RSIZE$ is the log ratio of the market value of the firm to the market value of the S&P 500 index, $STDEBT$ is the percentage of total debt that is short term, $DIST$ is an indicator variable with the value one if the industry is in distress, and HHI is the Herfindahl index. Variables not listed in the table below were not selected by the LASSO procedure. Accounting data are taken from Compustat and market data are obtained from CRSP. Results are shown using all available firm-months where data on the predictors are available for a lag of 1, 6, 12 and 24 and 36 months respectively. *, **, *** denotes significance at the 10%, 5% and 1% levels. N is the number of observations. Heteroscedasticity-corrected standard errors are given in parentheses.

Lags (in months)	1	6	12	24	36
Intercept	−0.24*	−0.23*	0.00	0.07	0.11
	(0.14)	(0.13)	(0.14)	(0.15)	(0.16)
RDEXPAVG	4.82***	4.59***	4.77***	3.52	6.39***
	(1.65)	(1.71)	(1.83)	(2.19)	(2.19)
INSIDER	−1.88	−1.73	−2.68	−3.75*	−2.87
	(1.99)	(1.88)	(1.98)	(2.12)	(2.15)
TANG	0.31**	0.42***	0.33**	0.34**	0.35**
	(0.15)	(0.14)	(0.15)	(0.16)	(0.17)
RSIZE	−0.03***	−0.03***	−0.01	−0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ILLIQ	−0.02	−0.02	−0.02	−0.02	−0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
R^2	8.60	9.76	7.12	5.63	8.37
N	416	429	405	361	304

Table 5: Portfolios Sorted on Equity Loss Rates.

The table shows empirical results for monthly portfolio returns in excess of the risk-free rate (given in percent) and t-values (given in parentheses) sorted by the predicted equity loss rate measure each January between 1981 and 2014. We estimate an expected equity loss rate (ELR) for all stocks where we have information on the predictor variables for the default probability and the equity loss rate measure using the calibrated 12 months models. We then sort these stocks into quintiles based on their expected equity loss rate measure and calculate value-weighted portfolio returns. We also report the results for a long-short-portfolio that goes long in the portfolio with the highest expected equity loss rate and goes short in the portfolio with the lowest expected equity loss rate. Panel A shows alphas for these portfolios where we regress the excess portfolio returns on a constant (Raw), and the five-factor Fama and French (2015) model (FF5). Panel B shows the loadings for the FF5 model for the portfolio excess returns, where Mkt.RF is the market risk factor, SMB is the Small-Minus-Big factor, HML is the High-Minus-Low factor, RMW is the profitability factor and CMA is the investment patterns factor. Panel C shows the average market capitalization of each portfolio (in million USD) and the estimated default probability (PD) and equity loss rate measure (both given in percent). The superscripts *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Excess Returns

	Low ELR	2	3	4	High ELR	High - Low
Raw	0.57^{**}	0.66^{***}	0.71^{**}	0.75^{**}	0.89^{**}	0.32
	(2.52)	(2.68)	(2.38)	(2.08)	(2.21)	(1.20)
FF5	-0.03	0.03	0.19	0.33^{**}	0.47^{***}	0.50^{***}
	(-0.56)	(0.40)	(1.65)	(2.39)	(2.98)	(2.81)

Panel B: Factor Loadings

	Low ELR	2	3	4	High ELR	High - Low
Mkt.RF	0.97^{***}	1.02^{***}	1.09^{***}	1.10^{***}	1.13^{***}	0.16^{***}
	(77.09)	(49.66)	(39.84)	(33.28)	(29.74)	(3.69)
SMB	-0.02	0.10^{***}	0.26^{***}	0.61^{***}	0.87^{***}	0.89^{***}
	(-1.20)	(3.20)	(6.32)	(12.43)	(15.27)	(13.94)
HML	-0.22^{***}	-0.06	-0.14^{***}	-0.34^{***}	-0.52^{***}	-0.30^{***}
	(-9.02)	(-1.59)	(-2.69)	(-5.37)	(-7.09)	(-3.65)
RMW	0.06^{**}	-0.03	-0.34^{***}	-0.60^{***}	-0.61^{***}	-0.67^{***}
	(2.36)	(-0.65)	(-6.14)	(-9.04)	(-8.07)	(-7.88)
CMA	0.11^{***}	-0.00	-0.07	-0.04	0.01	-0.10
	(2.94)	(-0.02)	(-0.90)	(-0.39)	(0.11)	(-0.77)

Panel C: Portfolio Characteristics

Market Capitalization	4,824	2,464	710	292	132
Probability of Failure	0.10	0.18	0.25	0.34	0.42
ELR	20.31	26.43	30.53	34.79	43.77

Table 6: Portfolios Sorted on Failure Probability

The table shows empirical results for monthly portfolio returns in excess of the risk-free rate (given in percent) and t-values (given in parentheses) sorted by the predicted defaulted probability each January between 1981 and 2014. We estimate an expected default probability (PD) for all stocks where we have information on the predictor variables for the default probability and the equity loss rate measure using the calibrated 12 months models. We then sort these stocks into quintiles based on their expected default probability and calculate value-weighted portfolio returns. We also report the results for a long-short-portfolio that goes long in the portfolio with the highest expected default probability and goes short in the portfolio with the lowest expected default probability. Panel A shows alphas for these portfolios where we regress the excess portfolio returns on a constant (Raw), and the five-factor model by Fama and French (2015) (FF5). Panel B shows the loadings for the FF5 model for the portfolio excess returns, where Mkt.RF is the market risk factor, SMB is the Small-Minus-Big factor, HML is the High-Minus-Low factor, RMW is the profitability factor and CMA is the investment patterns factor. Panel C shows the average market capitalization of each portfolio (in million USD) and the estimated default probability (PD) and equity loss rate measure (both given in percent). *, **, *** denotes significance at the 10%, 5% and 1% levels.

Panel A: Excess Returns

	Low PD	2	3	4	High PD	High - Low
Raw	0.63***	0.58*	0.51	0.40	0.07	−0.55*
	(2.80)	(1.84)	(1.46)	(1.05)	(0.17)	(−1.83)
FF5	0.03	0.01	−0.13	−0.27**	−0.49***	−0.53***
	(0.91)	(0.13)	(−1.54)	(−2.05)	(−2.66)	(−2.76)

Panel B: Factor Loadings

Mkt.RF	0.98***	1.11***	1.16***	1.17***	1.15***	0.17***
	(110.83)	(55.39)	(56.69)	(37.43)	(25.88)	(3.66)
SMB	−0.04***	0.60***	0.87***	1.09***	1.11***	1.15***
	(−3.03)	(20.07)	(28.60)	(23.33)	(16.82)	(16.88)
HML	−0.20***	−0.03	0.05	0.05	0.06	0.26***
	(−11.97)	(−0.89)	(1.20)	(0.91)	(0.67)	(2.97)
RMW	0.04**	−0.30***	−0.44***	−0.51***	−0.94***	−0.98***
	(2.25)	(−7.38)	(−10.65)	(−8.12)	(−10.60)	(−10.70)
CMA	0.10***	−0.24***	−0.16***	−0.10	0.09	−0.01
	(3.73)	(−4.10)	(−2.65)	(−1.13)	(0.70)	(−0.04)

Panel C: Portfolio Characteristics

Market Capitalization	7,292	702	268	114	45
Probability of Failure	0.02	0.05	0.09	0.20	0.92
ELR	25.17	28.76	31.74	34.15	36.00

Table 7: Independent Portfolio Sorts

We sort stocks between 1981 and 2014 independently into quintiles according to their expected default probability and expected level of the equity loss rate measure and then calculate value-weighted portfolio returns for the 25 portfolios. Panel A reports the associated monthly alphas (in percent) and t-values of all portfolios using the five-factor model of Fama and French (2015) as a risk correction. Panel B shows the average estimated default probability (in percent) of each portfolio, Panel C shows the average estimated equity loss rate (in percent) of each portfolio. *, **, *** denotes significance at the 10%, 5% and 1% levels.

Panel A: Excess Returns

Portfolio	Low ELR	2	3	4	High ELR	High - Low
Low PD	−0.02	0.06	0.31**	0.45**	0.77***	0.78***
	(−0.31)	(0.65)	(1.99)	(2.21)	(2.87)	(2.76)
2	0.04	0.02	−0.08	0.03	0.25	0.22
	(0.32)	(0.16)	(−0.60)	(0.18)	(1.28)	(0.90)
3	−0.38***	−0.35**	−0.19	0.36***	0.42**	0.80***
	(−2.67)	(−2.50)	(−1.42)	(2.64)	(2.58)	(3.63)
4	−0.76***	−0.63***	−0.39**	0.01	0.51**	1.28***
	(−2.95)	(−3.63)	(−2.18)	(0.04)	(2.52)	(4.03)
High PD	−1.27***	−1.14***	−0.83***	−0.45*	0.48*	1.76***
	(−2.78)	(−4.23)	(−3.55)	(−1.93)	(1.93)	(3.66)
High - Low	−1.26***	−1.20***	−1.14***	−0.90***	−0.28	
	(−2.72)	(−4.15)	(−3.96)	(−2.91)	(−0.78)	

Panel B: Probability of Failure

Portfolio	Low ELR	2	3	4	High ELR
Low PD	0.02	0.02	0.02	0.02	0.02
2	0.05	0.05	0.05	0.05	0.05
3	0.08	0.09	0.09	0.09	0.09
4	0.19	0.19	0.20	0.20	0.21
High PD	0.82	0.93	0.89	0.90	0.98

Panel C: ELR

Portfolio	Low ELR	2	3	4	High ELR
Low PD	19.67	26.01	30.21	34.78	40.88
2	20.03	26.41	30.39	34.83	41.86
3	20.87	26.52	30.54	34.79	42.90
4	21.80	26.68	30.63	34.70	44.12
High PD	23.33	26.90	30.75	34.84	45.12

Table 8: Fama-MacBeth Regressions.

This table shows the results of a Fama-MacBeth regression using individual monthly stock returns (in percent) and lagged firm characteristics. ELR_{t-1} is the predicted loss rate in case of bankruptcy in the prior month and $FAIL_{t-1}$ is the predicted failure probability in the prior month. ELR_{t-1} and $FAIL_{t-1}$ are derived from the monthly re-calibrated (12-month) prediction models. Ret_{t-1} (RET) is the stock return of the previous month. The subsequent variable definitions follow Lewellen (2015): ROA_{Y-1} is income before extraordinary items (IB) divided by book value of total assets (AT) from the prior fiscal year, $LogSize_{t-1}$ is the log of market value of equity (PRC*SHROUT) in the prior month, $LogB/M_{t-1}$ is the log of the ratio of book value of equity (CEQ) and market value of equity in the prior month, $Ret_{t-2,t-12}$ is the stock return from months -12 to -2. $LogIssues_{t-1,t-36}$ is log growth of split-adjusted shares outstanding (SHROUT*CFACSHR) from months -36 to -1. $Accruals_{Y-1}$ is working capital accruals based on Sloan (1996) in the prior fiscal year, $LogAG_{Y-1}$ is log growth in total assets in the prior fiscal year. Yearly accounting data comes from Compustat and is assumed to be known four months after fiscal year end, market data is from CRSP (mnemonics from both databases are given in parentheses). All explanatory variables are standardized by subtracting the mean and dividing by the standard deviation and winsorized at the 1%/99%-level. We correct t-statistics (reported in parentheses) with the Newey-West procedure using four lags. *, **, *** denotes significance at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	1.09***	1.05***	1.10***	1.06***	1.08***	1.11***
	(3.47)	(3.34)	(3.50)	(3.37)	(3.48)	(3.62)
$FAIL_{t-1}$		−0.20***		−0.17**	−0.25***	−0.07
		(−2.80)		(−2.36)	(−3.03)	(−0.96)
ELR_{t-1}			0.34***	0.32***	0.30***	0.34***
			(4.03)	(3.73)	(3.35)	(3.90)
RET_{t-1}	−0.52***	−0.55***	−0.52***	−0.55***	−0.54***	
	(−8.78)	(−9.10)	(−8.95)	(−9.25)	(−9.16)	
ROA_{Y-1}	0.29***	0.24***	0.32***	0.27***		0.29***
	(3.80)	(3.39)	(4.47)	(4.29)		(4.61)
$Ret_{t-2,t-12}$	0.42***	0.38***	0.43***	0.40***	0.41***	0.46***
	(4.34)	(4.11)	(4.47)	(4.29)	(4.40)	(5.06)
$LogSize_{t_1}$	−0.09	−0.14**	0.11	0.06	0.09	0.10
	(−1.14)	(−1.98)	(1.34)	(0.72)	(1.09)	(1.22)
$LogBM$	0.29***	0.28***	0.27***	0.26***	0.28***	0.36***
	(4.18)	(4.11)	(3.84)	(3.80)	(4.03)	(5.05)
$LogIssues_{t-1,t-36}$	−0.25***	−0.25***	−0.24***	−0.24***	−0.30***	−0.23***
	(−6.49)	(−6.40)	(−6.16)	(−6.14)	(−6.29)	(−5.80)
$Accruals_{Y-1}$	−0.12***	−0.13***	−0.13***	−0.14***	−0.09***	−0.13***
	(−3.67)	(−3.94)	(−3.89)	(−4.14)	(−2.81)	(−4.02)
$LogAG_{Y-1}$	−0.16***	−0.17***	−0.14***	−0.15***	−0.10***	−0.12***
	(−4.95)	(−5.17)	(−4.43)	(−4.60)	(−2.97)	(−3.91)