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

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Abstract

We examine the relation between the risk of failure and average stock returns in light of two potential sources of failure risk; the probability that a firm will fail and shareholders' losses conditional on failure. We suggest a simple model for predicting shareholder losses upon default and show that our forecast estimates predict realized default outcomes for shareholders. Forming portfolios on our forecast estimates, we find that five-factor alphas increase for higher levels of expected shareholder losses and that the negative alphas for highly distressed stocks are no longer economically or statistically significant if shareholders expect high default losses.

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1 Introduction

Is there a risk premium associated with financial distress? This question is addressed in Campbell, Hilscher, and Szilagyi (2008), who estimate a failure prediction model for a panel of firms. The authors find the surprising result that firms with a high probability of failure command *lower* average returns than firms with a low probability of failure. Their results contrast with the predictions of Chan and Chen (1991) and Fama and French (1996), who suggest that characteristics such as market capitalization and book-to-market ratios reflect compensation for a positive premium for distress risk.[1]

Campbell, Hilscher, and Szilagyi (2008) focus on default risk generated by probability of failure. However, default risk is generally modeled with two components: probability of default and loss given default. If equity claims are valueless upon failure, then only probability of default matters for assessing the risk of financial distress. Empirical evidence suggests, however, that equity frequently retains value even in the case of a bankruptcy.[2] If there is cross-sectional variation in these losses, the risk of loss given default may be an important omitted variable in assessing failure risk. This issue is considered explicitly in Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011), who show that negative risk premia for financial distress may arise in a context in which shareholders hold a strategic default option. In support of this explanation, Favara, Schroth, and Valta (2012) show that equity across countries bears less risk if the national bankruptcy code favors shareholders or if shareholders have a high level of bargaining power, and Hackbarth, Haselmann, and Schoenherr (2015)

[1] 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.

[2] Franks and Torous (1989, 1994), Eberhart, Moore, and Roenfeldt (1990), Weiss (1990), and Betker (1995) find that shareholders frequently receive a part of the reorganized firm value in Chapter 11 bankruptcy. Clark and Weinstein (1983) show that of 162 bankrupt firms in their sample, 83 firms retained equity value after the bankruptcy proceedings. More recently, 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 equity 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.

find that the 1978 Bankruptcy Reform Act, which shifted bargaining power to shareholders, has reduced equity risk at the expense of creditors.

In this paper, we empirically investigate whether cross-sectional variation in *ex-ante* shareholder expected losses given default impact inferences about the relation between failure risk and expected returns. A principal contribution of the paper is a methodology designed to predict the magnitude of shareholder losses upon firm failure, where failure is defined in the context examined in Campbell, Hilscher, and Szilagyi (2008). Our approach complements default prediction models that have evolved in the finance literature over the past 50 years (see, e.g., Altman (1968); Ohlson (1980); Shumway (2001)). While the dependent variable in default prediction models is a dummy variable that differentiates between default and survival, measuring loss given default of equity is less straightforward. We make use of the fact that a significant fraction of stocks still trades after a bankruptcy filing and measure realized loss given default as the abnormal buy-and-hold stock return over a three-day horizon spanning the day of the bankruptcy filing (for a similar application, see, e.g., Clark and Weinstein (1983); Li (2013)).[3] The predicted abnormal return is our measure of expected loss given default for equity (ELGD) and is similar to the recovery-of-market-value convention used in the bond pricing literature by Duffie and Singleton (1999). We utilize a set of characteristics hypothesized to be related to ELGD, and select predictor variables using the absolute shrinkage and selection operator (LASSO) of Tibsharanit (1996) to maximize predictive power.

We find that our predictors explain 12% of the variation in realized ELGD at a 12-month forecast horizon, which is of comparable magnitude to the explanatory power that predictors in default prediction models achieve (Campbell, Hilscher, and Szilagyi (2008)). Comparing our fitted forecast values for ELGD with realized bankruptcy outcomes, we find a statistically and

[3]Stocks are not necessarily delisted by an exchange following a bankruptcy filing. Instead, stock delistings occur if a listing requirement of the exchange is violated, such as a very low share price persists or trading volumes drop to zero. In other cases, stocks are delisted when the distressed firm is acquired by another firm.

economically strong relation between our measure and more favorable bankruptcy outcomes for shareholders. This result also holds if we restrict the comparison to firms that are delisted before the bankruptcy filing, suggesting that the forecast model also applies to firms that are not used to calibrate the prediction model.

Using the fitted values of our forecast model for ELGD, we study the relation between expected ELGD, failure probability, and expected stock returns. We find that portfolios of firms with high expected losses have higher average and factor risk-adjusted average returns than firms with low expected losses; differences in high and low expected loss quintile (decile) portfolios have Fama and French (2016) five-factor alphas of 75 basis points (109 basis points) per month. Sorting on both failure probability and expected loss suggests that there are separate compensations for probability of default and ELGD. For each failure probability quintile, there is an economically and statistically significant and positive five-factor alpha for high loss given default firms in excess of low loss given default firms. However, the relation between five-factor alpha and default probability depends on the level of ELGD. For firms that have a high ELGD, the difference in adjusted expected returns between high failure probability firms and low failure probability firms is statistically insignificant. When firms have intermediate or low ELGD, the relation between default probability and excess returns becomes negative again.

Our results presented in this paper complement extant empirical results that examine the distress premium puzzle. Dichev (1998), Griffin and Lemmon (2002), and Campbell, Hilscher, and Szilagyi (2008) show that firms with high bankruptcy probabilities earn lower average returns. Chava and Purnanandam (2010) argue that much of the distress premium puzzle arises from the experience of investors in the 1980s realizing substantially lower-than-expected returns on high default probability securities. Conrad, Kapadia, and Xing (2014) show that high distress firms also exhibit positive skewness consistent with investor preferences that favor lottery-like payoffs. Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) show that the distress premium puzzle is empirically concentrated in firms with firm- and industry-characteristics that indicate high levels of shareholder recovery. Davydenko and Strebulaev (2007) examine strategic default decisions on the debt side and find a statistically significant, but economically weak effect on credit spreads. We add to this literature by providing a simple forecast model for ELGD. Forming portfolios on our fitted forecast values for ELGD, we empirically confirm the importance of shareholder losses as an additional dimension of failure risk.

2 Theoretical Link Between Expected Stock Returns, Failure Likelihood, and ELGD

In order to obtain predictions for the role of ELGD and its interaction with default probability for the cross-section of equity returns, we consider an augmented Merton (1974) model of default risk. Following Fan and Sundaresan (2000) and Garlappi, Shu, and Yan (2008), shareholders and creditors in our setup engage in a bargaining game with asymmetric bargaining power to restructure the debt of a distressed firm and avoid liquidation. Higher bargaining power of shareholders and a worse outside option of creditors (higher liquidation costs) translate to smaller ELGD and lower expected stock returns. The relation between expected returns and default probability depends on the value of the bargaining option. When the value of the bargaining option is low, or equivalently ELGD is high, expected returns are increasing, as expected, in default probability. However, when the value of the bargaining option is sufficiently high, expected returns are *decreasing* in default probability. Intuitively, the value of the bargaining option offsets the effect of failure probability on expected returns.

The bargaining option is motivated by the empirical fact that the majority of (large) firms in financial distress opt for a restructuring of company debt (in a private workout or formal bankruptcy procedure) rather than firm liquidation. Creditors typically aim to avoid a liquidation of the firm as it can incur additional bankruptcy costs such as fire-sales or the loss of intangibles (see, e.g., Bris, Welch, and Zhu (2006); Acharya, Bharath, and Srinivasan

(2007)). Gilson, John, and Lang (1990) show that in their sample of 169 financially distressed firms with public equity that 80 firms restructured in a private workout, while 89 firms filed for Chapter 11, of which only 4 were eventually liquidated. Even though creditors have more senior claims and shareholder claims can be dismissed by a judge in a reorganization plan (cram-down), shareholders can delay the restructuring process which imposes higher bankruptcy costs on creditors (see, e.g., Franks and Torous (1989)). This setup incentivizes creditors to compensate shareholders to facilitate the restructuring process.[4]

In the following section, we briefly describe the main features of the model. Further details are available in Appendix A.1. The starting point for our analysis is the basic Merton (1974) setup with a firm whose value V_t follows a geometric Brownian motion. The firm has a single zero-coupon bond outstanding with maturity T and notional value K. We augment the setup by assuming that shareholders can decide whether they repay creditors or strategically file for default at maturity. The bargaining between creditors and shareholders at default is a Nash bargaining solution with asymmetric bargaining power. If the firm value is sufficiently high at maturity, shareholders payout creditor claims and own the remaining firm value (no default). At lower levels of firm value at maturity, shareholders (strategically) decide to default on the debt payment and bargain with creditors about the distribution of the firm value. If bargaining fails, the firm is liquidated and shareholders receive nothing. If bargaining is successful, debt is exchanged into equity and both groups split the firm value according to the bargaining result (debt-equity swap) as in Fan and Sundaresan (2000).

The bargaining result depends on the (percentage) liquidation costs of the firms' assets α and the bargaining power of shareholders η. As we show in Appendix A.1 using standard

[4] In the credit risk literature, strategic default motives and bargaining in bankruptcy are relatively common (Hart and Moore (1994, 1998); Anderson and Sundaresan (1996); Fan and Sundaresan (2000); Davydenko and Strebulaev (2007)). In the equity market literature, strategic default is much less well-established. Some exceptions are Garlappi, Shu, and Yan (2008), Favara, Schroth, and Valta (2012), and Hackbarth, Haselmann, and Schoenherr (2015) who build on the model by Fan and Sundaresan (2000). Additional models relating to bankruptcy costs and expected stock returns include Garlappi and Yan (2011) and George and Hwang (2010).

option pricing techniques, the equity value S_t at time $t < T$ is:

$$S_t = (1-\rho) \cdot V_t + \rho \cdot (V_t \cdot N(d_1) - K' \cdot e^{-r(T-t)} \cdot N(d_2)), \tag{1}$$
$$\text{with } \rho = 1 - \alpha \cdot \eta.$$

ρ represents the fraction of firm value that shareholders cannot recover in bargaining ($0 \leq \rho \leq 1$), $K'(= K/\rho)$ is the default threshold for firm value at maturity, incorporating the strategic default option, T is the maturity date of the debt, r is the continuously compounded risk-free rate, and $N(\cdot)$ is the standard normal cumulative distribution function.[5] The equity price is equal to the sum of $(1-\rho) \cdot V_t$, which represents the minimum value that shareholders receive (in case of a default), and ρ times the value of a standard call option (with modified default threshold K'). For $\rho = 1$, the model is equal to the standard Merton (1974) model, for $\rho = 0$, equity value equals firm value as shareholders have no incentive to pay creditors. The (instantaneous) expected excess stock return $\mu_S - r$ is given by:

$$\mu_S - r = (\mu - r) \cdot \frac{V_t}{S_t} \cdot S_V, \tag{2}$$

where μ is the expected asset return and S_V is the first derivative of the equity value with respect to the asset value.[6] In Appendix A.1, we analytically show that higher values of ρ lead to higher expected stock returns, i.e. a decrease in shareholder losses increases the relative value of the default bargaining option and lowers the expected stock return.

The interaction effect between shareholder losses and default likelihood on expected

[5]The arguments of the cumulative normal, d_1 and d_2 are the standard arguments from option pricing:

$$\begin{aligned} d_1 &= \frac{1}{\sigma\sqrt{T-t}}\left(\ln\left(S_t/K'\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)\right) \\ d_2 &= d_1 - \sigma\sqrt{T-t} \end{aligned}$$

where σ is the volatility of the firm value.

[6]As we abstract from taxes, firm value and asset value of the firm are identical in our model.

stock returns is more complex. To gain a better understanding of this relationship, we simulate our model and calculate monthly realized stock returns. We draw parameters for the instantaneous expected asset return (μ), asset volatility (σ), and initial leverage (K/V_0) for a sample of 100,000 firms. Further details on the simulation procedure can be found in Appendix A.2. We calculate twelve months of realized monthly stock returns for a (constant) debt maturity of one year and a risk-free rate of 4%. Figure 1 shows the resulting average realized stock returns for stocks grouped in quintiles according to their failure likelihood for different values of ρ (0.2, 0.4, 0.6, 0.8).

For high values of shareholder losses ($\rho = 0.8$), average stock returns increase with higher levels of failure likelihood. This case conforms with standard intuition, suggesting that when shareholders experience large losses, expected returns are increasing in default probability. In this scenario, the default bargaining option, which lowers expected stock returns, accounts for only a small fraction of total equity value. The leverage effect on the standard Merton (1974) call option price component, which is positively related to expected equity returns, dominates the effect of shareholders' bargaining option. As a result, expected returns are increasing in failure probability as in the standard Merton case.

As shareholder losses decrease, the bargaining option becomes more valuable. The value of this option increases as failure probability rises, such that for high failure probabilities, the value of the bargaining option is sufficiently high such that expected stock returns are lower in the highest failure quintile than in lower quintiles. This effect becomes stronger as ρ decreases from 0.6 to 0.4, such that when $\rho = 0.4$, expected returns are *decreasing* in failure probability. Interestingly, if the value of the bargaining option is sufficiently high, the relation between failure probability and average returns is close to flat, with the bargaining option offsetting the leverage effect inherent in equity.

These results indicate that it is possible that the decreasing effect of failure likelihood on realized stock returns is stronger for stocks with medium levels of shareholder losses than for those with high levels of shareholder losses. The effects of increasing levels of shareholder losses also depend on the level of failure likelihood and a similar relationship applies. The difference between average stock returns of stocks with high and low losses is strongest for stocks in the highest failure quintile as the default bargaining option constitutes a larger fraction of total equity value compared to stocks in the lowest failure quintile. Therefore, we would expect the effect of shareholder losses on (expected) stock returns to be stronger among stocks whose default probability reaches a certain threshold.

3 Measurement and Prediction of Shareholder Losses at Bankruptcy

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. In this section, we describe how we use abnormal buy-and-hold stock returns at bankruptcy as an information source about post-default bankruptcy outcomes. We then present a prediction model that uses firm and industry characteristics that are known to be linked to shareholders' bankruptcy losses and calibrate it to abnormal stock returns at bankruptcy. Finally, we show that our prediction values are able to capture favorable bankruptcy outcomes for shareholders.

3.1 Abnormal Stock Returns as a Measure for Shareholders' Bankruptcy Losses

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 a reference. Previous research documents 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 (Clark and Weinstein 1983, Datta and Iskandar-Datta 1995, Li 2013). Clark and Weinstein (1983) also find that three-day abnormal stock returns around bankruptcy are much lower for stocks that subsequently become worthless than for stocks that retain value during a bankruptcy.

Abnormal stock returns can be informative about post-bankruptcy outcomes for several reasons. Jiang, Li, and Wang (2012) show that abnormal stock returns around the day of the bankruptcy filing contain information on the presence of specialized distressed (hedge funds), who are able to identify firms with a higher likelihood of favorable bankruptcy outcomes for shareholders. In addition, abnormal stock returns can reflect information about the bankruptcy procedure through news coverage or firm statements. Tashjiana, Lease, and McConnell (1996) find that cumulative abnormal stock returns on the bankruptcy filing day are on average 3.19% in the case of a pre-packaged Chapter 11 filing as compared to a two-day average abnormal return of -16.7% for traditional Chapter 11 filings as found in Gilson, John, and Lang (1990). These empirical findings encourage us in our assumption that changes in equity value around bankruptcy filings convey significant information on post-bankruptcy payments to shareholders. We use the information contained in abnormal stock returns at bankruptcy to proxy for ultimate shareholder losses following bankruptcy. To replicate the impact of bankruptcy news on a distressed stock investor, we measure the buy-and-hold abnormal stock return during the three-day window around the bankruptcy filing:

$$BHAR_{i,t} = \prod_{\tau=-1}^{\tau=1} (1 + r_{i,t+\tau}) - \prod_{\tau=-1}^{\tau=1} (1 + r_{m,t+\tau}), \tag{3}$$

where $r_{i,t+\tau}$ is the return on stock i at day τ relative to the bankruptcy announcement, and $r_{m,t+\tau}$ is the stock market return (measured as the return of the S&P's 500 index).

We retrieve daily stock market data from CRSP for common shares of non-financial firms (SIC code between 6000 and 6999) listed at either NYSE, AMEX, or NASDAQ. Default data is obtained from Chava and Jarrow (2004) and contains bankruptcy filing dates of 2,991 stocks between 1964 and 2014.[7] In order to ensure that our measure is not driven by illiquid stock price data, we drop very illiquid stocks[8] and winsorize positive abnormal buy-and-hold stock returns above the 95% level.

Table 1 shows descriptive statistics for our sample of 401 abnormal buy-and-hold returns around a bankruptcy filing together with single-day abnormal stock returns. We find that stocks experience an average buy-and-hold return of -34.2% for the three days around a bankruptcy filing and that the day before (-3.6%), the day of (-18.1%), and the day after (-14.4%) a bankruptcy filing show the strongest stock price reaction within a ten-day window around bankruptcy filing. Both findings are consistent with earlier empirical evidence on abnormal stock returns around bankruptcy filings (Clark and Weinstein 1983, Datta and Iskandar-Datta 1995, Li 2013). Importantly for our study, there is considerable variation in the degree to which investors earn abnormal returns around the filing of bankruptcy. The standard deviation of abnormal buy-and-hold returns over the three-day window is 29.4%, compared to a mean of -34.2%, 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 maximum buy-and-hold return in our sample (after winsorization) is 13.7% and 61 out of the 401 observations have a positive abnormal buy-and-hold return for the three-day window around bankruptcy. At the other extreme, the worst performance of a

[7]The default database has been updated in Chava (2014) and Alanis, Chava, and Kumar (2018). In a few cases where firms file multiple times for bankruptcy, we only use the first bankruptcy filing.

[8]We require a stock to have non-missing return data and a positive trading volume for all three days around bankruptcy. We also drop stocks with more than one zero-return day or a market capitalization of less than one million USD on the day before the bankruptcy filing.

firm filing for bankruptcy was a loss of 95.4% over the three days surrounding the bankruptcy filing.

3.2 Prediction Model for Abnormal Stock Returns at Bankruptcy

In order to use predicted abnormal buy-and-hold returns at bankruptcy as a measure for post-bankruptcy outcomes for shareholders, we utilize a set of firm- and industry-specific variables in a linear regression specification:

$$BHAR_{i,t} = a_0 + \mathbf{a}'\mathbf{x}_{i,t-j} + e_{i,t}, \tag{4}$$

where $\mathbf{x}_{i,t-j}$ are firm- and industry-specific characteristics measured at month $t-j$ relative to the month of the bankruptcy filing. We choose predictor variables that are related to more favorable bankruptcy outcomes for shareholders. Based on our theoretical model, post-bankruptcy payments to shareholders are larger for higher levels of a firm's liquidation costs (outside option for creditors) and bargaining power of shareholders. We employ a number of empirical proxies to capture shareholder bargaining power and liquidation costs (Appendix B.1 provides more details on the construction of the variables). Predictor variables are based on monthly stock market data from CRSP and annual balance sheet data from Compustat (lagged by six months).

To measure shareholder bargaining power, we use three different variables: Our first variable is the ratio of research and development expenses to total assets (RDEXP).[9] 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. Our second variable is the ratio of convertible

[9] Not all firms report research and development expenses. We follow Berger, Ofek, and Swary (1996) in setting missing values to zero.

debt to total debt (CONVDEBT), which we use as a proxy for the level of coordination and sophistication of creditors. Hedge funds are particularly important investors for financially distressed firms. Jiang, Li, and Wang (2012) find in their sample, covering 474 firms that filed for Chapter 11 between 1996 and 2007, that 90% of firms had a publicly observable hedge fund involvement with convertible debt being a preferred investment class. Brown, Grundy, Lewis, and Verwijmeren (2012) find that between 2000 and 2008, hedge funds provided 73% of the financing of newly issued convertibles. We argue that investors (hedge funds) who are focusing on distressed debt investments are more sophisticated and better-coordinated creditors. Therefore, we expect shareholder bargaining power to be lower if the fraction of convertible debt to total debt is higher. We follow Garlappi, Shu, and Yan (2008) and use firm size (SIZE) as a third proxy for shareholder bargaining power. Firm size is measured by the natural logarithm of the market value of assets. We expect firm size to be positively related to shareholder's bargaining power as smaller firms tend to have fewer creditors who closely monitor the firm giving creditors an information advantage over shareholders. Empirically, Franks and Torous (1994) and Betker (1995) confirm that shareholders of larger firms are more likely to receive a payment in default.

We use five different variables to measure firm liquidation costs. Our first variable is the measure of Berger, Ofek, and Swary (1996) for firm liquidation values (LIQUVAL). Higher firm liquidation values lower the incentive of creditors to reach an agreement with shareholders (Bergman and Callen 1991) and therefore decrease the chances of shareholders to recover value after bankruptcy (Garlappi, Shu, and Yan 2008, Hackbarth, Haselmann, and Schoenherr 2015). Our second variable is the industry asset specificity of financially distressed industries (INDASxDISTRESS), which is used as a proxy for potential fire-sales. Fire-sale effects lower the liquidation value of a firm's assets if the assets are specific and if competitors are liquidity constrained (Shleifer and Vishny 1992). Acharya, Bharath, and Srinivasan (2007) empirically show that fire-sale effects lower recovery rates of defaulted corporate bonds. To measure fire-sale effects, we follow Acharya, Bharath, and Srinivasan

(2007) and use the median ratio of asset specificity to book value of total assets in an industry multiplied by a financial distress dummy variable that is one if the median stock return in the industry is below -30% in the past twelve months and zero otherwise. We use two alternative specifications for measuring fire-sales. The first alternative specification follows Acharya, Bharath, and Srinivasan (2007) and replaces the distress dummy in the former variable with the median of the inverse interest coverage ratio of the industry (INDASxILLIQ). Our second alternative measure for fire-sale effects captures the cash endowment of an industry (INDCASH). The variable is calculated as the median ratio of cash and short-term investments to the book value of assets. As the fifth proxy for liquidation costs, we use a dummy variable that takes the value of one if a firm operates in the utility industry and zero otherwise (UTILITY). Utility firms are typically characterized by having high asset liquidation values (low liquidation costs).

Our model for predicting post-bankruptcy shareholder recovery rates (losses) is given by:

$$\begin{aligned} BHAR_{i,t} =& a_0 + a_1 RDEXP_{i,t-j} + a_2 LIQUVAL_{i,t-j} + a_3 CONVDEBT_{i,t-j} + a_4 UTILITY_{i,t-j} + \\ &+ a_5 SIZE_{i,t-j} + a_6 INDAS \times DISTRESS_{i,t-j} + a_7 INDAS \times ILLIQ_{i,t-j} + \\ &+ a_8 INDCASH_{i,t-j} + u_{i,t}. \end{aligned} \tag{5}$$

Summary statistics for the explanatory variables are presented in Table 2. We follow the default prediction model of Campbell, Hilscher, and Szilagyi (2008) and choose a default prediction horizon of twelve months ($j = 12$). To judge whether a predictor variable is suited to forecast abnormal buy-and-hold stock returns at bankruptcy, we employ the least absolute shrinkage and selection operator (lasso) approach of Tibsharanit (1996). We apply the lasso procedure to select among the predictor candidates those with the highest forecast power (for details on the selection see Appendix B.1). The lasso procedure selects the following variables to predict abnormal stock returns at bankruptcy: ratio of research and development expenses (*RDEXP*), firm liquidation value based on Berger, Ofek, and Swary (1996) (*LIQUVAL*), median industry cash ratio (*INDCASH*), ratio of convertible to total debt (*CONVDEBT*).

Table 3 provides the in-sample results for predicting abnormal buy-and-hold stock returns at bankruptcy using different time horizons. The number of firms generally drops with the horizon; this decrease is due to the more limited availability of accounting data for firms at longer lags relative to the bankruptcy filing date. The results of the estimation are similar across all horizons. All four predictor variables have highly similar coefficient values at all forecast-horizons and the signs of the coefficient values are consistent with our theoretical predictions. Accordingly, a higher ratio of research and development expenses, higher firm liquidation values, a higher ratio of convertible debt, and higher industry cash holdings lead to lower abnormal buy-and-hold stock returns at bankruptcy. The economic significance of each predictor variable is high with a one standard deviation increase in the predictor variables resulting in a decrease of the abnormal buy-and-hold stock return at bankruptcy between 2.9 and 5.6 percentage points. The in-sample explanatory power is comparable to the explanatory power achieved in default prediction models with the same forecast-horizon and ranges from 11% to 13% as measured by regression R^2.

In summary, the results reported in Table 3 suggest that variables hypothesized to affect post-bankruptcy shareholder losses consistently predict abnormal buy-and-hold stock returns at bankruptcy. At the twelve-month horizon, the model explains 12% of the in-sample variation in abnormal buy-and-hold stock returns at bankruptcy. We proceed using this preferred model to calculate predicted abnormal buy-and-hold stock returns at bankruptcy in the remainder of the paper.

3.3 Predicted Abnormal Stock Returns and Realized Bankruptcy Outcomes for Shareholders

The empirical results of the previous section suggest that variables theoretically linked to shareholder's bargaining power and firm liquidation costs predict abnormal stock returns at bankruptcy. In this section, we test whether predicted abnormal buy-and-hold stock returns are suited to predict more favorable post-bankruptcy outcomes for shareholders.

Ideally, we would like to directly compare our predicted abnormal stock returns with the percentage of defaulted firm value that shareholders can (not) receive after a bankruptcy filing. Unfortunately, we are not aware of any database that collects comprehensive post-bankruptcy information on shareholders. Therefore, we use two different bankruptcy characteristics which measure whether a bankruptcy outcome is more likely to be beneficial for shareholders. The first characteristic that we use is a dummy variable that indicates whether an equity committee has been formed during the bankruptcy to represent shareholder interests or not ($D_{Committee}$). During a bankruptcy procedure, equity holders can organize themselves in a committee to interact with the firm's management and to gain influence on the formulation of the restructuring plan. Using a sample of 75 bankruptcies, Betker (1995) finds that the existence of an equity committee increases absolute priority violations in favor of shareholders. Therefore, we expect the existence of an equity committee to be positively related to our predicted abnormal stock returns. An alternative characteristic that we use is a dummy variable that is one if a firm emerges from bankruptcy ($D_{Emergence}$). We argue that shareholders of a firm that remains intact until bankruptcy resolution (has not been liquidated or acquired) are more likely to receive a payment. This assumption is based on the empirical finding that deviations from the absolute priority rule are rare for liquidations and typically lead to a loss of 100% for shareholders.

We use data on bankruptcy characteristics from the UCLA-LoPucki Bankruptcy Research Database (BRD), which covers firms that filed for restructuring (Chapter 11) or liquidation (Chapter 7) since 1979. To be included in the BRD, a firm must have filed a 10-K report with the Securities and Exchange Commission within three years before the bankruptcy filing and have assets of more than 100 million USD. We exclude bankruptcies of financial firms (SIC code between 6000-6999), subsequent bankruptcies of the same firm, and a few observations with a missing Compustat identifier. For 100 bankruptcies, the BRD reports the distributions made to secured creditors, unsecured creditors, and shareholders after bankruptcy. The distribution data is not comprehensive enough to match it with our predicted values for abnormal stock returns at bankruptcy,[10] but we are able to relate the data on distributions to our bankruptcy characteristics that proxy for favorable shareholder outcomes. Panel A of Table 4 shows that in 34 out of the 100 bankruptcies between 1980 and 2012 with data on bankruptcy distributions, shareholders received a payment. In 23 cases, equity holders formed a committee, and in 80 cases, firms emerged from bankruptcy. The average amount of distributions to secured creditors, unsecured creditors, and shareholders is 1.085 billion USD, including a few very large distributions. On average, shareholders recover 2.9% of all distributions in bankruptcy. If we restrict the sample to bankruptcies with positive payments to shareholders (Panel B), we find that shareholders receive on average 8.5% of all distributions. Panel C relates the existence of an equity committee and firm emergence to the number of cases with positive payments to shareholders. If an equity committee is not present, shareholders received a payment in only 13 out of 73 cases, while out of 23 cases with an equity committee, shareholders receive a payment in 21 cases. A similar (but less strong) pattern can be observed for our dummy variable capturing firm emergence, with the percentage of cases involving a payment to shareholders rising from 15% (no emergence) to 39% (emergence). Both relationships show statistical significance (p-value of 0.000 and 0.047) using a Wilcoxon signed ranked test.

To test whether predicted abnormal stock returns at bankruptcy are related to our proxies for shareholder outcomes, we create predicted abnormal stock returns at bankruptcy using our twelve months prediction model from the previous section. To allow our variables to capture time-series changes in the legal environment, we calibrate the prediction model using a rolling window of 15 years of data. This procedure obtains out-of-sample forecast results at the firm level for the time period from 1984 to 2014. We match predicted abnormal stock

[10] Shares from firms in the BRD do not necessarily trade at a (major) exchange, are delisted before the bankruptcy, or have missing balance sheet data.

returns calculated twelve months before the bankruptcy filing to the bankruptcy case data in the BRD, and winsorize predicted abnormal stock returns at the 5%/95%-level. The first and second column in Table 5 show the results of two probit regressions (marginal effects), using the dummy variable for the existence of an equity committee or firm emergence as the dependent variable, and our predicted abnormal stock returns as the explanatory variable. We find that our predicted values of abnormal stock returns are highly statistically significant predictors of the existence of an equity committee and firm emergence as indicated by the z-values. This relationship is economically strong, as a one standard deviation increase in our prediction value increases the likelihood of having an equity committee by 44.6% (8.6 percentage points) and an 11.5% higher likelihood for firm emergence (5.0 percentage points). Of particular interest to us are those firms that do not have a *realized* abnormal stock return at bankruptcy as the lack of these firms in our prediction sample could potentially introduce a bias. Therefore, we perform the same probit analysis separately for bankruptcies with and without a realized abnormal stock return at bankruptcy. Columns 3 to 6 in Table 5 show that the marginal effects and the level of statistical significance are of comparable magnitude with the effect for firm emergence being stronger among bankruptcy observations with realized abnormal stock return (marginal effect of 2.1) than for those without (marginal effect of 1.4). These results suggest that our prediction model is also able to forecast favorable shareholder outcomes for firms with missing return data at bankruptcy.

To summarize, the empirical results in this section suggest that our forecasted abnormal stock returns are economically and statistically strong predictors of favorable bankruptcy outcomes for shareholders and that this result also holds for firms with missing stock market data at bankruptcy.

4 Expected Stock Returns, Shareholder Losses, and Default Probabilities

In the following sections, we study the implications of shareholder losses on expected stock returns. Based on our theoretical model, we expect stocks with higher (lower) shareholder losses to earn higher (lower) expected stock returns. The default likelihood together with shareholder losses account for overall default risk. Therefore, we examine the risk compensation for shareholder losses at different levels of default probability and study if shareholder losses are able to shed more light on the distress anomaly.

4.1 Shareholder Losses and Expected Equity Returns

We use monthly CRSP stock returns of common stocks listed on NYSE, AMEX, or NASDAQ for our asset pricing tests and adjust stock returns using CRSP delisting returns.[11] Each month between 1984 and 2014, we calculate predicted out-of-sample abnormal stock returns at bankruptcy using the twelve months prediction horizon and a rolling calibration window of 15 years.[12] We use the negative values of the predicted abnormal stock returns at bankruptcy as an estimate for post-default shareholder losses ($LGD_t := -\widehat{BHAR}_t$) and sort stocks into quintiles on the basis of this measure in the following month. The ranking is then used to form value-weighted portfolios. Following Campbell, Hilscher, and Szilagyi (2008), we exclude stocks with a stock price below 1 USD in the month of portfolio formation.

Summary statistics for the results of this procedure are presented in Table 6. We present average raw excess returns for each of the quintile portfolios, alphas with respect to the Fama

[11] We exclude financial firms (SIC code 6000-6999) and do not use stock return data after a company has defaulted (here, we use the broader default definition of Campbell, Hilscher, and Szilagyi (2008), see Section 4.2). Following Shumway (1997), we adjust stock returns with CRSP delisting stock returns if the delisting code is 500 or between 520 and 584 and impose a delisting stock return of -30% if the delisting return is missing.

[12] We have very few bankruptcy observations before 1971. To be consistent with the calibration of the default probability model, we start calibrating our model in 1971 and do not use predicted values before 1984.

and French (2016) five-factor model, and factor loadings. The table shows that the excess returns on the quintile portfolios increase with shareholder losses, suggesting that investors demand higher (lower) average returns for firms that are expected to have high (low) losses in case of bankruptcy. Firms in the highest shareholder loss quintile earn an average return of 91 basis points per month compared to 59 basis points per month for firms in the lowest quintile. This difference of 32 basis points, representing an average premium of approximately 3.9% per annum is economically fairly large but is not statistically different from zero at conventional statistical 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 shareholder loss-sorted portfolios relative to adjustment for the five factors explored in Fama and French (2016). In contrast to the raw returns, the results indicate that adjusting for risk present in these five factors, bearing higher shareholder losses leads to both an economically large and statistically significant higher average risk premium. Like the raw returns, excess returns on the quintile portfolios increase across quintiles. The bottom quintile portfolio earns an average excess return of -11 basis points per month that is indistinguishable from zero (t-value=-1.55), while the top quintile portfolio earns an average excess return of 65 basis points (t-value=4.38). These excess returns combine to suggest that a portfolio long high shareholder losses firms and short low shareholder losses firms earns an average excess return of 75 basis points per month (t-value=4.23).

In order to get some insight into the sources of covariation that dominate the shareholder loss portfolios, we present loadings on the five risk factors in Panel B of Table 6. The table indicates that the portfolios exhibit significant covariation with all of the factors with the exception of the investment factor, CMA. Loadings also tend to move in a near-monotonic pattern across quintiles; high shareholder loss 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 are less profitable. The difference in loadings between the high shareholder loss and low shareholder loss 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 four characteristics of the quintile portfolios; market capitalization, probability of failure implied by our estimates of Campbell, Hilscher, and Szilagyi (2008) failure model, shareholder loss predicted by our model, and asset book-to-market ratios. By construction, shareholder loss increases across quintiles; the average firm in the top quintile is expected to lose 43.8% of its equity value upon declaration of bankruptcy, while the average firm in the bottom quintile is expected to lose 21.6% of its value. While nowhere near as extreme as the variation in actual losses shown in the data, this difference of more than 22.2% in anticipated losses seems to us to be economically quite significantly different. As suggested by the factor loadings, firms in the high shareholder loss portfolio are on average considerably smaller than those in the low shareholder loss portfolio. Finally, the statistics suggest a correlation between the probability of failure and shareholder loss. Firms in the top quintile have on average a predicted rate of failure of 0.043%, while those in the bottom quintile have a predicted failure rate of 0.039%. These results suggest that the effect of failure probability and shareholder loss are positively correlated, and we next examine the degree to which we can disentangle these effects.

4.2 Shareholder Losses, Probability of Failure, and Average Returns

In order to explore the links between shareholder losses and the probability of failure, we first conduct an analysis similar to that in Campbell, Hilscher, and Szilagyi (2008) and document that our sample firms with high probabilities of failure have low average returns relative to those with a low probability of failure. We follow Campbell, Hilscher, and Szilagyi

(2008) in estimating failure probability using a set of accounting and market-based variables. Similarly, the shareholder loss model uses both accounting and market-based variables to forecast expected shareholder losses.

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

$$\begin{aligned} FAIL_{i,t+\tau} = \quad & b_0 + b_1 NIMTAAVG_{i,t} + b_2 TLMTA_{i,t} + b_3 EXRETAVG_{i,t} + b_4 SIGMA_{i,t} \\ & + b_5 RSIZE_{i,t} + b_6 CASHMTA_{i,t} + b_7 MB_{i,t} + b_8 PRICE_{i,t} + e_{i,t+\tau}. \end{aligned} \tag{6}$$

Accounting variables are obtained from quarterly Compustat files and stock market variables are obtained from CRSP. 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.[13] 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 USD. Detailed variable descriptions are available in Appendix C. We calibrate the failure probability model similar to our prediction model for shareholder loss and estimate a default probability for each stock every month for the time period from 1984-2014 using a twelve months prediction horizon, and a rolling sample window of 15 years. The failure probability model is extensively examined in Campbell, Hilscher, and Szilagyi (2008); here we simply compare results using a different time frame. The results of the estimation are presented in Table C.2 in Appendix C.2. As shown in the table, the

[13] We follow the original paper and use a broader default definition by additionally including stock delistings due to financial reasons (CRSP delisting codes 560, 574, 580, or 584) and default credit ratings from S&P's ('D' default and 'SD' for selective default) to estimate the probability of failure.

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 effects on failure probability, while leverage, market-to-book, and volatility exert positive 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).

We sort firms into deciles on the basis of the predicted probability of failure each month and hold the firms in value-weighted portfolios. Summary statistics for these portfolios are presented in Table 7. Raw returns decrease across deciles from 68 basis points per month for the lowest probability of failure decile to -14 basis points per month for the highest probability of default decile; the difference of 82 basis points per month is marginally statistically significant. Adjusting for the Fama and French (2016) factors, a strategy long the lowest probability of default decile and short the highest probability of default decile earns an excess return of 89 basis points per month, statistically significant at the 5% threshold. This difference is of comparable magnitude to the results for firms sorted on shareholder losses.

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 a low probability of default. These results are similar to those documented for portfolios sorted on shareholder losses. One difference in the results for the probability of default relative to shareholder loss is the fact that firms with low probabilities of default appear to covary more with growth firms, while the high probability of default firms exhibit a positive loading on the HML factor. The difference between the high probability of default and low probability of default firms' loading is statistically significantly positive and of opposite sign to the difference for shareholder loss. Like the results for shareholder loss, 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 patterns for characteristics of firms sorted on probability of default compared to those of firms sorted on shareholder loss. Market capitalizations of firms decrease across probability of default deciles. Probabilities of default increase more steeply across default probability deciles than shareholder loss quintiles, ranging from 0.02% on average for the lowest decile firms to 0.78% for the highest decile firms. Finally, shareholder losses exhibit a non-linear relationship across deciles, though less steeply than those for portfolios sorted on predicted shareholder losses. The shareholder loss rates decrease from 30.9% for the bottom decile of default probability firms to 27.5% for the fourth decile and then again increase to 31.3% for the highest decile. Thus, as suggested above, there are strong commonalities in probability of default and shareholder losses in terms of factor loadings and market capitalization.

To try to tease out differences in probability of default and shareholder losses, we proceed sorting firms independently into portfolios according to shareholder loss and probability of failure. We sort stocks into quintiles based on failure probability and into quantiles of low (0%-30%), medium (30%-70%), and high (70%-100%) expected shareholder loss at bankruptcy. Given our results thus far, there is some concern that there is insufficient independent variation in probability of failure and shareholder loss to generate a complete set of portfolios based on independent sorts. However, in each month of our sample, we are able to find a sufficient number of intersections. Not surprisingly, there are on average fewer firms at the intersection of low shareholder loss and high probability of default quintiles (214 stocks on average).

The table also presents excess returns on each portfolio relative to the Fama and French (2016) five-factor model. The patterns across quantiles of probability of failure and shareholder loss documented in univariate sorts remain the same but are generally more extreme than those reported above. For firms with low shareholder loss, the difference in the excess return on high probability of failure and low probability of failure firms is -0.83% per month (t-value is -2.68), for firms with medium shareholder losses, the excess return is -1.25% per month (t-value is 3.63). Firms with high probabilities of failure exhibit a difference across high and low shareholder loss quantiles of 1.30% per month, also statistically significantly different than zero at the 1% critical level. Across low and medium shareholder loss quantiles, average excess returns of high and low probability of failure firms decrease monotonically, while average excess returns of high shareholder loss firms do not increase across probability of failure quintiles.

Of particular interest is the pattern of excess returns for firms with high shareholder loss at default. 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 the announcement of bankruptcy, that they do not require average returns that are statistically different for firms with a high probability of default than a low probability of default. That is, the anomalous pattern documented in Campbell, Hilscher, and Szilagyi (2008) is no longer statistically present. In contrast, the pattern documented in Campbell, Hilscher, and Szilagyi (2008) appears to be most severe if investors expect medium or 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 shareholder loss at bankruptcy, 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 modest or low.

4.3 Shareholder Losses at Bankruptcy, Probability of Failure, and the Cross-Section of Expected Returns

The evidence in the preceding section suggests that expected shareholder losses at bankruptcy 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 shareholder losses. In each month $t+1$, we regress excess returns on a set of firm characteristics, predicted probability of failure, and predicted shareholder loss ($LGD_t := -\widehat{BHAR}_t$):

$$ER_{i,t+1} = \gamma_{0,t} + \sum_k \gamma_{k,t} X_{i,k,t} + \gamma_{Fail,t} Fail_{i,t} + \gamma_{LGD,t} LGD_{i,t} + u_{i,t+1}. \tag{7}$$

The variables $\mathbf{X}_{i,t}$ are a set of firm-specific characteristics that have been documented to be related to average returns. We additionally tease out interaction effect between default probabilities and shareholder losses using dummy variables that take the value of one if a stock has a low default probability (shareholder loss) in the 0%-20% quantile in the previous month, denoted as $D_{LowFail,t-1}$ ($D_{LowLGD,t-1}$), a medium default probability (shareholder loss) in the 20%-80% quantile in the previous month, denoted as $D_{MediumFail,t-1}$ ($D_{MediumLGD,t-1}$), or high default probability (shareholder loss) in the 80%-100% quantile in the previous month, denoted as $D_{HighFail,t-1}$ ($D_{HighLGD,t-1}$) and zero otherwise. We report average point estimates of the coefficients (in percent), as well as t-statistics calculated using autocorrelation and heteroskedasticity-consistent standard errors. As before, we exclude stocks with stock prices below one USD in the previous month.

One issue that demands consideration is which firm-specific characteristics, $\mathbf{X}_{i,t}$ to include in the regression. Harvey, Liu, and Zhu (2016) 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 shareholder loss. In particular, we include profitability (ROA_{Y-1}), log size ($LogSize_{t-1}$), log book-to-market ($LogBM_{t-1}$), 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 (Rev_{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 (2016).

We follow Lewellen (2015) and winsorize all independent variables each month at the 1% and 99%-level. We additionally standardize all independent variables each month by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation. We can therefore directly compare the coefficient estimates, which reflect the impact on the stock return of a one standard deviation shock to the independent variable. Estimation results are presented in Table 10. The first column of the table presents results including just the firm-specific characteristics, restricting $\gamma_{FAIL,t} = \gamma_{LGD,t} = 0$. 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 (2016), among others. Consistent with Fama and French (1992), the book-to-market 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 column of the table, we include shareholder losses at bankruptcy (LGD_{t-1}) as explanatory variables. 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 factor increase from 0.13 to 0.20 after including shareholder loss. When we include dummy variables for different levels of default probability in the third column, we find that the shareholder loss effect on average returns is stronger for firms more likely to default. The coefficient value increases from 0.14 (t-value 1.67) for firms in the lowest quintile of default likelihood to 0.52 (t-value 4.29) for firms in the highest default quintile.

In the fourth column, we include failure probability ($Fail_{t-1}$) as an independent variable. 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, but the effect is statistically only marginally significant. If we interact default probability with our dummy variables for low, medium, and high shareholder losses, we find that stocks with low expected shareholder losses exhibit a negative influence on average stock returns, while stocks with high expected shareholder losses exhibit a positive influence of default probability on average returns, consistent with our theoretical predictions. In the seventh column, we present the results of the unrestricted regression. Including failure probability and shareholder loss, the slope coefficient of default probability decreases and the effect is no longer statistically significant at conventional levels, while the effect of shareholder losses remains highly statistically significant.

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 shareholder losses, we restrict its coefficient to zero and report the results in the fifth column. Surprisingly, the effect of failure probability loses its statistical significance if one excludes the short-term reversal factor. One possible explanation for this finding is that the excess stock return measured at the prior month enters as a 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, 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.

We additionally explore the relevance of financial distress risks for larger firms and repeat the analysis for firms having a market value of equity larger than the 10th-percentile of firms listed at NYSE. As firms under financial distress risk usually experience a decline in the market value of equity in the months before the bankruptcy filing, this restricted sample is most likely characterized by stocks, which are less affected by financial distress. Table 10 shows the result of the analysis for firms with an equity value above the 10th-percentile of NYSE stocks in the previous month. In column 2, we find that the effect of shareholder losses on average stock returns is weaker than before, but remains statistically significant at the 5%-threshold. As column 3 shows, for firms in the highest quintile of default likelihood, the effect remains economically and statistically strong, which indicates that shareholder losses are also relevant among larger stocks. For failure probability, both, the economic and statistical magnitude decline and only stocks with a low expected shareholder loss at bankruptcy exhibit a (statistically weak) negative impact on average stock returns.

The results in this section suggest several interesting findings. First, there appears to be a robust positive premium associated with expected shareholder loss. 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, 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

Researchers have long speculated that 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 puzzling negative relation between the probability of failure and future average returns. The literature suggests differences in shareholder losses upon bankruptcy as one potential explanation for this finding, based on the fact that shareholders are frequently able to recover part of the firm value following default. Empirical evidence supporting this explanation, however, remains limited and previous studies rely on single firm- and industry-level characteristics as estimates for expected shareholder losses rather than attempting to measure these losses directly.

This paper produces the first attempt that we are aware of to directly measure shareholder losses upon default. Our approach echoes the vast literature addressing the estimation of default probabilities and uses firm and industry characteristics to measure the extent of shareholder losses upon announcement of a bankruptcy filing. We then use our forecast estimates to study the relation between failure likelihood, shareholder losses, and expected stock 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 shareholder losses are expected to be relatively low, and statistically indistinguishable from zero for firms in which equity loss rates are expected to be high. With these findings, we add to the insight that distress risk is more multi-faceted than probability of default alone.

Finally, we show in Fama and MacBeth (1973) regressions that the premium for shareholder losses at bankruptcy is robustly positive controlling for other cross-sectional return predictors and 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 Theoretical relationship between expected stock returns and bankruptcy losses for shareholders

A.1 Merton (1974) model and shareholder losses at default

We provide a simple extension of the Merton (1974) model to show how bankruptcy losses for shareholders impact expected stock returns. As in the basic Merton (1974) model, we assume a firm with an outstanding zero-coupon bond with maturity T and notional K. The asset value process under the physical measure is given by

$$\frac{dV_t}{V_t} = \mu \cdot dt + \sigma \cdot dW_t^P \tag{A.1}$$

V_t denotes the asset value at time t, μ is the expected asset return, σ is the volatility of the asset value process, and W_t^P is a standard Brownian motion. The asset value is identical to firm value in our setup as we abstract from taxes. At maturity, shareholders can decide whether to repay creditors or strategically default on the debt payment. If shareholders repay creditors, they receive $\max(0, V_T - K)$. If shareholders default on the debt payment, they enter into a Nash bargaining game with creditors that allows for asymmetric bargaining power. If bargaining is successful, debt is exchanged into equity (debt-to-equity swap) and the asset value is distributed among both groups according to the following sharing rule:

$$\theta^\star = \underset{0 \leq \theta \leq \alpha}{\operatorname{argmax}} (\theta \cdot V_T)^\eta \cdot ((1-\theta) \cdot V_T - (1-\alpha) \cdot V_T))^{1-\eta} = \alpha \cdot \eta \tag{A.2}$$

θ is the percentage of firm value which shareholders receive as a result of the bargaining game, α is the proportional bankruptcy costs (with $0 \leq \alpha \leq 1$), and η is the bargaining power coefficient of shareholders (with $0 \leq \eta \leq 1$). We set $\rho := 1 - \alpha \cdot \eta$ with $0 < \rho \leq 1$.[14] If bargaining fails, the firm is liquidated and shareholders receive nothing. For a similar

[14] We exclude the trivial case that $\rho = 0$ in our calculations below for simplicity. One can easily show that in this case, equity value equals firm value and shareholders will always file for default.

type of bargaining setup see Leland (1994), Fan and Sundaresan (2000), Davydenko and Strebulaev (2007), and Garlappi et al. (2008). Shareholders will always file for bankruptcy if it is beneficial for them (firm value falls below a certain threshold). More specifically, shareholders file for bankruptcy if

$$\begin{aligned} &\max(0, V_T - K) < (1-\rho) \cdot V_T, \\ &\Leftrightarrow V_T < K/\rho. \end{aligned} \tag{A.3}$$

Using risk-neutral valuation, the equity value S at time $t < T$, setting $K' := K/\rho$, is given by

$$S_t = E_t^Q\{e^{-r\cdot(T-t)}((V_T - K) \cdot 1_{\{V_T \geq K'\}} + (1-\rho) \cdot V_T \cdot 1_{\{V_T < K'\}})\}. \tag{A.4}$$

The expression above can be rewritten as

$$= \underbrace{e^{-r(T-t)} \cdot E_t^Q\{(V_T - K) \cdot 1_{\{V_T \geq K'\}}\}}_{(1)} + \underbrace{e^{-r(T-t)} \cdot E_t^Q\{(1-\rho) \cdot V_T \cdot 1_{\{V_T < K'\}}\}}_{(2)}. \tag{A.5}$$

We can solve each expectation separately using standard option pricing techniques:

$$(1) : e^{-r(T-t)} \cdot E_t^Q\{(V_T - K) \cdot 1_{\{V_T \geq K'\}}\} = V_t \cdot N(d_1) - K \cdot e^{-r(T-t)} \cdot N(d_2) \tag{A.6}$$

$$(2) : e^{-r(T-t)} \cdot E_t^Q\{(1-\rho) \cdot V_T \cdot 1_{\{V_T < K'\}}\} = (1-\rho) \cdot V_t \cdot N(-d_1), \tag{A.7}$$

with (note that d_1 and d_2 are expressed as functions of K')

$$\begin{aligned} d_1 &= \frac{1}{\sigma\sqrt{T-t}} \cdot (\ln V_t - \ln K' + (r + \frac{\sigma^2}{2})(T-t)) \\ d_2 &= d_1 - \sigma\sqrt{T-t} = \frac{1}{\sigma\sqrt{T-t}} \cdot (\ln V_t - \ln K' + (r - \frac{\sigma^2}{2})(T-t)). \end{aligned}$$

Using the fact that $N(-d_1) = 1 - N(d_1)$, we obtain

$$\begin{aligned} S_t &= V_t \cdot N(d_1) - K \cdot e^{-r(T-t)} \cdot N(d_2) + (1-\rho) \cdot V_t \cdot N(-d_1) \\ &= (1-\rho) \cdot V_t + \rho \cdot (V_t \cdot N(d_1) - K' \cdot e^{-r(T-t)} \cdot N(d_2)). \end{aligned} \tag{A.8}$$

Equation A.8 shows that equity can be interpreted as a portfolio containing the firm-value and a standard call option with strike price K'. The fractions $1-\rho$ and ρ serve as portfolio weights. In this model, it can be shown that the instantaneous expected excess return on equity is

$$\mu_S - r = (\mu - r) \cdot \frac{V_t}{S_t} \cdot S_V. \tag{A.9}$$

In order to show the relationship between ρ and (instantaneous) expected stock returns, we need to obtain the first derivative of the option elasticity $\frac{V_t}{S_t} \cdot S_V$ with respect to ρ. We start by calculating S_V using Equation A.8:

$$S_V = (1-\rho) + \rho \cdot N(d_1). \tag{A.10}$$

Using Equation A.8 and Equation A.10, we can rewrite $EL = \frac{V_t}{S_t} \cdot S_V$ for our model as

$$EL = \left(1 - e^{-r(T-t)} \cdot \frac{K}{V_t} \cdot \frac{N(d_2)}{1 - \rho N(-d_1)}\right)^{-1}. \tag{A.11}$$

For simplicity, we set $h(\rho) = \frac{N(d_2)}{1-\rho N(-d_1)}$ and first solve

$$\frac{\delta h(\rho)}{\delta \rho} = \frac{e^{r(T-t)} \cdot (\sigma\sqrt{T-t})^{-1} \cdot \phi(d_1) \cdot S_t/K + N(d_2) \cdot N(-d_1)}{(1-\rho N(-d_1))^2} > 0, \tag{A.12}$$

where $\phi(\cdot)$ is the density function of the standard normal distribution (for this result, we have employed $\phi(d_2) = \phi(d_1) \cdot \frac{V_t}{K} \cdot e^{r \cdot (T-t)}$ and Equation A.8). Using Equation A.12, we can obtain the first derivative of the option elasticity with respect to ρ, which proves the final result:

$$\frac{\delta EL}{\delta \rho} = \underbrace{-\left(1 - \frac{K}{V_t} \cdot e^{-r(T-t)} \cdot h(\rho)\right)^{-2}}_{<0} \cdot \underbrace{\left(-e^{-r(T-t)} \frac{K}{V_t}\right)}_{<0} \cdot \underbrace{\left(\frac{\delta h(\rho)}{\delta \rho}\right)}_{>0} > 0. \tag{A.13}$$

A.2 Simulation

This section provides details on the simulation results shown in Figure 1. We simulate the model above and report average monthly realized stock returns for stocks sorted by failure probability using different values of ρ (0.2, 0.4, 0.6, 0.8). We assume a continuously compounded risk-free rate of 4%, a default horizon (constant maturity) of one year, and sample twelve months of realized stock returns for each firm in our simulation. We randomly draw parameter values for the expected asset return (μ), asset volatility (σ), and (initial) leverage ratio (K/V_0) for 100,000 firms using truncated normal distributions with the following parameters:

- Asset return (μ): mean 5%, standard deviation 5%, lower limit 1%, upper limit 15%
- Asset volatility (σ): mean 20%, standard deviation 20%, lower limit 5%, upper limit 60%
- Initial leverage ratio (K/V_0): mean 60%, standard deviation 10%, lower limit 20%, upper limit 90%

B Predictor Variables for Abnormal Stock Returns at Bankruptcy

B.1 Predictor Variable Selection Procedure

In order to select the predictor variables for abnormal stock returns at bankruptcy with the highest forecasting power, we use the lasso (least absolute shrinkage and selection operator) procedure of Tibsharanit (1996). The lasso procedure chooses a sparse set of variables in a regression setup by setting some of the regression coefficients to zero. As we employ a linear function of the predictor variables, the objective function of the lasso procedure is:

$$\min_{a_0,a} \frac{1}{2N} \sum_{i=1}^{N} (BHAR_{i,t} - a_0 - a' x_{i,t-12})^2 + \lambda \, ||a||_1 \tag{B.14}$$

where $x_{i,t-12}$ are the firm- and industry-specific predictor variables described in Appendix B.1, measured twelve months before the default event, a_0 is a constant, a is a parameter vector, and λ is the penalty parameter of the lasso procedure (for the L_1-norm of a). Intuitively, the lasso procedure chooses a parameter set that minimizes the squared error of the regression model and additionally adds a penalty term for increasing the number of predictors. To account for different measurement units, the variables entering the lasso procedure are standardized before applying the procedure.

We apply the lasso procedure using 401 bankruptcies with information about realized abnormal stock returns at bankruptcy and all predictor variables. We employ the R software package glmnet based on Friedman, Hastie, and Tibshirani (2010) to estimate the lasso results. The results of the lasso selection are provided in the left graph in Figure B.1, which shows the path of the coefficient values for each predictor (after standardization) for different levels of the penalty parameter (displayed as the natural logarithm of λ). The upper axis indicates the number of coefficients which are different from zero at the respective value of the penalty parameter.

In order to evaluate the forecasting power of each predictor, we apply a five-fold cross-validation procedure (with a random selection of observations into sub-samples). The right graph in Figure B.1 shows the results of the cross-validation with the mean-squared error as a function of the natural logarithm of the penalty parameter. The first dashed line refers to the value of $ln(\lambda)$ at which the minimal mean-squared error is achieved, the second dashed line refers to the largest value of the penalty parameter that is within one standard error of the minimum mean-squared error. Based on the cross-validation results, we choose the following four predictor variables which have the highest forecasting power: $RDEXP$, ratio of research and development expenses ($RDEXP$), firm liquidation value based on Berger, Ofek, and Swary (1996) ($LIQUVAL$), median industry cash ratio ($INDCASH$), ratio of convertible to total debt ($CONVDEBT$).

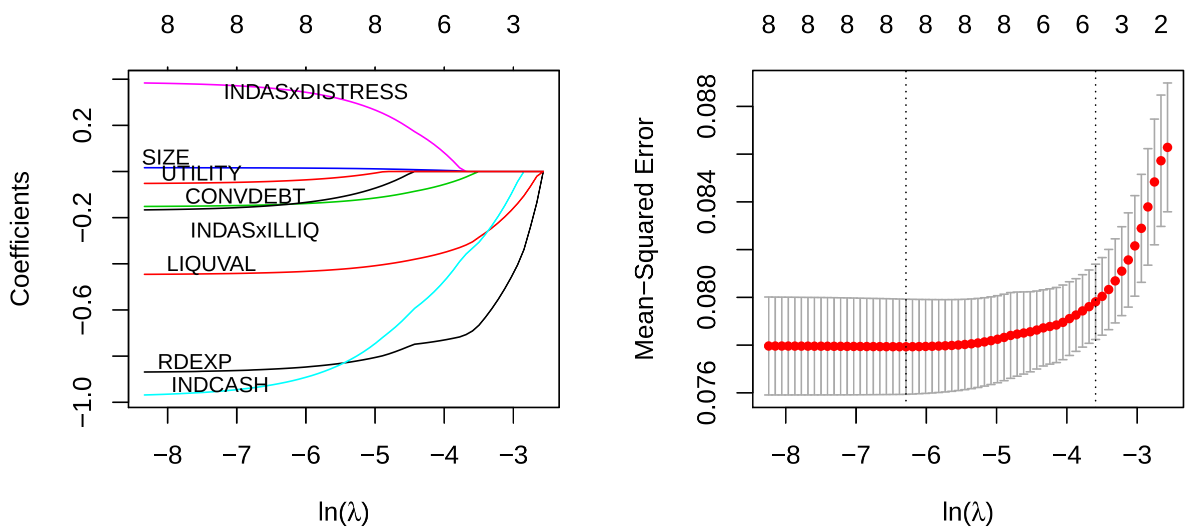
Table B.1: Predictor Variables for Abnormal Stock Returns at Bankruptcy

The table shows the construction of the variables used in the prediction model for abnormal buy-and-hold stock returns. Accounting values are based on annual Compustat data, stock market data is from CRSP (mnemonics are reported in parentheses) and measured twelve months before the bankruptcy filing. Missing values of the variables CONVDEBT, INDAS×DISTRESS, and INDAS×ILLIQ are imputed using sample means. Variables are winsorized at the 5%/95%-level.

Variable	Definition
RDEXP	Ratio of research and development expenses (XRD) divided by the market value of assets. The latter is defined as the market value of equity (PRC×SHROUT) and book value of liabilities (LT). Missing values of XRD are replaced by zeros following Berger, Ofek, and Swary (1996).
LIQUVAL	To measure firm liquidation value, we employ the measure of Berger, Ofek, and Swary (1996): $LIQUVAL = (0.715 \cdot RECT + 0.547 \cdot INVT + 0.535 \cdot PPENT + CHE)/AT$ We use the Compustat items total receivables (RECT), total inventories (INVT), net property, plant and equipment (PPENT), cash and short-term investments (CHE), and book value of assets (AT).
CONVDEBT	The ratio of convertible debt to total debt is defined as the ratio of convertible debt (DCVT) to the sum of debt in current liabilities (DLC) and long-term debt (DLTT).
UTILITY	Dummy variable that takes the value of one for firms in the utility industry (SIC code between 4900 and 4999) and zero otherwise.
SIZE	Firm size is measured as the natural logarithm of the market value of assets, defined as the market value of equity (PRC×SHROUT) plus book value of liabilities (LT).
INDAS×DISTRESS	Industry asset specificity in distressed industries is defined as the product of industry asset specificity and a dummy variable that captures industry distress. We measure industry asset specificity using the value of machinery and equipment divided by the book value of total assets (AT). If available, we use the Compustat item PPENME to measure machinery and equipment. If PPENME is not available, we use the Compustat item FATE. The dummy variable for industry distress equals one if the rolling twelve months industry stock return is below -30% and zero otherwise, following Acharya, Bharath, and Srinivasan (2007). We use three-digit SIC codes as industry classification and aggregate asset specificity and industry stock returns across stocks using the median.
INDAS×ILLIQ	Alternative measure for asset specificity in distressed industries using the median level of illiquidity of firms in the industry to capture distress: The definition is similar to the variable INDAS×DISTRESS, replacing the dummy for industry distress with median industry illiquidity. Industry illiquidity is defined as the inverse of the interest coverage ratio. The latter is defined as the difference between current assets (ACT) and inventories (INVT) divided by current liabilities (LCT).
INDCASH	Industry cash endowment is the median cash ratio in the industry. We measure the cash ratio as the ratio of cash and short-term investments (CHE) divided by the market value of assets. The latter is defined as the market value of equity (PRC×SHROUT) and book value of liabilities (LT).

Figure B.1: Results of Lasso Selection Procedure

The figures show the results of a lasso (least absolute shrinkage and selection operator) procedure based on Tibsharanit (1996) for choosing among predictor variables (see Appendix B.1) those with the highest forecasting power for abnormal stock returns at bankruptcy. The lasso procedure is implemented using 401 firms that filed for bankruptcy between 1965 and 2014 and predictor candidates lagged by twelve months. The left figure shows the coefficient path of each (standardized) predictor variable depending on the natural logarithm of the penalty parameter λ. The right graph shows the mean-squared error of a five-fold cross-validation procedure as a function of the natural logarithm of the penalty parameter λ. The first dashed line in the right figure refers to the value of $ln(\lambda)$ at which the minimal mean-squared error is achieved, the second dashed line refers to the largest value of the penalty parameter that is within one standard error of the minimum mean-squared error. The upper axes in both figures show the number of predictor variables that are selected for each value of $ln(\lambda)$.



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, use quarterly Compustat and monthly CRSP data, and winsorize all variables at the 5%/95%-level. 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 the sum of market value of equity (PRC×SHROUT) and book value of total liabilities (LTQ).
TLMTA	Total liabilities (LTQ) divided by market value of total assets (PRC×SHROUT+LTQ).
EXRETAVG	Moving average of the difference of the natural logarithm of the (gross) stock return minus the natural logarithm of the (gross) market return (SPRTRN) over the previous twelve months using geometrically declining weights.
SIGMA	Standard deviation of annualized daily stock returns over the previous three months (calculated if at least five stock returns are available).
RSIZE	Logarithm of the ratio of market value of equity (PRC×SHROUT) and market capitalization of all S&P's 500 firms (TOTVAL).
CASHMTA	Ratio of cash and short-term investments (CHEQ) and market value of total assets (PRC×SHROUT+LTQ).
MB	Ratio of the market value of equity (PRC×SHROUT) and the adjusted book value of equity. Following Campbell, Hilscher, and Szilagyi (2008), book value of equity is calculated as in 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. If stockholder's equity is missing, the sum of book value of common equity (CEQQ) and the par value of preferred stock (PSTKQ) is used. If the later data is also missing, stockholder's equity is calculated as the difference between total assets (ATQ) and total book value of liabilities (LTQ). The book value of preferred stock is calculated using the item PSTKRQ, or PSTKQ if the former is missing. In a second step, a 10% difference between the market value of equity and stockholder's equity is added (adjusted book value of equity is replaced with a value of 1 USD if still negative).
PRICE	Natural logarithm of stock price (PRC), with stock price being winsorized at 15 USD.

Table C.2: Default Probability Prediction Results

The table shows estimation results of the logit default probability prediction model from Campbell, Hilscher, and Szilagyi (2008). The dependent variable is a dummy variable that takes the value of one if a firm defaults in a given month and zero otherwise. We use the extended failure definition of Campbell, Hilscher, and Szilagyi (2008) to capture defaults and calibrate the model using all data from 1973 to 2014. The extended default definition includes bankruptcies from Chava and Jarrow (2004) (updated in Chava (2014) and Alanis, Chava, and Kumar (2018)), S&P's credit ratings ('D' - default, and 'SD' - selective default), and includes share delistings due to financial reasons. Explanatory variables are lagged by twelve months relative to the default event, are calculated using quarterly Compustat (lagged by four months) and monthly CRSP stock market data, and are winsorized at the 5%/95%-level. We present coefficient values of the logit model and z-scores (in parentheses) from the paper of Campbell, Hilscher, and Szilagyi (2008) and for our sample. Mc Fadden's pseudo-R^2 values are provided at the end of the table.

	CHS (2008) 1963-2003	Our sample 1973-2014
Intercept	−9.16	−9.14
	(30.89)	(34.90)
NIMTAAVG	−20.26	−13.64
	(18.09)	(18.02)
TLMTA	1.42	1.57
	(16.23)	(20.41)
EXRETAVG	−7.13	−6.31
	(14.15)	(16.23)
SIGMA	1.41	0.40
	(16.49)	(6.72)
RSIZE	−0.04	−0.18
	(2.09)	(9.43)
CASHMTA	−2.13	−1.86
	(8.53)	(10.16)
MB	0.08	0.17
	(6.33)	(17.54)
PRICE	−0.06	−0.46
	(1.40)	(13.70)
N	1,565,634	1,666,009
Failures	1,968	3,217
Pseudo-Rsq	11.40	14.01

Figure 1: Simulation results

This graph shows average monthly realized stock returns (in percent) that result from a model simulation with stocks being group into quintiles according to failure probability. We randomly draw parameter values for expected asset return (μ), asset volatility (σ), and initial leverage ratio (K/V_0) for a total of 100,000 firms. Using these firm parameter values, we simulate twelve months of realized returns using a (constant) debt maturity of one year and a continuously compounded risk-free rate of 4%. Further details on the simulation can be found in Appendix A.2.

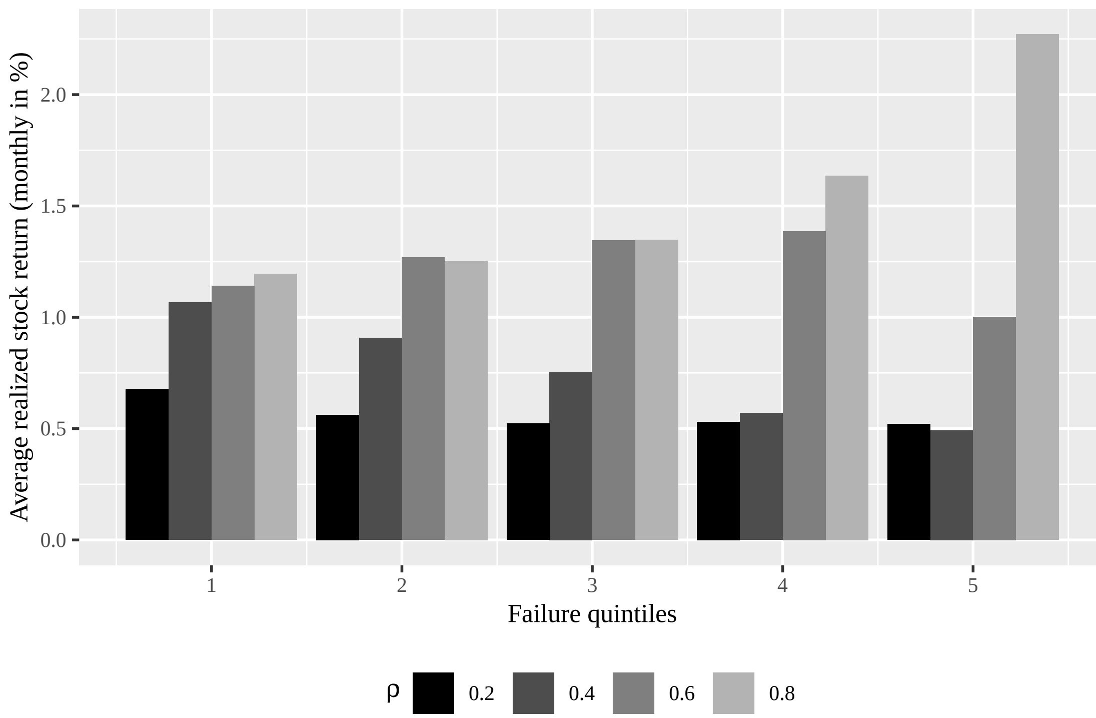


Table 1: Summary Statistics for Abnormal Stock Returns at Bankruptcy Filing

The table shows summary statistics for daily abnormal stock returns for a sample of 401 firms that filed for bankruptcy between 1965 and 2014. Average daily abnormal stock returns (AR_t) are shown for a ten-day window around the bankruptcy filing together with the average abnormal buy-and-hold stock return ($BHAR_t$) for a three-day window around the bankruptcy filing. Abnormal stock returns are calculated by subtracting the return of the S&P's 500 index. Daily abnormal stocks are included in the sample if the stock traded on all three days around the bankruptcy filing (N is the number of stock observations for each day). Daily abnormal stock returns and $BHAR_t$ are winsorized at the 95%-level.

	Mean	Std	Min	Q25	Median	Q75	Max	N
AR_{t_D-5}	-0.023	0.138	-0.764	-0.071	-0.006	0.023	0.250	397
AR_{t_D-4}	-0.015	0.120	-0.732	-0.058	-0.004	0.032	0.226	399
AR_{t_D-3}	-0.031	0.124	-0.833	-0.062	-0.008	0.014	0.178	399
AR_{t_D-2}	-0.032	0.150	-0.802	-0.079	-0.009	0.022	0.235	401
AR_{t_D-1}	-0.036	0.148	-0.840	-0.084	-0.014	0.024	0.231	401
AR_{t_D+0}	-0.181	0.264	-0.966	-0.326	-0.096	0.004	0.186	401
AR_{t_D+1}	-0.144	0.278	-0.936	-0.333	-0.104	0.027	0.299	401
AR_{t_D+2}	0.024	0.212	-0.630	-0.099	-0.002	0.121	0.491	393
AR_{t_D+3}	0.004	0.185	-0.590	-0.090	-0.003	0.102	0.422	386
AR_{t_D+4}	-0.012	0.175	-0.645	-0.085	-0.004	0.045	0.396	376
AR_{t_D+5}	-0.004	0.157	-0.665	-0.072	-0.002	0.058	0.366	374
$BHAR_t$	-0.342	0.294	-0.954	-0.595	-0.340	-0.070	0.137	401

Table 2: Descriptive Statistics of Predictor Variables.

This table shows summary statistics of firm- and industry-level variables used as predictor candidates for abnormal buy-and-hold stock returns at bankruptcy filing. Variables are based on monthly CRSP stock market data and annual Compustat data, refer to 401 firms that filed for bankruptcy between 1965 and 2014, and are calculated twelve months before the bankruptcy filing of the firm. $RDEXP$ is the ratio of research and development expenses to the market value of assets, $LIQUVAL$ is the firm liquidation value based on Berger, Ofek, and Swary (1996), $CONVDEBT$ is the ratio of convertible to total debt, $SIZE$ is the natural logarithm of the market value of total assets, $INDCASH$ is the median ratio of cash to market value of assets in the industry. $INDAS \times DISTRESS$ and $INDAS \times ILLIQ$ measure the intensity of industry fire-sales and are based on Acharya, Bharath, and Srinivasan (2007). $UTILITY$ is a dummy variable that takes the value of one if a firm is a utility firm. Industry classifications are based on three-digit SIC codes, predictor variables are winsorized at the 5%/95%-level.

	Mean	Std	Min	Q25	Median	Q75	Max
RDEXP	0.024	0.046	0.000	0.000	0.000	0.019	0.156
LIQUVAL	0.524	0.111	0.311	0.459	0.532	0.586	0.744
CONVDEBT	0.099	0.204	0.000	0.000	0.000	0.100	1.000
SIZE	5.310	1.541	2.878	4.031	5.179	6.547	8.110
INDCASH	0.068	0.049	0.011	0.031	0.053	0.092	0.190
INDAS×DISTRESS	0.033	0.079	0.000	0.000	0.000	0.000	0.000
INDAS×ILLIQ	0.201	0.152	0.035	0.084	0.149	0.267	0.555
UTILITY	0.035	0.184	0.000	0.000	0.000	0.000	1.000

Table 3: In-Sample Prediction of Abnormal Stock Returns at Bankruptcy for Different Lags

The table shows the results of regressing abnormal three-day buy-and-hold stock returns at bankruptcy on four variables identified by the least absolute shrinkage and selection operator (lasso) as predictor variables (see Appendix B.1). In-sample regression results are reported for different lags of the predictor variables (1, 3, 6, 12, and 24 months) relative to the bankruptcy filing month. A detailed description of the predictor variables can be found in Appendix B.1. N is the number of bankruptcies that enter the regression, depending on data availability. Heteroscedasticity-robust t-values are given in parentheses.

	t-24	t-12	t-6	t-3	t-1
Intercept	0.01	0.00	−0.07	−0.11	−0.11
	(0.17)	(0.00)	(−1.09)	(−1.55)	(−1.52)
RDEXP	−1.25	−0.94	−1.00	−0.99	−0.68
	(−2.64)	(−2.51)	(−3.10)	(−3.69)	(−3.01)
LIQUVAL	−0.50	−0.51	−0.38	−0.32	−0.31
	(−3.56)	(−3.75)	(−2.89)	(−2.47)	(−2.30)
CONVDEBT	−0.16	−0.14	−0.14	−0.17	−0.18
	(−2.58)	(−1.97)	(−2.08)	(−2.58)	(−2.81)
INDCASH	−0.68	−0.59	−0.45	−0.32	−0.47
	(−1.61)	(−1.62)	(−1.28)	(−0.95)	(−1.36)
N	359	401	419	430	428
R^2	0.13	0.12	0.12	0.12	0.11

Table 4: Bankruptcy Outcomes for Shareholders

This table shows bankruptcy outcomes for shareholders for a sample of 100 firms that filed for bankruptcy between 1980 and 2012. Default data is from UCLA-LoPucki Bankruptcy Research Database (BRD) and includes all bankruptcies with information on post-bankruptcy distributions. Panel A contains summary statistics on $D_{Payment}$, a dummy variable that is one if shareholders receive a payment after bankruptcy, $D_{Committee}$, a dummy variable that is one if an equity committee has been formed (zero otherwise), $D_{Emergence}$, a dummy variable that is one if the firm emerges from bankruptcy (zero otherwise), *Total Distributions*, the sum of all distributions made to creditors and equity holders (in bn USD), *Relative Equity Share*, the amount of distributions made to equity holders relative to total distributions. Panel B reports the same items but restricts the sample to firms with non-zero payments to equity holders after bankruptcy. In Panel C, we group the number of bankruptcies according to the existence of an equity committee (emergence from bankruptcy) and whether shareholders received a payment after bankruptcy. $\#\{Pay = 1\}/N$ reports the relative amount of observations with payments to shareholders for each group, $p - value$ refers to a Wilcoxon signed rank test that compares the mean of $D_{Payment}$ between the respective groups.

	Mean	Std	Q25	Median	Q75	N
Panel A: Summary - All Bankruptcies						
$D_{Payment}$	0.340	0.476	0.000	0.000	1.000	100
$D_{Committee}$	0.232	0.424	0.000	0.000	0.000	99
$D_{Emergence}$	0.800	0.402	1.000	1.000	1.000	100
Total Distributions	1.085	2.493	0.104	0.290	0.861	100
Relative Equity Share	0.029	0.073	0.000	0.000	0.010	100
Panel B: Summary - Bankruptcies with Post-Default Payments to Shareholders						
$D_{Committee}$	0.618	0.493	0.000	1.000	1.000	34
$D_{Emergence}$	0.912	0.288	1.000	1.000	1.000	34
Total Distributions	0.784	1.153	0.096	0.281	0.958	34
Relative Equity Share	0.085	0.106	0.012	0.041	0.128	34

Panel C: Payments to Shareholders and Bankruptcy Case Characteristics

	N	$D_{Payment} = 1$	$D_{Payment} = 0$	$\#\{Pay = 1\}/N$	p-value
$D_{Committee} = 0$	76	13	63	0.171	0.000
$D_{Committee} = 1$	23	21	2	0.913	
$D_{Emergence} = 0$	20	3	17	0.150	0.047
$D_{Emergence} = 1$	80	31	49	0.388	

Table 5: Bankruptcy Outcomes for Shareholders and Predicted Abnormal Stock Returns

This table shows the probit regression results of regressing a dummy variable capturing the existence of an equity committee ($D_{Committee}$) and a dummy variable for firm emergence ($D_{Emergence}$) on predicted abnormal stock returns at bankruptcy. Default data is from the UCLA-LoPucki Bankruptcy Research Database and covers firms that filed for bankruptcy between 1985 and 2014. Predicted abnormal stock returns at bankruptcy ($B\widehat{HA}R_{t-12}$) are calculated twelve months before the bankruptcy filing. Predicted values are available from 1984, calibrated over a 15-year rolling estimation window, and winsorized at the 5%/95%-level. The first two columns show results for all bankruptcies with information on bankruptcy outcomes, the third and fourth (fifth and sixth) column restrict the sample to firms without (with) data on realized abnormal stock returns at bankruptcy ($BHAR_t$). The table shows marginal effects, robust z-values (in parentheses), and Mc Fadden's pseudo-R^2.

	Full sample		Bankruptcies without $BHAR_t$		Bankruptcies with $BHAR_t$	
	$D_{Committee}$	$D_{Emergence}$	$D_{Committee}$	$D_{Emergence}$	$D_{Committee}$	$D_{Emergence}$
	(1)	(2)	(3)	(4)	(5)	(6)
$B\widehat{HA}R_{t-12}$	1.003	1.684	1.046	1.414	1.278	2.145
	(3.515)	(4.445)	(3.250)	(3.130)	(2.326)	(2.326)
Pseudo-Rsq	0.023	0.037	0.034	0.025	0.025	0.083
N	425	446	309	319	116	127
Log Likelihood	-204.93	-261.97	-132.31	-190.80	-67.273	-70.267

Table 6: Portfolios Sorted on Shareholder Losses at Bankruptcy

The table shows empirical results for monthly portfolio alphas for the period 1984-2014 using stocks sorted by shareholder losses at bankruptcy. Shareholder losses at bankruptcy (LGD) are based on out-of-sample forecasts of abnormal stock returns at bankruptcy ($LGD := -\widehat{BHAR}$), estimated every month using a twelve months prediction horizon. We sort stocks into quintiles based on shareholder losses in the previous month and calculate value-weighted portfolio returns. We also report results for a long-short-portfolio that goes long in the portfolio with the highest shareholder losses and goes short in the portfolio with the lowest shareholder losses (we additionally report long-short portfolio returns using decile sorts). Panel A shows portfolio returns in excess of the risk-free rate (RAW) and alphas for the five-factor model by Fama and French (2016) (FF5). Panel B shows loadings for the FF5 model, 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 descriptive statistics for each portfolio, including average estimated default probabilities (in percent), shareholder losses, market capitalization (in mn USD), and the ratio of book to market value of assets based on the previous month. Alphas are reported in percent, t-values are given in parentheses.

	Low LGD	2	3	4	High LGD	H-L$_{20\%}$	H-L$_{10\%}$
Panel A: Excess Returns							
RAW	0.59	0.64	0.75	0.81	0.91	0.32	0.62
	(2.60)	(2.87)	(3.29)	(2.64)	(2.31)	(1.19)	(1.84)
FF5	−0.11	−0.13	0.07	0.50	0.65	0.75	1.09
	(−1.55)	(−1.97)	(0.90)	(4.40)	(4.38)	(4.23)	(4.93)
Panel B: Factor Loadings							
MKT-RF	0.96	0.99	0.96	0.98	1.09	0.13	0.03
	(58.33)	(60.57)	(52.99)	(35.41)	(30.41)	(2.99)	(0.57)
SMB	−0.04	−0.04	−0.01	0.02	0.34	0.38	0.93
	(−1.59)	(−1.49)	(−0.43)	(0.41)	(6.45)	(5.97)	(11.83)
HML	−0.09	−0.08	−0.06	−0.27	−0.55	−0.46	−0.34
	(−3.06)	(−2.61)	(−1.67)	(−5.21)	(−8.23)	(−5.67)	(−3.34)
CMA	0.04	0.18	0.12	−0.24	−0.10	−0.14	−0.17
	(0.85)	(4.06)	(2.49)	(−3.16)	(−1.05)	(−1.19)	(−1.16)
RMW	0.17	0.21	0.06	−0.50	−0.77	−0.94	−1.03
	(5.49)	(7.11)	(1.73)	(−9.73)	(−11.60)	(−11.73)	(−10.33)
Panel C: Portfolio Characteristics							
Prob. of Failure	0.039	0.037	0.033	0.033	0.043		
LGD	0.216	0.273	0.308	0.359	0.438		
Market Cap.	3,446	3,038	2,452	1,742	716		
B/M	0.569	0.565	0.528	0.468	0.456		

Table 7: Portfolios Sorted on Failure Probability

The table shows empirical results for monthly portfolio alphas for the period 1984-2014 using stocks sorted by expected failure probabilities. Expected failure probabilities (*Fail*) are based on out-of-sample forecasts of the model of Campbell, Hilscher, and Szilagyi (2008), estimated every month using a twelve months prediction horizon. We sort stocks into deciles based on expected failure probability in the previous month and calculate value-weighted portfolio returns. We also report results for a long-short-portfolio that goes long in the portfolio with the highest expected failure probability and goes short in the portfolio with the lowest expected failure probability (we additionally report long-short portfolio alphas using quintile sorts). Panel A shows portfolio returns in excess of the risk-free rate (RAW) and alphas for the five-factor model by Fama and French (2016) (FF5). Panel B shows loadings for the FF5 model, 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 descriptive statistics for each portfolio, including average estimated default probabilities (in percent), shareholder losses, market capitalization (in mn USD), and the ratio of book to market value of assets based on the previous month. Alphas are reported in percent, t-values are given in parentheses.

	Low Fail	2	3	4	5	6	7	8	9	High Fail	H-L$_{10\%}$	H-L$_{20\%}$
Panel A: Excess Returns												
RAW	0.68	0.73	0.76	0.62	0.68	0.45	0.53	0.20	0.17	−0.14	−0.82	−0.62
	(3.05)	(3.25)	(3.30)	(2.35)	(2.27)	(1.34)	(1.44)	(0.47)	(0.35)	(−0.26)	(−1.78)	(−1.62)
FF5	0.10	0.15	0.04	−0.12	−0.10	−0.24	−0.16	−0.41	−0.57	−0.80	−0.89	−0.77
	(1.31)	(2.40)	(0.54)	(−1.28)	(−0.83)	(−1.56)	(−1.01)	(−2.22)	(−2.32)	(−2.27)	(−2.37)	(−2.66)
Panel B: Factor Loadings												
MKT-RF	0.90	0.92	0.97	1.07	1.14	1.18	1.22	1.24	1.40	1.39	0.49	0.49
	(49.35)	(59.13)	(58.83)	(46.22)	(38.10)	(31.46)	(30.67)	(27.32)	(23.20)	(16.17)	(5.29)	(6.99)
SMB	−0.04	−0.07	0.03	0.06	0.26	0.33	0.55	0.76	0.92	0.95	1.00	0.98
	(−1.55)	(−2.91)	(1.41)	(1.85)	(5.94)	(6.03)	(9.46)	(11.48)	(10.45)	(7.63)	(7.39)	(9.49)
HML	−0.16	−0.21	−0.16	−0.11	−0.06	0.17	0.31	0.35	0.36	0.43	0.59	0.56
	(−4.79)	(−7.11)	(−5.24)	(−2.59)	(−1.06)	(2.38)	(4.23)	(4.08)	(3.18)	(2.70)	(3.45)	(4.26)
CMA	0.14	0.07	0.03	0.01	−0.07	−0.34	−0.31	−0.38	−0.05	−0.02	−0.15	−0.12
	(2.76)	(1.74)	(0.75)	(0.21)	(−0.84)	(−3.35)	(−2.90)	(−3.13)	(−0.28)	(−0.08)	(−0.61)	(−0.61)
RMW	−0.04	0.01	0.26	0.12	0.09	−0.15	−0.36	−0.62	−0.82	−1.10	−1.07	−0.90
	(−1.09)	(0.25)	(8.37)	(2.85)	(1.68)	(−2.15)	(−4.93)	(−7.38)	(−7.41)	(−6.98)	(−6.27)	(−6.94)
Panel C: Portfolio Characteristics												
Prob. of Failure	0.021	0.027	0.033	0.041	0.051	0.067	0.094	0.144	0.253	0.776		
LGD	0.309	0.281	0.277	0.275	0.277	0.284	0.290	0.301	0.308	0.313		
Market Cap.	7,925	4,974	3,649	2,459	1,606	1,086	553	283	167	78		
B/M	0.480	0.516	0.542	0.600	0.652	0.704	0.740	0.767	0.784	0.811		

Table 8: Independent Portfolio Sorts

The table shows empirical results for monthly portfolio alphas for the period 1984-2014 using stocks independently sorted by shareholder losses at bankruptcy and failure probability. Shareholder losses at bankruptcy (LGD) are based on out-of-sample forecasts of abnormal stock returns at bankruptcy ($LGD := -\widehat{BHAR}$), estimated every month using a twelve months prediction horizon. Expected failure probabilities ($Fail$) are based on out-of-sample forecasts of the model of Campbell, Hilscher, and Szilagyi (2008), estimated every month using a twelve months prediction horizon. We sort stocks into quintiles for failure probability and into quantiles representing stocks with low (0%-30%), medium (30%-70%), and high (70%-100%) expected shareholder losses and calculate value-weighted portfolio returns. We also report results for long-short-portfolios using the highest and lowest portfolios across both sorting variables. The table shows alphas for the five-factor model by Fama and French (2016) (FF5). Panel B shows average estimated default probabilities (in percent) and shareholder losses. Alphas are reported in percent, t-values are given in parentheses.

	Low Fail	2	3	4	High Fail	H-L
Panel A: Excess Returns						
Low LGD	−0.07	−0.08	−0.27	−0.38	−0.90	−0.83
	(−0.96)	(−0.95)	(−1.92)	(−1.97)	(−3.06)	(−2.68)
Medium LGD	0.18	−0.02	−0.27	−0.53	−1.07	−1.25
	(2.26)	(−0.14)	(−1.80)	(−2.84)	(−3.39)	(−3.63)
High LGD	0.69	0.28	0.48	0.44	0.40	−0.28
	(4.49)	(1.64)	(2.74)	(2.08)	(1.24)	(−0.81)
H-L	0.75	0.36	0.75	0.81	1.30	
	(4.20)	(1.83)	(3.39)	(3.38)	(3.81)	
Panel B: Portfolio Characteristics						
Probability of Failure						
Low LGD	0.025	0.036	0.056	0.111	0.443	
Medium LGD	0.023	0.036	0.057	0.112	0.432	
High LGD	0.022	0.036	0.057	0.115	0.450	
Loss Given Default						
Low LGD	0.232	0.229	0.231	0.229	0.227	
Medium LGD	0.307	0.305	0.305	0.308	0.309	
High LGD	0.398	0.403	0.418	0.434	0.448	

Table 9: Fama-MacBeth Regressions

This table shows the results of a Fama-MacBeth regression using individual monthly stock returns between 1984 and 2014. Firm characteristics (independent variables) are lagged by one month. LGD_{t-1} is the predicted shareholder loss at bankruptcy, based on out-of-sample forecasts of abnormal stock returns at bankruptcy ($LGD := -\widehat{BHAR}$), estimated every month using a twelve months prediction horizon. $FAIL_{t-1}$ is the predicted failure probability, based on out-of-sample forecasts of the model of Campbell, Hilscher, and Szilagyi (2008), estimated every month using a twelve months prediction horizon. $D_{(\cdot)}$ are dummy variables that take the value of one if the firm is in the 0%-20% quantile (*Low*), 20%-80% quantile (*Medium*), or 80%-100% quantile (*High*) of failure probability (shareholder loss) in the previous month. Rev_{t-1} (RET) is the stock return of the previous month and zero otherwise. The subsequent variable definitions (CRSP/Compustat mnemonics given in parentheses) 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, $LogBM_{t-1}$ 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. Control variables are constructed using annual Compustat (lagged by six months) and monthly CRSP stock market data. All explanatory variables are standardized each month by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation and winsorized at the 1%/99%-level. Stocks with a stock price below one USD in the previous month are excluded. Coefficients are reported in percent. We correct t-statistics (in parentheses) with the Newey-West procedure using four lags.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
LGD_{t-1}			0.28	(3.21)									0.28	(3.02)
$LGD_{t-1} \times D_{HighFail,t-1}$					0.52	(4.29)								
$LGD_{t-1} \times D_{MediumFal,t-1}$					0.21	(2.41)								
$LGD_{t-1} \times D_{LowFail,t-1}$					0.14	(1.67)								
$Fail_{t-1}$							−0.13	(−1.80)	−0.03	(−0.43)			−0.08	(−1.02)
$Fail_{t-1} \times D_{LowLGD,t-1}$											−0.35	(−3.88)		
$Fail_{t-1} \times D_{MediumLGD,t-1}$											−0.17	(−2.09)		
$Fail_{t-1} \times D_{HighLGD,t-1}$											0.19	(2.10)		
ROA_{Y-1}	0.13	(1.64)	0.20	(2.99)	0.24	(3.44)	0.10	(1.34)	0.11	(1.44)	0.14	(1.86)	0.18	(3.30)
$Ret_{t-2,t-12}$	0.31	(3.95)	0.32	(4.16)	0.33	(4.23)	0.28	(3.84)	0.34	(4.89)	0.29	(3.89)	0.30	(4.21)
$LogSize_{t_1}$	−0.04	(−0.55)	0.01	(0.16)	−0.00	(−0.02)	−0.08	(−1.15)	−0.06	(−0.81)	−0.09	(−1.35)	−0.01	(−0.11)
$LogBM$	0.20	(2.81)	0.23	(3.42)	0.23	(3.47)	0.20	(2.93)	0.28	(3.84)	0.21	(3.00)	0.23	(3.52)
$LogIssues_{t-1,t-36}$	−0.24	(−5.95)	−0.21	(−5.00)	−0.20	(−4.86)	−0.23	(−5.99)	−0.22	(−5.80)	−0.22	(−5.80)	−0.21	(−5.20)
$Accruals_{Y-1}$	−0.08	(−3.14)	−0.09	(−3.59)	−0.10	(−3.80)	−0.09	(−3.38)	−0.08	(−3.20)	−0.09	(−3.64)	−0.09	(−3.77)
$LogAG_{Y-1}$	−0.18	(−4.82)	−0.16	(−4.72)	−0.16	(−4.71)	−0.18	(−4.83)	−0.15	(−4.16)	−0.17	(−4.77)	−0.16	(−4.65)
Rev_{t-1}	−0.43	(−6.65)	−0.44	(−7.02)	−0.44	(−6.97)	−0.46	(−6.93)			−0.45	(−6.84)	−0.46	(−7.26)

Table 10: Robustness - Fama-MacBeth Regressions with NYSE 10% Breakpoints

This table shows the results of a Fama-MacBeth regression using individual monthly stock returns between 1984 and 2014 for firms with a market value of equity larger than the 10th-percentile of stocks listed at the NYSE in the previous month. Firm characteristics (independent variables) are lagged by one month. LGD_{t-1} is the predicted shareholder loss at bankruptcy, based on out-of-sample forecasts of abnormal stock returns at bankruptcy ($LGD := -\widehat{BHAR}$), estimated every month using a twelve months prediction horizon. $FAIL_{t-1}$ is the predicted failure probability, based on out-of-sample forecasts of the model of Campbell, Hilscher, and Szilagyi (2008), estimated every month using a twelve months prediction horizon. $D_{(\cdot)}$ are dummy variables that take the value of one if the firm is in the 0%-20% quantile (Low), 20%-80% quantile ($Medium$), or 80%-100% quantile ($High$) of failure probability (shareholder loss) in the previous month. Rev_{t-1} (RET) is the stock return of the previous month and zero otherwise. Rev_{t-1} (RET) is the stock return of the previous month. The subsequent variable definitions (CRSP/Compustat mnemonics given in parentheses) 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, $LogBM_{t-1}$ 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. Control variables are constructed using annual Compustat (lagged by six months) and monthly CRSP stock market data. All explanatory variables are standardized each month by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation and winsorized at the 1%/99%-level. Coefficients are reported in percent. We correct t-statistics (in parentheses) with the Newey-West procedure using four lags.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
LGD_{t-1}			0.18	(2.30)									0.18	(2.22)
$LGD_{t-1} \times D_{HighFail,t-1}$					0.33	(3.32)								
$LGD_{t-1} \times D_{MediumFal,t-1}$					0.13	(1.53)								
$LGD_{t-1} \times D_{LowFail,t-1}$					0.12	(1.39)								
$Fail_{t-1}$							−0.08	(−0.95)	−0.01	(−0.18)			−0.05	(−0.54)
$Fail_{t-1} \times D_{LowLGD,t-1}$											−0.17	(−1.95)		
$Fail_{t-1} \times D_{MediumLGD,t-1}$											−0.08	(−0.90)		
$Fail_{t-1} \times D_{HighLGD,t-1}$											0.07	(0.75)		
ROA_{Y-1}	0.12	(1.94)	0.16	(2.84)	0.18	(3.17)	0.09	(1.51)	0.12	(1.88)	0.11	(1.97)	0.14	(2.78)
$Ret_{t-2,t-12}$	0.23	(2.56)	0.23	(2.67)	0.23	(2.73)	0.20	(2.43)	0.25	(3.15)	0.20	(2.46)	0.21	(2.62)
$LogSize_{t_1}$	−0.06	(−0.88)	−0.02	(−0.31)	−0.03	(−0.42)	−0.08	(−1.39)	−0.06	(−1.03)	−0.09	(−1.45)	−0.04	(−0.70)
$LogBM$	0.13	(1.81)	0.15	(2.43)	0.16	(2.51)	0.10	(1.44)	0.15	(1.98)	0.11	(1.55)	0.12	(1.99)
$LogIssues_{t-1,t-36}$	−0.16	(−5.07)	−0.15	(−4.55)	−0.15	(−4.53)	−0.16	(−5.23)	−0.16	(−5.33)	−0.15	(−5.10)	−0.15	(−4.80)
$Accruals_{Y-1}$	−0.07	(−2.40)	−0.07	(−2.38)	−0.07	(−2.44)	−0.08	(−2.52)	−0.08	(−2.62)	−0.08	(−2.76)	−0.07	(−2.46)
$LogAG_{Y-1}$	−0.13	(−3.30)	−0.12	(−3.32)	−0.12	(−3.30)	−0.13	(−3.28)	−0.11	(−3.08)	−0.12	(−3.25)	−0.12	(−3.25)
Rev_{t-1}	−0.24	(−3.85)	−0.25	(−4.18)	−0.25	(−4.23)	−0.28	(−4.62)			−0.28	(−4.62)	−0.28	(−4.88)