Distress Effects in Stock Returns

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Abstract

This thesis addresses a fundamental topic in financial economics: the effects of distress risk in the cross section of equities returns. Initial results show that both raw and risk-adjusted excess returns are rising in distress risk, and the remainder of this thesis examines the general robustness of the distress premium. Accordingly, the additional excess returns to stocks having heightened levels of financial distress are contingent upon the stock price being low. These findings are then extended to demonstrate that these same stocks are also microcap firms, thus attributing the anomalous behaviour of distressed stocks to a common factor with many other market anomalies. The economic implication is that arbitrage profits are likely to be limited due to the high transaction costs alongside the limited investment capacity with associated low-priced, microcap stocks.

Keywords: Bankruptcy prediction, distress disk, distress premium, asset pricing anomalies

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1. Introduction

The notion of distress risk entails that firms with certain characteristics have a heightened probability of being unable to service their outstanding financial obligations. If this risk is largely undiversifiable, investors demand additional returns as compensation for holding the stocks of these firms. In efficient markets, investors can only earn abnormal returns through bearing additional systematic risk (see Fama 1970). The additional compensation is reflected by discounting the expected future earnings of a firm appropriately to reflect the current price. Distress risk is positively priced in US markets, yet the existing evidence is largely inconclusive regarding the existence/sign of a distress risk premium. Empirical results have often labelled it as an anomaly in stock returns, as the returns to distress are conflictingly attributed to conventional risk-factor explanations.

Negative relationships between distress and returns have been obtained by Dichev (1998) whom uses Ohlson's (1980) O-score and Altman's (1968) Z-score. Agarwal and Taffler (2008) also use the Z-score as a proxy of distress, finding that distressed stocks underperform safe stocks, unconditionally and when controlling for either size or book to market. Campbell, Hilscher, and Szilagyi (2008) find that excess returns are nearly monotonically declining in failure risk. Conversely, Vassalou and Xing (2004) find distressed stocks outperform if they are also small and have high book-to-market ratios. Garlappi and Yan (2011) find that highly distressed, high-priced stocks exhibit a value premium that increases over a limited range of distress risk.

Chava and Purnanandam (2010) show that when using the Implied Cost of Capital (ICC) as the proxy for expected returns, there is a positive relationship between distress risk and expected returns. This is evidence that distress risk is systematic as investors *expected* to receive additional compensation for their exposure. They show that despite these increasing expected returns to distress risk, investors were negatively surprised by higher-than-expected bankruptcy filings alongside lower-than-expected cash flow realizations during the mid to late 1980s.

Motivated with this background, this thesis revisits the question of whether there exists a premium for financially distressed stocks and, consequently, if it can be fully explained by benchmark risk controls. We find a positive premium for distress risk in general that is robust to both the Fama and French (2015) Five-Factor model and the Hou, Mo, Xue and Zhang (2018) q^5 model. The remainder of this thesis examines the robustness of this distress premium along several avenues. First, distress risk related anomalies are known to be pronounced among low-priced firms. Second, size correlates strongly with distress risk and many market anomalies are known to be the result of microcap stocks (Hou, Xue, and Zhang 2018). Distressed, small stocks with low prices are all associated with increased information asymmetries leading heightened transaction costs. These avenues are used to obtain an inference on the economic significance of the distress premium (i.e. arbitrage potential).

To obtain a proxy for financial distress, this thesis uses data monthly and quarterly market and accounting information covering the years 1999-2018. We follow Campbell et al. (2008) to construct ratios of net income/total assets, total liabilities/total assets, and cash and short-term investments/total assets. These measures are designed to capture profitability, leverage, and liquidity, respectively. Market-based variables include a firm's most recent excess return over the market, the volatility of its daily returns over the previous three months, and relative size, taken as the logarithm of a firm's market capitalization divided by the total market capitalization of the S&P 500 index. We estimate a discrete time hazard model, introduced by Shumway (2001), to obtain monthly probabilities of default. This approach is also used by Chava and Jarrow (2004), and Campbell et al. (2008), among others. To test the relationship between distress risk and returns, we implement a monthly expanding window to obtain the most informative proxy of financial distress.

Using the estimated probabilities of default from the expanding window, we sort firms into deciles of failure probabilities and form portfolios that hold each decile. Our initial results exhibit nearly monotonically increasing excess returns to distress. The least distressed portfolio has an average excess return of 0.6% (t=1.99) per month, climbing to 1.1% (t=2.71) in the sixth decile and to 2% (t=4.99) in the top decile. Long-short portfolios go long in the top decile(quintile) of distress risk earn excess returns of 1.4% (t=3.47) and 1.2% (t=3.41) per month, respectively. We then raise the price cut off from $1 to $5 for comparison These results sample exhibit a similar pattern but have a slightly higher return of 2.3% (t=5.58) in the top decile. The excess returns in all deciles of distress are strongly significant. Moreover, correcting for risk using the Fama and French (2015) Five-Factor and Hou, Mo, Xue and Zhang (2018) q^5-Factor model yields significant mispricing coefficients in both price-filters samples. However, for a third sample that sorts using the cut off values from the first but groups into portfolios only stocks in the second, the difference is not significant at any level. Our initial results are thus conditional in that the additional excess returns to stocks having heightened levels of financial distress decline to the extent that the price of these stocks is high. We extend this analysis to consider the size implications of our results. Independently double sorting on size and distress reveals that the low-priced stocks responsible for the heightened returns to distress are also microcap stocks. Because the low-priced stocks responsible for our anomalous returns to distress risk are also microcaps, we have supporting evidence that attributes the distress anomaly to a common factor with other anomalies, consistent with Hou, Xue, and Zhang (2018).

This thesis contributes to the literature first by providing additional evidence of a premium for financially distressed stocks, in line with empirical evidence presented by Griffin and Lemmon (2002), Vassalou and Xing (2004), Garlappi and Yan (2011), as well as the theoretical prediction of Chava and Purnanandam (2010). Second, we attribute the risk-corrected, anomalous returns to the effects of distressed and low-priced stocks. We have extended this to demonstrate that these same stocks are also microcap firms. This is significant for the distress premium because the implication is that any related arbitrage opportunities are likely to be limited due to the high transaction costs (i.e. lower stock liquidity) associated with microcap stocks with low prices.

The rest of this thesis will proceed as follows: Section 2 will present the related literature and our hypothesis development. Section 3 will cover our research design including selected data and implemented methodology. Section 4 will present our empirical findings, and Section 5 will conclude.

2. Literature Review and Hypothesis Development

2.1 Review of Bankruptcy Prediction

Intuitively, the risk of bankruptcy boils down to whether a firm has the solvency to service their outstanding financial obligations. Researchers have been meaningfully forecasting corporate bankruptcy since Beaver (1966). Most notable is the early study of Altman (1968), whose Z-score is still accepted as a proxy for financial distress. Improved variants have been introduced over the years. [1] Subsequent developments in reduced-form modelling included the O-Score from Ohlson (1980) where a probabilistic inference on financial distress is obtained via limited dependent variable analysis. These form approaches employ simple and publicly available accounting information to obtain measures of profitability, liquidity, and indebtedness to assess a firm's financial health. Associated methodological issues relating to selection-biases in sampling procedures involving distressed firms are discussed by Zwijewski (1984).

Also popular are structural models derived from option-pricing theory following Merton (1974) and Black and Scholes (1973). By modelling market equity as a call option on a firm's assets, the market value of assets and the volatility thereof are estimated by simultaneously solving two equations. These estimates are then used to compute a firm's distance to default (DD), which is interpreted as the number of standard deviations of asset growth a firm's market value of assets is above its liabilities. The cumulative normal distribution is then used to obtain a probabilistic inference of failure. This measure of distress can be found in Hillegeist, Keating, Cram, and Lundstedt (2004) where they evaluate its ability in predicting default, and in Vassalou and Xing (2004), and Garlappi and Yan (2011) where it is used to investigate the nature of the distress risk

[1] See Altman (1993) and Altman and Sanders (1997) for a review of the modifications made to the original Z-Score.

premium. Moody's KMV (Kealhofer, McQuown, and Vasicek, MKMV) uses this framework and an extensive history of default observations in their proprietary database. [2]

The more recent literature has tended to the discrete time hazard model of Shumway (2001), where he demonstrates that a discrete time hazard model is equivalent to a multi-period logistic regression. Using a hazard model helps to alleviate the estimation-related biases introduced in a static estimation. This approach has also been applied by Chava and Jarrow (2004) whom explore industry effects on failure probability. A related literature assesses the relative performance of these various competing approaches.

Despite their stronger theoretical underpinning, structural measures of distress have been shown to underperform their reduced-form counterparts. Though Hillegeist et al. (2004) recommend using the structural approach over either the Z-score or O-score due to its containing larger default-related information, Agarwal and Taffler (2008) demonstrate that traditional Z-scoring yields superior results over the structural measure in terms of the economic cost of misclassification. The predictive accuracies of the two are similar. Agarwal and Bauer (2014) demonstrate that the hazard model of Shumway (2001) is not only an improvement over its predecessors in terms of predictive accuracy, but that its information content subsumes theirs as well.

Other reduced form improvements to the hazard model of Shumway (2001) include a mixed-logit model introduced by Hensher and Jones (2004), which accounts for heterogeneity between firms. Alternatively, non-parametric approaches are also shown to have respectable forecasting ability, such as Bayesian modelling. More intensive techniques include forward intensity

[2] See Crouhy, Galai, and Mark (2000), as well as Crosbie and Bohn (2002) for a detailed description of the KMV procedure.

modelling (see Duan, Sun, and Wang 2011, and Duffie, Saita, and Wang 2007), as well as neural networking, though this thesis does not work with these approaches.

One major shortcoming of financial distress prediction models, especially in financial research, is its general inability to incorporate financial firms into the prediction. Financial firms have fundamentally different capital structures and including their accounting positions in any prediction would bias the parameter estimation. A possible remedy for this is discussed in Duan (1994, 2000), though it is limited to structural modelling approaches. Using their approach would introduce an undesirable level of complexity, however, and thus we adhere to the standard in the literature and avoid financial firms in our analysis.

2.2 Returns to Distressed Stocks

In efficient markets, investors can only earn abnormal returns through bearing additional systematic risk (Fama 1970). Distress risk is systematic only if it is priced. If distress risk is systematic, then the returns of these stocks tend to move together and their risk cannot be diversified away, and investors demand additional returns as compensation (Campbell et al. 2008, Chan and Chen 1991, and Fama and French 1992). The additional compensation is reflected by the current price, obtained by discounting the expected future earnings of a firm appropriately to reflect the level of risk.

Chava and Purnanandam (2010) show that when using the Implied Cost of Capital as the proxy for expected returns, there is a positive relationship between distress risk and expected returns. [3] They show that despite these increasing expected returns to distress risk, investors were negatively surprised by higher-than-expected bankruptcy filings alongside lower-than-expected cash flow

[3] A firm's ICC is estimated by using analysts estimated of future earnings and the current stock price to back out the discount implied by the two.

realizations. These negative realizations are reflected when replacing ICC with realized returns. Using different sample periods ranging over 1952-2005, they show that the underperformance of distressed stocks (in terms of realized returns) is concentrated in the 1980s, while the corresponding relationship for expected returns remains positive for all subsamples and for the entire period. Concentrated underperformance of stocks in the late 1980s is also noted by Campbell et al. (2008), whose sample of distressed returns covers the period of 1981-2003. Ultimately, this is evidence that the distress risk factor is priced because investors *expected* to receive additional compensation for their exposure.

Negative relations between distress and returns have been obtained by Dichev (1998) whom uses these results to argue that current prices do not impound the available financial distress information. Campbell et al. (2008) find nearly strictly declining average excess returns across deciles of distress risk. They suggest that stocks with high distress tend to be overpriced given their anomalously low returns, but they do not find evidence of corrections during earnings announcements as these stocks outperform during these brief events. Their results are consistent with Griffin and Lemmon (2002) whom report the highest abnormal earnings announcement returns for distressed stocks. Agarwal and Taffler (2008) find that distressed stocks underperform safe stocks, unconditionally and when controlling for either size or book to market. Interestingly, they find that nearly all returns of safe stocks in each quintile of size and BM earn larger and more significant returns than distressed. These results are counter to the notion that distress risk is proxied for by size and book-to-market factors.

Several studies have found a nonnegative relationship between distress risk and returns. Vassalou and Xing (2004) find a positive distress premium for the smallest firms and the two highest quintiles of BM. Through asset pricing tests they also determine that this risk is systematic and is priced in the cross section of returns beyond the information contained in SMB and HML from Fama and French (1993). Da and Gao (2010) partially attribute the results of Vassalou and Xing (2004) to price reversals, implying that any realized distress premium is likely to be short-lived. Garlappi, Shu, and Yan (2006) find no significant difference between distressed and non-distressed returns. Garlappi and Yan (2011) investigate the role of shareholder recovery in the returns of distressed stocks and find that momentum returns are stronger for those whose potential shareholder recovery is higher. They also show that increasing returns to distress risk exist over a limited range of default probability when there is potential for shareholder recovery.

The existing empirical evidence presents a substantial puzzle for the distress premium. In the risk-return relationship, it is the expected return that matters, as this is the basis upon which a stock is currently priced (Chava and Purnanandam 2010). From this perspective, one would expect to see that distress risk is priced in stock returns. To test whether investors are rewarded for bearing additional exposure to distress risk, we establish the following null hypothesis:

H1: Stock with higher distress risk, as measured by their probability of default, do not outperform non distressed stocks.

Complicating the relationship between distress risk and returns is that distressed stocks tend to be less covered by analysts than non distressed stocks, as well as smaller and of lower price. Such stocks are more prone to mispricing by investors. Generally, overpriced stocks have failed to account for risk exposure and will thus experience negative returns (declines in price) as this risk is incorporated into prices. Underpricing works similarly but in reverse pattern. These characteristics associated with mispricing are also related to stock liquidity via the transaction costs channel. Thus, it may be the case that any statistically significant distress premium will lack economic significance, as the increased cost of trading in these distressed stocks will severely limit arbitrage potential.

3. Research Design

3.1 Data Selection

3.1.1 Default and Exit Indicators

The first decision in distress prediction is the definition of default. We employ a binary decision variable, so the only possible outcomes are default or survival. There are four definitions of default used in this thesis, all of which are standard in the literature. The primary decision indicator used is the month in which firms file for Chapter 7 or Chapter 11 bankruptcy. Distressed stocks are commonly delisted for financial reasons prior to the date of default. Firms that have delisted for financial reasons are considered to have defaulted and the dependent variable will equal to one in the month of their delisting. Some firms continue to report returns after they have declared bankruptcy. For these firms, the date of declaration will be taken as the date of default and our dependent variable will equal one in that month. As well, firms that delist for non-financial reasons but declare bankruptcy at some point in the future will be deemed to have defaulted at the date of delisting, and the dependent variable will equal to one then. We do not consider delisting for reasons related to mergers or acquisitions to be defaults (except when followed by a formal bankruptcy filing), thus in the month of their exits the dependent variable will remain equal to zero.

The data for firms that exit via default or otherwise are obtained from the Audit Analytics and Bloomberg databases. We obtain the date of bankruptcy declaration, and the date of bankruptcy filing in case the former is missing. We include CIK identifiers for merging Audit Analytics and Bloomberg data, and CUSIP identifiers for merging with our explanatory set. Our exits due to delisting are obtained from the CRSP delisting database; the delisting dates are merged with CRSP monthly data and a firm’s date of exit is determined as above. We exclude financial firms from our sample due to their characteristically different capital structures. We also exclude stocks without observable data for at least six months prior to default. Additionally, firms that exit our sample are not allowed re-entry. Our final sample contains 1004 failures and 677,971 firm-month observations ranging from 1999 to2018. Table 1 reports on the failure properties of our sample.

In each year, we record the number of active firms and the number of exits that correspond to our definition of failure. We use these to calculate the annual failure rate, which is obtained by dividing the number of defaults by the sum of the number of failures and active firms. These are the number of sample firms prior to excluding those in the financial industry, but after removing those without at least six months of observability prior to default. The period of 1999-2003 covers the Dot-com crash. The bankruptcy rate climbs rapidly to just over 4% in 2001 and then steadily declines throughout the following years. After this, the failure rate remains relatively low until the Global Financial Crisis (GFC). The rate climbs to 2.2% and 2.06% in 2008 and 2009, respectively, after which it declines and remains below 1% for the remainder of the sample. Lastly, in 2016 our failure rate experiences another slight increase, though it is negligible compared to the level seen during the GFC and Dot-com crash.

3.1.2 Bankruptcy Prediction Variables

We obtain firms' market and accounting variables from the Centre for Research in Securities Prices (CRSP) and COMPUSTAT, respectively, for all public firms that have available data. In constructing our explanatory variables, we largely follow Campbell et al. (2008). First, they find heightened explanatory power from using the market value of total assets as supposed to its book value. We follow their procedure in constructing our measure of total assets. and use the sum of market value of equity and book value of liabilities to obtain MTA, the denominator in our accounting ratios. This value is also adjusted by 10% of the difference between market and book equity to avoid outliers as in Cohen, Polk, and Vuolteenaho (2003). The variables included in our bankruptcy prediction are as follows:

NIMTA: The ratio of quarterly net income divided by total assets is used to capture the profitability position of a company. Distress is known to be negatively related to this factor, so we expect to observe a significant and negative coefficient on this factor.[4]

TLMTA: Total liabilities divided by total assets is used to capture firm leverage. Risk exposure increases with added leverage, and we expect this variable to have a positive coefficient.

CASMHTA: The ratio of quarterly cash holdings divided by total assets is used to capture the liquidity position of a company. Higher liquidity is associated with lower distress risk, so we expect to observe a significant and negative coefficient on this factor.

MB: The market-to-book ratio is the month-end market capitalization of a firm divided by its quarterly book value of equity. Market value of equity is simply the most recently observable product of price and shares outstanding. Our book value of equity is calculated following Davis, Fama, and French (2000), using shareholders equity, plus deferred taxes, and investment tax credits, minus the book value of preferred stock. If shareholder's equity is missing, stockholder's equity or common equity is used, plus the carrying value of preferred stock. If the redemption value of preferred stock is available, we use that instead. Lastly, if these are missing, we measure shareholder's equity as the difference between total assets and liabilities, as in Fama and French (2006). We replace any remaining negative book-values of equity with $1, and, like our market

[4] Campbell et al. (2008) calculate a geometrically declining moving average for this variable, though for simplicity we do not.

value of assets, we adjust the book value of equity by 10% of the difference between market and book value of equity and market value of equity, following Cohen, Polk, and Vuolteenaho (2003), and Campbell et al. (2008).

SIGMA: We calculate a three-month rolling window standard deviation of daily stock returns as a measure of return volatility. Specifically, instead of using the rolling three-month mean, we follow Campbell et al. (2008) and calculate an annualized three-month rolling window of daily squared returns and take the square root as the value of sigma. We require a firm have at least 5 nonzero daily observations. In this case, we report sigma as missing and replace it with the annual cross-sectional mean.

LOGPRICE: We take the log of firm price per share to incorporate distressed stocks' tendency to have lower prices.

RSIZE: RSIZE is the size of a firm relative to the S&P 500 composite index, to capture a measure of market share rather than absolute size. Relative size is a standard explanatory variable in distress prediction, used by Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008), among others. Firms with higher market shares are expected to be relatively safe, so we expect to obtain a negative coefficient.

EXRET: We use the most recently available excess return over the S&P 500 index as a gauge of firm performance. The variable is calculated as the log difference of a firm's gross-returns over the S&P 500 Index. Because poor past performance is associated with potential financial distress, high past returns should decrease the prospects of default.

Following the literature on distress prediction, we replace missing observations with the one most recently available. This does not cause an econometric problem due to observability, as noted by Shumway (2001). Calendar and fiscal dates are properly aligned, and variables are then lagged by two months so that every observation used in the monthly predictions is observable at the time of estimation, as in Campbell et al. (2008). We truncate our sample at the 99th and 1st percentile to limit the influence of outliers.

We also include several macroeconomic variables to capture information that is common to all firms and may impact bankruptcy likelihoods. We include the change in the quarterly US GDP (GDP GROWTH), the quarterly US unemployment rate (UNRATE), the spread between the 10-year and 3-month U.S. treasury rates, and the implied volatility on the S&P 500 index (VIX). These variables are obtained from the Federal Reserve Bank of St Louis (FRED) database, except for the VIX and the Treasury rate, which are obtained from CRSP. [5]

Table 2 reports the summary statistics for our bankruptcy predictor variables. Variables are reported after the adjustments described above. Panel A reports the mean, standard deviation, minimum, maximum, and number of firm-month observations in our entire sample, Panel B reports the same statistics for our failure group. This failure group contains all the firms whose exit falls under our definition of default as in the data section. Excluding financial firms from our analysis results in the difference between the total failures observed in Table 1 and Panel B of Table 2. Panel C reports the t-statistics for tests of mean differences between the groups.

Initial comparison of the failure sample with the full sample reveal highly intuitive differences between the groups: in the month prior to defaulting, bankrupt firms are less liquid, report underperformance, and are more highly levered. Panel C overwhelmingly rejects the null hypothesis that the two groups characteristics are the same. The average CASHMTA for defaulted

[5] https://research.stlouisfed.org

firms is 0.075 compared to the full sample mean of 0.104; NIMTA is just below 0 for the entire sample but is -0.065 for failed firms; TLMTA is 0.697 for the failure group compared to 0.320 for the entire sample. The log of prior gross excess returns of failed stocks is much lower than the full sample, having an average -13.4% per month compared to -0.4% for the entire sample. These lower returns are accompanied by higher volatility, with failed firms' having annualized average sigma is 143% compared to 58.6% for the whole sample. Defaulted stocks are smaller and have lower prices as well. Failed firms' average RSIZE is -13.739 compared to -10.553 for the entire sample and failed firms' logprice is 0.32 compared to the whole sample of 2.66. MB is also larger for non-bankrupt firms, suggesting higher book-to-market values are associated with heightened levels of distress.

3.1.3 Asset Pricing Data

For our portfolio analysis, we obtain monthly and daily returns from CRSP for all publicly available companies, as well as prices, shares outstanding, delisting dates and returns in case they are missing in the delisting dataset. Like before, we require a firm to have at least 6 months of returns data available for it to be included in our analysis. We obtain the excess returns of the market over the one-month risk free Treasury rate (MKTRF), the factor mimicking portfolios SMB, HML, and RMW, CMA from the Kenneth French website. [6] The factor mimicking portfolios REG, RIA, RME, and ROE in the Hou, Mo, Xue, and Zhang's (2018) q^5-factor from global-q.org.

As potential control variables, we take the log of price multiplied by shares outstanding to calculate beginning of month firm-size. Because of scaling, we take the log of size in thousands of

[6] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

dollars. We take the reciprocal of the MB used previously as the book-to-market ratio. For the analysis in this section, we initially remove stocks whose price is less than $1 per share, though we revisit explicitly the consistency of our results across price-based samples. This is the same price filtering procedure used by Garlappi and Yan (2011).

3.2 Methodology

3.2.1 Discrete-Time Hazard Model of Bankruptcy Prediction

The probability of default over the next period will be assessed using the discrete-time hazard method introduced by Shumway (2001). In his article, he demonstrates that a discrete-time hazard model is equivalent to a multi-period logistic regression and improves over its static alternative by allowing for the incorporation of time varying information. This outperformance has been repeatedly validated in the literature that followed. This approach is also employed by Chava and Jarrow (2004) and Campbell et al. (2008), among others. At the beginning of each month, we use the most recently available information to estimate the probability that a firm will exit our sample due to failure during the month with the logit specification:

$$PD_{t-1}(Y_{it}=1|Y_{i-1}=0)=\frac{1}{1+e^{(-\alpha-\beta x_{i,t-1})}}. \quad (1)$$

A binary decision variable is employed, so the possible outcomes are default (Y=1) and survival (Y=0). $PD_{t-1}(Y_{it}=1)$ is the probability that a firm will default during the following month, estimated at the beginning of the month. $X_{i,t-1}$ is the vector of covariates that are lagged to ensure their observability at the time of estimation; β is the vector of slope coefficients, and α is a constant. The model is estimated on the full sample period covering the period of 1999-2018 as well as on two separate subperiods covering 1999-2008 and 2009-2018. Since we calculate our explanatory variables largely following Campbell et al. (2008), we do not expect to find substantial differences in coefficient values, and we do not expect our coefficient signs to differ. The results, discussed in later sections, show consistency across samples.

For robustness, we estimate a firm's distance to default (DD) following Campbell et al. (2008) and Hillegeist et al. (2004) where the methodology is discussed in detail. DD measure is employed to capture the discrepancy between alternative leading models. In short, estimating distance to default relies upon option pricing theory, and requires iterating two simultaneous equations for the unobserved market value of assets and their volatility until they are consistent with observed values of market equity and volatility, and book values of liabilities. We compare the explanatory power of DD in isolation and when included alongside our explanatory variables. For the next section, after confirming the general consistency of the primary model (i.e. Hazard model), we use it to implement a monthly expanding window estimation.

3.2.2 Returns to Distressed Stocks

The purpose of obtaining a monthly default probability is to have a measure on which to examine related differences in firms' returns. Since this uses monthly rebalancing, upon their exit, the holdings of firms are naturally liquidated. By design, once removed from our sample, a firm cannot gain re-entry as it will have no estimated default probabilities on which to be ranked. We carefully handle the returns to delisting stocks. Regardless of the definition of the exit, firms that delist in any given month, their final (i.e. delisting) return can typically be found in CRSP. When these returns are missing, using the most recently available return can induce an upward bias. We thus we follow Shumway (1997) and use the median delisting return to replace any missing delisting returns in the CRSP.

At the beginning of each month, firms are ranked on their probability of default into deciles and grouped into portfolios.[7] Hou, Xue, and Zhang (2018) demonstrate that many market anomalies are the result of overweighting microcap stocks in portfolio analysis primarily by

[7] In the initial version of this thesis, smaller ranges were employed around the tails of the distribution to better isolate the most/least distressed stocks, whom are also the most likely to experience distress-related effects. We form portfolios holding percentiles 1-5, 5-10, 10-20, 20-40, 40-60, 60-80, 80-90, 90-95, 95-99, 99-100, as in Campbell et al. (2008).

calculating equally weighted returns. They find that the significance of roughly 20% of their tested anomalies hinges on the use of equally weighted returns. To avoid the pitfall, the empirical analysis in this thesis is conducted on value-weighted portfolio measures. We create decile (quintile) spreads that go long in the top distress decile (quintile) and short in the bottom. The sample is restricted to exclude stocks whose price is less than $1 to limit the influence of liquidity and microstructural issues, though we revisit the consistency of our results across various price-based samples following Garlappi and Yan (2011).

Our portfolio analysis will be conducted using Ordinary Least Squares linear regression. Coefficients' significance will be assessed using heteroskedastic-robust standard errors following White (1980). The regressions are specified as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1\left(R_{m,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_{i,t}. \tag{2}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1\left(R_{m,t} - R_{f,t}\right) + \beta_2 REG_t + \beta_3 RIA_t + \beta_4 RME_t + \beta_5 ROE_t + \epsilon_{i,t}. \tag{3}$$

The dependent variable is portfolio *i's* excess return over the risk-free rate, denoted by $R_{f,t}$, and *t* is the month. $\left(R_{m,t} - R_{f,t}\right)$ captures the market effect in both models. Equation 2 is the Fama and French (2015) five-factor model, in which variables SMB, HML, RMW, and CMA capture the effects of size, book-to-market, profitability, and investment, respectively. Equation 3 is the Q-factor model of Hou, Xue, and Zhang (2015), augmented with an expected growth factor REG from Hou, Mo, Xue, and Zhang (2018). [8] RIA, RME, and ROE capture investment, size, and profitability effects, respectively.

[8] The interchangeable referencing of q^5 and Q-Factor models in the upcoming discussion of results should not be interpreted as using the Q-Factor model in Hou, Xue, and Zhang (2015). The augmented q^5 model of Hou, Mo, Xue and Zhang (2018) is used, and Q-Factor reference pertains to q^5 specifically.

Many aspects of returns can be explained through profitability and investment channels (see Hou, Xue, and Zhang 2015). For example, smaller firms associated with lower profitability and heightened investment are notoriously anomalous to the Fama and French (2015) model. Alternatively, a higher book-to-market ratio is consistent with lower earnings and heightened financial distress (Fama and French 1995) and this value effect is captured by HML. Smaller firms with lower profitability are also more likely to be distressed. Size effects are captured by SMB and RME, respectively; the impacts of profitability on the returns to distressed stocks are captured by RMW, and ROE, respectively.

These factors should be able to explain distress effects if they pervade beyond the market factor. If these factors adequately explain the variation in returns to increasing distress, the estimated intercept terms would be expected to be indistinguishable from zero. The first step of the following analysis is to examine whether distress risk is captured by these benchmark factor-proxies adequately.

4. Empirical Results

4.1 Hazard Model

Table 3 reports the hazard model results. We estimate the hazard model by following Campbell et al. (2008). We also include a model that includes macroeconomic variables for comparison. The first column contains the results based on the whole sample, and the second and third columns report the results based on separate subsamples covering 1999-2008 and 2009-2018, respectively. Columns of 4-6 report the same for the model that excludes macroeconomic explanatory variables. The accounting-based predictors used by Campbell et al. (2008) show significant factor loadings with the expected sign. Specifically, liquidity, profitability, size, price, and prior return decrease the probability that a firm will experience failure. The magnitude of the coefficients for prior profitability (NIMTA) and liquidity (CASHMTA) appear to have the strongest impact on a firm's financial health. Leverage, volatility, and MB heighten a firm's probability of failure as well. The signs of these coefficients are consistent across our subsamples.

When macroeconomic variables are accounted for, the sign and significance of their coefficients are less consistent across the subsamples. The quarterly GDP growth has a positive and significant sign in the subperiod of 2009-2018, as opposed to the negative and significant sign for the subperiod of 1999-2008. Thus, it's unsurprising that the coefficient of GDP growth turns to be negligible and insignificant when testing on the full sample. The term spread (10y-3m) is weakly positive for the subsample of 1999-2008, as opposed to the stronger significance in the later subperiod of 2009-2018.

The fitness of model is relatively steady with or without macro variables. As indicated by the McFadden Pseudo R-Squared, the explanatory power of the latter subperiod (2009-2018), in relative terms, is approximately 30% higher than the former subperiod (1999-2008), and 20%

higher than that of the entire sample period. Figure 1 displays the predicted failure rate alongside the observed rate. The model follows the pattern of observed defaults rather well over time except for the years around 2009, where the predicted bankruptcy rate is significantly higher than that observed. This overestimation is slightly surprising given that this is during the Global Financial Crisis, although there are also significant bailout effects present during this period (see Duan, Sun, and Wang 2011).

In unreported results, we test the failure rate on the distant to default measure (DD) with and without the other predictor variables and find minimal added explanatory power. DD still contains respectable explanatory power, obtaining a Pseudo R-Squared of roughly 20% when tested alone. In both cases, it shows significant coefficient with the expected negative sign, though obtains a substantially larger magnitude when it is tested alone. Because DD represents the distance between assets and liabilities, a larger distance should imply a decreased probability of default. To control for industry and year effects, we add dummy variables to estimate models. We find these to be of limited value in both their significance level and impact on the model's explanatory power. [9] To be consistent with Campbell et al. (2008), we employ the distress measure estimated based on the firm-specific predictive variables without macro variables for the asset pricing test in the following subsection. We also implement an expanding window estimation so that the estimated probabilities of default are the most informative proxies of financial distress.

4.2 Distress Effects in Stock Returns

We lose two years from the beginning of our sample due to the expanding window estimation, as well one month at the end from merging next month returns with default probabilities. There

[9] Unreported results are available upon request.

are 215 monthly observations for each portfolio. Because distress anomalies are more pronounced for small and low-priced firms, we conduct the robustness check based on various sampling price cut-off points. A price-based filtering rule will naturally exclude many of the most distressed stocks in our sample. As Table 2 shows that the average price of firms is roughly \$1.37 (logprice=\$0.32) per share at the beginning of the period during which a firm experiences failure. The first includes only stocks with a price per share of no less than \$1 (hereafter \$1 sample), and the second sample contains stocks with prices of no less than \$5 (hereafter \$5 sample). The third sample begins with the cut-off points from the first sample including \$1 stocks, sorts into portfolios, then remove stocks with prices of less than \$5 per share within each portfolio. The rational of the third sample is to check how significantly each distress-sorted portfolio is affected by removing small price stocks (less than \$5). Panel A of Table 4 presents the raw excess returns over the risk-free rate for the three samples. The characteristics of these portfolios are reported in Panel B-Panel D for the respective price-filtered samples.

There is a wide range of distress, with elevated levels clearly being concentrated in the upper ranges of our sample. The portfolios containing the most distressed stocks are also associated with lower profitability (NIMTA), higher leverage (TLMTA), higher firm-specific returns volatility (SIGMA), and higher portfolio volatility (Portfolio SD). The first two rows of Panel A show that excess returns are increasing in distress risk for high and low-priced stocks. For the sample using a cut off of \$1 per share, the average excess return in the lowest distress decile is 0.6% (t=1.99) per month, climbing to 1.1% (t=2.71) in the sixth decile and to 2% (t=4.99) in the top decile. The columns labelled LS9010 and LS8020 contain the spreads between the top and bottom decile and quintile of distress, respectively. The returns for the portfolios LS9010 and LS8020 are 1.4% (t=3.47) and 1.2% (t=3.41) per month, respectively. The \$5 cut off sample exhibits a similar pattern but has a slightly higher excess return of 2.3% (t=5.58) in the top decile. The return spreads for LS9010 and LS8020 are 1.7% (t=5.86) and 1.3% (t=5.80) with 1% significance level, respectively. Although there is a larger distress premium in the $5 sample, it does not bode well for a risk-based argument as the average probability of default (PD) for these firms is roughly one fifth of that in Panel A (i.e. 0.5% vs 0.09%). The average PD of top distress decile in the sample of $5 cut-off drops to 0.0288%, as opposed to the average 0.0803% of PD for the top distress decile in the sample of $1 cut-off.

As for the third comparison sample, removing low-priced stocks has nonnegligible impact on the most distressed decile portfolio. Within the most distressed decile (decile 10), about 72% of its holdings are eliminated due to stricter filtering with the number of firms declining from 264 in Panel B to 59 in Panel D. These excluded small-price stocks appear to be responsible for the heightened returns to distress, as the pattern in distressed raw excess returns consequently shifts into a hump-shape relationship, rising to 1% (t=2.26) by the 8th decile, and then declining thereafter. The long-short portfolio returns turn to be insignificant, and their magnitudes are virtually zero.

Table 5 reports the regression results based on the Fama and French (2015) Five-Factor model. Panel A reports the results based on the first sample with $1 cut-off, Panel B contains that for the second sample with $5 cut-off, and Panel C contains the results for the third comparison sample. The pattern in our excess returns is robust to risk-correction using the Fama and French (2015) Five-Factor model. Regression alphas are rising in distress in Panel A and Panel B and yield a slight hump-shape in Panel C. In Panel A, portfolio alphas rise from 0.2% (t=1.92) per month to 1.4% (t=3.83) per month. The alphas for the portfolios LS9010 and LS8020 are 1.1% (t=5.74) and 0.9% (t=5.39) per month, respectively. The pattern persists in Panel B for the $5 price-filter. In panel C, alphas are highest in deciles 5-7 of distress portfolios at 0.3% per month (t=2.77, 2.83, 2.12, respectively), and lose their significance thereafter.

Portfolio market betas are strongly significant and rising in distress risk, indicating that heightened distress risk is associated with larger systematic risk exposure. Interestingly, a lower systematic risk exposure is not the reason for the low excess returns in Panel C of Table 4. In Table 5, the pattern in market beta persists even in Panel C where these excess returns have declined. The book-to-market factor, HML, increasingly enters the regression with significance as the price cut-off rises, and the loadings are consistent with book-to-market being positively associated with heightened levels of distress. In the low-risk portfolios, HML enters negatively, indicating the concentration of growth stocks among non distressed stocks. It loses significance in the middle deciles, but regains it in the upper deciles, entering with a positive sign.

Value effects have a stronger impact on distressed returns when the distress level of high-priced firms tends to that of low-priced firms. Between Panel B and Panel C, its magnitude in the top distress decile more than doubles from 0.35 to 0.748 and remains significant at 1%; between Panel A and Panel C, it rises from 0.654 to 1.045 (significant at 1%) for the LS9010 portfolio. A similar comment could be made for the size factor and distress risk, though SMB's magnitudes are generally consistent across the different samples. Given the evidence of lower profitability among distressed firms, the lack of significance of RMW and CMA are surprising. In all three samples, the investment (CMA) and profitability (RMW) factors do not capture much additional information on the returns to distress risk. RMW enters with sporadic significance in the lower deciles of distress, though with the expected positive sign, while CMA does not show any pricing with significance.

Table 6 contains the regression results for the same portfolios using the Hou, Xue, and Zhang (2015) Q-Factor model, augmented with Hou, Mo, Xue, and Zhang's (2018) expected growth factor. The pattern in our excess returns is also robust to this risk-correction. The factors included in this regression explain more of the variation in returns of distressed stocks than those from the five-factor model, as indicated by their higher R-Squared value, yet their mispricing (alpha) terms have larger magnitudes compared to the alpha terms mispriced by the Fama French 5 factor model. In Panel A, the intercept term for the highest distress decile is 2% per month (t=6.12), and the LS9010 and LS8020 alphas are 1.9% (t=5.54) and 1.5% (t=4.91) per month. The R-Squared statistics for these portfolios are 0.6043 and 0.6094, compared to 0.2214 and 0.2349 for the corresponding portfolios in the five-factor regression.

All the variables in this Q-factor model appear to be significantly linked to differences in levels of distress risk, except for the expected growth factor, REG. Although REG in the long-short portfolios of Panel C obtains significant and negative loadings of -0.549 (t=2.03) and -0.362 (1.95), it is largely insignificant in Panel A and Panel B. This insignificance of REG is surprising compared to its improvements noted in Hou, Mo, Xue, and Zhang (2018). Its weak relationship with distress risk might be due to the subsuming by the other included factors, though we do not pursue this further in this thesis.

Market beta loadings are positive and highly significant with relatively flat magnitude, and are insignificant in the long-short portfolios. Contrary to our results using the Fama and French (2015) Five-Factor model, the Q-factor model's investment and profitability factors enter here with consistent significance. Low-risk stocks have negative loadings on the investment factor, RIA, which is consistent with the negative relationship between investment and returns (Fama and French 2015, Hou, Xue, and Zhang 2015). In Panel A, RIA obtains a significant loading of -0.255

(t=6.00) in the bottom distress decile. Remaining negative, the values of these RIA slopes rise until 5th distress decile, after which the significance is lost. Among low-priced stocks, only LS9010 has a significant loading on RIA of 0.544 (t=2.18). This pattern is more pronounced for the sample in Panel B, with RIA loading significantly at 0.332 (t=2.97) in the top decile of distress, and at 0.604 (t=4.77) for LS9010 and 0.409 (t=3.78) for LS8020. These factor loadings are consistent with both the negative return-investment relationship and that distressed firms tend to invest less.

The low profitability associated with distressed firms is captured by ROE, whose loadings and significance are largely robust to the price filter used. In every sample, it enters significantly with a positive sign in the lowest-risk portfolio, but switches to negative by the third decile and continues to decline. Its only insignificance is in the 3rd and 4th decile in Panel B. Lastly, like the SMB size factor, RME is consistently priced significantly with increasing magnitude of coefficient as distress risk increases. The loadings on RME are largely robust to the employed price filter as well. Again, these factor loadings are consistent with size declining in distress risk, as shown in Table 4.

4.3 Price, Size, and Distress Risk

The regression results shown in the previous subsection imply that the anomalous behavior of distressed stocks is concentrated among low-priced stocks. In this subsection, we investigate the subsample based on the low-priced stocks that are removed due to stricter filter. To obtain this subsample, we reverse the procedure used previously by sorting firms based on a $1 price filter, and then removing stocks priced *greater* than $5 per share. The results are reported in Table 7. Panel A contains the average monthly excess returns over the risk-free rate, as well as the average size, average level of distress, and the number of firms in each portfolio. Panel B contains the regression alphas using both the Fama and French (2015) Five-Factor model and Hou, Mo, Xue, and Zhang (2018) Q-Factor model. Only the excess returns of deciles 7 through 10 are included, that is because the lower deciles based on this subsample have too few firms for reliable testing.

The excess return in the 7th decile is 2.1% (t=4.33) per month and climbs to 2.7% (t=4.73) per month. Decile 9 has an average default probability of 0.08% while in decile 10 the value is 0.5%.[10] Regression alphas are similar in sign and magnitude to these raw returns in both models, and consistently significant with 1% level in the Fama and French Five-Factor model and the Q-factor model. However, the sizable difference in distress levels between the top two deciles compared to the small difference in excess returns makes it less clear if the cause of these anomalous returns is a trade-off with distress risk.

For further insight, we turn to the size implications of these results, as size shows the strongest trend with distress risk in Table 4. The consistency of the pattern previously observed in the size-factor loadings indicates the concentration of microcap stocks within these high-risk portfolios. [11] Low price stocks are not necessarily microcap stocks. However, if the low-priced stocks responsible for our anomalous distress returns are also microcaps, then we will have evidence that attributes the distress anomaly to a common factor with other anomalies (Hou, Xue, and Zhang 2018). To control the size effect, we perform double sorts on size and distress, ranking stocks independently into quintiles of each at the beginning of the month and forming portfolios on the intersections. The following two subsamples are used. Like before, a $1 price filter is used for both

[10] For reference, Campbell et al. (2008) finds an average default probability of approximately 0.11% and 0.4% in their 9th and 10th deciles, respectively.

[11] Microcap stocks are typically identified as stocks whose size is less than the bottom quintile breakpoint of the NYSE stocks or NYSE-AMEX-Nasdaq. They can also be defined based on their market capitalization, ranging from $50 million to $300 million. When using in-sample breakpoints, microcaps are typically defined as the firms in the smallest size group(s).

samples, but the second removes stocks priced below $5 after sorting (i.e. the $5 sample is omitted). The results are reported in Table 8.

Panel A contains the excess returns over the risk-free rate for both samples. Panel B through Panel D contain the average number of firms, the average size, and the average default probabilities. The sample filtered at $1 per share is on the left, and the double filtered sample on the right. Immediately apparent from Panel B is the strong relationship between distress risk and size: the dispersion of firms among the intersection portfolios is virtually symmetrical and centres on the upward diagonal. Of the approximately 520 firms within each quintile, both the largest and safest portfolio alongside the smallest and most distressed contain 320 of these. It's evident that these smallest stocks are also the lowest priced stocks by comparing the number of firms between the left and right of Panel B. Of the 326 firms in the smallest, most distressed portfolio, only 89 remain after removing firms priced under $5 from the original sort. Furthermore, the smallest and most distressed portfolio has an excess return of 2.3% per month, significant at 1% level, that declines to 1% per month.

Of the 10 quintile spreads available for testing, only the middle spreads of size and distress contain enough firms for reliable testing. Among the portfolios containing enough firms, the excess returns are strongly increasing in distress risk. On the left side of the table, the largest risk-related difference is 0.17% per month and is between the most distressed small portfolio and the safest large portfolio; while on the right, the spread drops to 0.4% per month.

Overall, we have shown that returns to distressed stocks are anomalous to risk correction using the Fama and French (2015) Five-Factor and Hou, Mo, Xue, and Zhang (2018) Q-Factor model. And the anomalous distress return can be largely attributed to the effects of not only distressed, but also low-priced stocks. We have extended our analysis to demonstrate that these low-priced stocks are also microcap firms. Removing low-priced stocks within sorted portfolios most impacts only firms in the most distressed portfolios. The implication for the distressed firms is significant that any related arbitrage opportunities are likely to be limited due to the high transaction costs associated with microcap stocks with low prices. Recently, Brogaard, Li, and Xia (2017) demonstrate that stock liquidity has an increasingly alleviating impact for firms with heightened levels of distress, in that realized increases in stock liquidity lower the risk of distressed stocks substantially more than for already non-distressed stocks. Consistent with the interpretation of our results, if a lack of liquidity is responsible for the risk of the most distressed stocks, it further reinforces that these stocks are unsuitable for arbitrage.

As stated briefly above, the drastic change in the magnitude of distressed portfolios' HML loadings in Table 5 imply an increasing value effect. To investigate this, in unreported results, we independently sort stocks into quintiles of both distress risk and book-to-market and calculate the corresponding distress spreads and value spreads. As expected, the pattern previously observed for HML is consistent with these results. For the $1 cut-off sample, the value premium is rising in default probability, and the long-short distress spreads are largest in both high and low book-to-market terciles. Consistent with the insignificant HMLs coefficients found in previous subsection, it suggests that distress effect cannot be captured by value effect. Results based on the $5 cut-off sample is similar, except that there is no apparent pattern in the value premium, counter to Garlappi and Yan (2011) whom find it rising for a sample using the same price filter. When we use the $1 sample cut offs for the $5 sample (where the distress effects disappear), the loading on HML doubles, and the value premium again increases in distress risk. Whether this is evidence of a potential trade-off among size, value, and distress, or simply a consequence of using coarser sorting procedures is not investigated any further.

5. Conclusion

The risk of financial distress is positively priced in the U.S. markets, yet the empirical nature of a distress risk premium is less clear. Using a sample that covers the latest two decades, we find a positive premium for distress risk in general that is robust to both the Fama and French (2015) Five-Factor model and the Hou, Mo, Xue and Zhang (2018) Q-Factor model. Overall, we have shown that the additional excess returns to stocks having heightened levels of financial distress declines to the extent that the price of these stocks is high.

Our analysis of distressed stock returns is conducted using monthly default probabilities that are estimated based on a monthly expanding window. The relationship between excess returns and distress is associated with smaller size and larger book-to-market, consistent with the distress factor hypothesis of Chan and Chen (1991) and Fama and French (1992). In contrast with the negative relation between heightened financial distress and lower realized returns (Dichev 1998, Agarwal and Taffler 2008, Campbell et al. 2008), our finding is more in line with the empirical results found by Griffin and Lemmon (2002) and Vassalou and Xing (2004). After establishing our initial results, we also conduct robustness check on the distress premium.

We have shown that the distress risk premium is robust to risk correction using the Fama and French (2015) Five-Factor and Hou, Mo, Xue, and Zhang (2018) Q-Factor model. We further find that the distress risk premium can be largely attributed to the effects of both distressed and low-priced stocks. This thesis contributes to the distress risk premium literature by extending the analysis and to the low-priced and microcap firms. This is helpful to understand the distress anomaly and to attribute much of the distress anomaly to a common factor with other known market anomalies (See Hou, Xue, and Zhang 2018).

Ultimately, our results also imply that any distress-risk related arbitrage opportunities are likely to be limited due to the high transaction costs and thus heightened illiquidity associated with microcap stocks having low prices. The unsuitability of these stocks for arbitrage is supported in Brogaard et al (2017) whom document that this lack of liquidity is a large contributor to the distress risk of these stocks in the first place. Evidently, future research will focus more attentively on the tendencies of these small, low-priced firms appearing to be responsible for the distress effect.

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Appendix: Tables and Figures

Table 1: Number of Active Firms, Failures, and the Failure Rate

The number of active firms, the number of bankruptcies and the bankruptcy rate for our sample of firms covering 1999-2018 is reported. To be include in this table, a firm must have a matching identifier in our explanatory dataset, and it must exit our sample between 1998-2018 in a manner that corresponds to our definition of failure. These are the number of sample firms prior to excluding those in the financial industry, and prior to excluding firms with insufficient observability. The bankruptcy rate for each year is calculated by dividing the number of defaults by the sum of active and failed firms.

Year	Active Firms	Failures	Bankruptcy Rate (%)
1999	4459	80	1.79
2000	4498	128	2.85
2001	4216	184	4.36
2002	3910	97	2.48
2003	3784	94	2.48
2004	3725	41	1.10
2005	3718	42	1.13
2006	3754	28	0.75
2007	3773	56	1.48
2008	3675	81	2.20
2009	3493	72	2.06
2010	3484	24	0.69
2011	3521	34	0.97
2012	3523	24	0.68
2013	3602	17	0.47
2014	3795	21	0.55
2015	3987	28	0.70
2016	4073	29	0.71
2017	4184	20	0.48
2018	4207	14	0.33

Table 2: Summary Statistics for Bankrupt and Non-Bankrupt Firms

This table reports the summary statistics for our bankruptcy predictor variables. CASHMTA is the sum of cash and short-term investments divided by market value of assets. Market value of assets is obtained by taking the sum of market equity and total liabilities. MB is the market-to-book-ratio. NIMTA is the ratio of net income/market value of assets. TLMTA is the ratio of total liabilities to market value of assets. Excess Return is the log of gross excess return of a firm over the S&P 500 index. Price is the logprice per share. Relative size is the log of a firm's market capitalization divided by the corresponding total of the S&P 500 index. Lastly, SIGMA is the square root of the sum firm's squared daily stock returns over the prior three-months, annualized. All variables are reported after the adjustments described in the data section and are constructed following Campbell et al. (2008). Panel A reports the mean, standard deviation, minimum, maximum, and number of firm-month observations in our entire sample. Panel B reports our failure group. Panel C contains the absolute value of the t-statistics for the tests of mean differences. The failure group contains all the firms whose exit falls under our definition of default as in the data section.

	CASHMTA	MB	NIMTA	TLMTA	Excess Return	LOGPRICE	RSIZE	SIGMA
				Panel A: Full Sample				
Mean	0.104	2.527	-0.002	0.320	-0.004	2.663	-10.557	0.586
StdDev	0.132	1.948	0.029	0.235	0.137	1.158	2.001	0.371
Minimum	0.000	0.164	-0.154	0.005	-0.437	-0.381	-14.892	0.123
Maximum	0.717	9.090	0.057	0.971	0.400	5.020	-5.697	1.799
Nobs	677961							
				Panel B: Failure Group				
Mean	0.075***	1.551	-0.065***	0.697***	-0.134***	0.320***	-13.739***	1.433***
StdDev	0.1132	2.9710	0.0624	0.2690	0.2551	1.0651	1.4253	0.4764
NObs	1004							
				Panel C: T-Statistics for Tests of Mean Differences				
	6.91	16.57	68.78	50.90	30.01	64.36	50.52	72.70

Table 3: Logistic Regression of Failure on Predictor Variables

This table reports the coefficient estimates from the logistic regression of bankruptcy on accounting, market, and macroeconomic variables. Estimation is conducted monthly. The variables are constructed as described in the data section, following Campbell et al. (2008), such that all covariates used in each monthly prediction are observable at the time of estimation. CASHMTA is the sum of cash and short-term investments divided by market value of assets. MB is the market-to-book-ratio. NIMTA is the ratio of net income/market value of assets. TLMTA is the ratio of total liabilities to market value of assets. Excess Return is the log of gross excess return of a firm over the S&P 500 index. Price is the Logprice per share. Relative size is the log of a firm's market capitalization divided by the corresponding total of the S&P 500 index. Lastly, SIGMA is the square root of a firm's daily stock returns over the prior three-months, annualized. Coefficients are reported first with the absolute value of their t-statistic reported below in parentheses. *,**,*** respectively denote significance at 10%, 5% and 1%.

Sample Period	1999-2018	1999-2008	2009-2018	1999-2018	1999-2008	2009-2018
Alpha	-11.537***	-8.426***	-15.431***	-12.224***	-10.374***	-16.295***
	(18.87)	(6.83)	(12.36)	(22.93)	(16.76)	(14.04)
CASHMTA	-2.455***	-2.498***	-2.191***	-2.543***	-2.491***	-2.617***
	(8.13)	(7.28)	(3.50)	(8.49)	(7.34)	(4.30)
NIMTA	-8.996***	-9.438***	-7.593***	-8.851***	-9.566***	-6.889***
	(15.44)	(14.08)	(6.27)	(-15.39)	(-14.42)	(-5.82)
TLMTA	2.857***	2.709***	3.434***	2.745***	2.657***	3.160***
	(17.38)	(14.60)	(9.37)	(16.83)	(14.39)	(8.85)
MB	0.106***	0.089***	0.172***	0.115***	0.094***	0.174***
	(5.22)	(3.78)	(4.16)	(5.73)	(4.01)	(4.36)
EXRET	-1.204***	-1.149***	-1.329***	-1.217***	-1.118***	-1.351***
	(8.11)	(6.76)	(4.32)	(8.26)	(6.65)	(4.43)
LOGPRICE	-0.742***	-0.677***	-0.902***	-0.698***	-0.712***	-0.894***
	(12.03)	(9.44)	(6.78)	(11.69)	(10.28)	(6.71)
RSIZE	-0.262***	-0.217***	-0.435***	-0.319***	-0.223***	-0.556***
	(7.14)	(5.17)	(5.47)	(8.94)	(5.37)	(7.23)
SIGMA	1.359***	1.093***	2.065***	1.136***	0.885***	1.407***
	(13.43)	(9.25)	(10.77)	(12.70)	(8.10)	(7.94)
GDP Growth	0.004	-0.067**	0.138***			
	(0.18)	(2.21)	(2.59)			
UNRATE	-0.075**	-0.319*	-0.062			
	(2.07)	(1.94)	(0.89)			
VIX	-0.018***	-0.021***	-0.020			
	(3.21)	(3.32)	(1.57)			
10y-3m	0.061**	0.111*	0.410**			
	(2.38)	(1.73)	(2.53)			
NObs	677961	352389	325572			
Failures	1004	773	231			
Pseudo R-Squared	0.3652	0.3374	0.4415	0.3594	0.3316	0.4209

Table 4. Firm Characteristics for Distress-Sorted Portfolios Using Different Price Cut offs

This table reports the value-weighted monthly excess returns over the risk-free rate and firm characteristics for portfolios formed on deciles of distress risk in samples formed using different price cut off points. The sample period covers January 2001- November 2018. The first sample includes stocks with prices of no less than $1 per share. The second similarly excludes stocks with prices of less than $5 per share. The third sample sorts stocks using the cut off points from the first sample but includes only stocks with prices greater than $5. Panel A contains the excess returns over the market. The columns labelled LS9010 and LS8020 contain the spreads between the top and bottom decile and quintile of distress, respectively. Panel B through Panel D contain the standard deviation of portfolio returns, average size, book-to-market, probability of default. CASHMTA through SIGMA are the same variables used in the hazard model estimation. The average returns are reported first, and the absolute value of their t-statistic is reported underneath in parentheses. *,**,*** respectively denote significance at 10%, 5% and 1%.

Portfolios	1	2	3	4	5	6	7	8	9	10	LS9010	LS8020
Panel A: Average Excess Returns												
Price>$1	0.006**	0.007**	0.008***	0.008**	0.010***	0.011***	0.012***	0.013***	0.016***	0.020***	0.014***	0.012***
	(1.99)	(2.19)	(2.60)	(2.39)	(2.73)	(2.71)	(2.89)	(2.99)	(3.27)	(3.69)	(3.47)	(3.41)
Price >$5	0.006**	0.007**	0.007**	0.009***	0.009**	0.011***	0.012***	0.014***	0.017***	0.023***	0.017***	0.013***
	(2.00)	(2.19)	(2.25)	(2.67)	(2.48)	(2.97)	(3.25)	(3.64)	(4.24)	(5.58)	(5.86)	(5.80)
Price>$5 &	0.006**	0.007**	0.008**	0.008**	0.010***	0.010**	0.010**	0.010**	0.008*	0.005	-0.001	0.000
Sort Price>$1	(1.98)	(2.18)	(2.58)	(2.38)	(2.68)	(2.59)	(2.55)	(2.26)	(1.86)	(0.84)	(0.23)	(0.06)
Panel B: Characteristics for Firms in Price>$1 Sample												
Portfolio SD	0.0203	0.0139	0.0179	0.0203	0.0243	0.0277	0.0316	0.0365	0.0451	0.0603	0.0645	0.0521
Size	16.0101	15.0238	14.4298	13.9857	13.5813	13.1724	12.7845	12.3443	11.8201	10.9771		
BM	0.5688	0.6317	0.6789	0.7446	0.8071	0.8521	0.9121	0.9744	1.0708	1.3006		
Firms	264	264	264	264	264	265	265	264	264	264		
PD	0.0015%	0.0027%	0.0041%	0.0060%	0.0086%	0.0129%	0.0205%	0.0361%	0.0803%	0.5030%		
CASHMTA	0.0934	0.0876	0.0891	0.0947	0.1016	0.1090	0.1109	0.1124	0.1114	0.0902		
TLMTA	0.1727	0.2113	0.2393	0.2654	0.2907	0.3151	0.3497	0.3850	0.4372	0.5718		
NIMTA	0.0103	0.0085	0.0074	0.0060	0.0045	0.0023	-0.0005	-0.0044	-0.0108	-0.0272		
SIGMA	0.3465	0.3859	0.4151	0.4498	0.4820	0.5192	0.5640	0.6291	0.7339	0.9693		
Panel C: Characteristics for Firms in Price>$5 Sample												
Portfolio SD	0.0201	0.0161	0.0153	0.0190	0.0205	0.0229	0.0260	0.0281	0.0296	0.0382	0.0444	0.0347
Size	16.1203	15.2020	14.6680	14.2521	13.9130	13.5942	13.2823	12.9715	12.6296	12.1110		
BM	0.5645	0.6152	0.6500	0.7012	0.7535	0.8049	0.8359	0.8818	0.9628	1.1034		
Firms	218	218	218	218	218	218	218	218	218	218		
PD	0.0013%	0.0024%	0.0034%	0.0047%	0.0063%	0.0086%	0.0119%	0.0175%	0.0288%	0.0920%		
CASHMTA	0.0952	0.0871	0.0868	0.0886	0.0912	0.0934	0.0925	0.0875	0.0797	0.0643		
TLMTA	0.1691	0.2027	0.2270	0.2500	0.2709	0.2947	0.3196	0.3600	0.4207	0.5748		
NIMTA	0.0106	0.0088	0.0079	0.0069	0.0057	0.0045	0.0031	0.0010	-0.0016	-0.0105		
SIGMA	0.3418	0.3781	0.4010	0.4268	0.4528	0.4781	0.5051	0.5370	0.5835	0.7000		
Panel D: Characteristics for Firms in Price>$5 Using Full-Sample Breakpoints												
Portfolio SD	0.0202	0.0139	0.0179	0.0202	0.0239	0.0271	0.0302	0.0336	0.0406	0.0648	0.0699	0.0517
Size	16.0110	15.0266	14.4375	14.0031	13.6169	13.2434	12.8987	12.5525	12.1756	11.7539		
BM	0.5686	0.6310	0.6771	0.7417	0.8028	0.8437	0.9063	0.9695	1.0795	1.2114		
Firms	264	264	263	262	258	251	237	206	150	59		
PD	0.0015%	0.0027%	0.0041%	0.0060%	0.0086%	0.0129%	0.0204%	0.0356%	0.0760%	0.2377%		
CASHMTA	0.0932	0.0871	0.0875	0.0909	0.0939	0.0938	0.0881	0.0800	0.0701	0.0551		
TLMTA	0.1727	0.2114	0.2396	0.2665	0.2940	0.3235	0.3699	0.4378	0.5464	0.6907		
NIMTA	0.0103	0.0085	0.0074	0.0061	0.0046	0.0027	0.0003	-0.0029	-0.0091	-0.0262		
SIGMA	0.3465	0.3857	0.4146	0.4483	0.4791	0.5126	0.5518	0.6021	0.6863	0.8715		

Table 5: Regression Results for Distress-Sorted Portfolios Using Different Price Cut offs

This table reports the regression results for portfolios formed on deciles of distress. The dependent variable is the value-weighted excess return over the risk-free rate. Panel A reports the results for stocks with a share price of no less than $1 per share. Panel B similarly excludes stocks with prices of less than $5 per share. Panel C uses the same decile cut offs as Panel A, but removes stocks priced less than $5 per share. Portfolios are rebalanced monthly in response to updated failure probabilities during January 2001 to November 2018. The columns labelled LS9010 and LS8020 contain the spreads between the top and bottom decile (quintile) of distress. The regression model implemented is:

$$R_{i,t}\text{-}R_{f,t}=\alpha_i+\beta_1(R_m\text{-}R_f)+\beta_2 SMB+\beta_3 HML+\beta_4 RMW+\beta_5 CMA+\epsilon_i.$$

Where $(R_{m,t}-R_{f,t})$ is the excess return on the market, and SMB, HML, RMW and CMA are the factors of Fama and French (2015). Coefficients are reported first with the absolute value of their t-statistic reported underneath in parentheses. T-statistic are obtained using heteroskedastic-robust standard errors following White (1980). *,**,*** respectively denote significance at 10%, 5% and 1%.

Decile Portfolio	1	2	3	4	5	6	7	8	9	10	ls9010	ls8020
Coefficient	Panel A: Regression Coefficients for Price>$1											
Alpha	0.002*	0.002*	0.002***	0.002**	0.003***	0.004***	0.005***	0.006***	0.009***	0.014***	0.011***	0.009***
	(1.92)	(1.94)	(3.45)	(2.11)	(3.03)	(3.30)	(3.27)	(3.22)	(3.20)	(3.83)	(5.74)	(5.39)
MKTRF	0.854***	1.007***	0.990***	1.034***	1.063***	1.059***	1.102***	1.140***	1.157***	1.203***	0.349**	0.249**
	(21.76)	(37.77)	(41.00)	(40.42)	(26.90)	(29.94)	(24.73)	(20.16)	(15.17)	(9.72)	(2.39)	(2.21)
SMB	0.397***	0.394***	0.538***	0.593***	0.651***	0.700***	0.720***	0.722***	0.776***	0.753***	0.357	0.369**
	(6.47)	(10.21)	(15.05)	(13.79)	(12.31)	(10.73)	(9.53)	(7.70)	(6.19)	(3.86)	(1.55)	(2.03)
HML	-0.298***	-0.123***	-0.084**	-0.057	-0.000	0.091	0.135	0.205**	0.296**	0.356**	0.654***	0.537***
	(6.90)	(3.60)	(2.27)	(1.39)	(0.01)	(1.31)	(1.54)	(2.02)	(2.33)	(2.15)	(3.60)	(3.62)
CMA	0.025	-0.017	-0.053	-0.005	-0.013	-0.106	-0.082	-0.088	-0.217	-0.059	-0.083	-0.142
	(0.27)	(0.28)	(1.03)	(0.08)	(0.14)	(0.83)	(0.55)	(0.46)	(0.83)	(0.18)	(0.21)	(0.42)
RMW	-0.044	0.076*	0.116***	0.098*	0.014	-0.067	-0.074	-0.151	-0.184	-0.367	-0.323	-0.291
	(0.48)	(1.96)	(3.04)	(1.96)	(0.21)	(0.88)	(0.86)	(1.32)	(1.28)	(1.55)	(1.08)	(1.29)
Adj R-sq	0.9056	0.9515	0.9555	0.9527	0.9307	0.9217	0.8956	0.8593	0.7730	0.6649	0.2214	0.2349
	Panel B: Regression Coefficients for Price>$5											
Alpha	0.002**	0.002*	0.002**	0.002***	0.002**	0.004***	0.005***	0.007***	0.009***	0.015***	0.012***	0.010***
	(2.06)	(1.79)	(2.21)	(3.41)	(2.15)	(3.60)	(4.37)	(5.11)	(5.79)	(7.11)	(4.36)	(4.29)
MKTRF	0.832***	0.984***	1.000***	0.990***	1.035***	1.043***	1.035***	1.064***	1.071***	1.111***	0.279***	0.183**
	(20.91)	(31.21)	(44.83)	(39.26)	(36.41)	(28.59)	(31.78)	(25.88)	(24.95)	(16.93)	(2.97)	(2.44)
SMB	0.379***	0.419***	0.433***	0.570***	0.609***	0.645***	0.713***	0.677***	0.724***	0.780***	0.402***	0.353***
	(6.05)	(8.46)	(13.54)	(13.68)	(14.21)	(14.39)	(12.38)	(9.50)	(10.08)	(7.53)	(2.67)	(2.93)
HML	-0.311***	-0.142***	-0.112***	-0.071*	-0.024	-0.003	0.066	0.126	0.227***	0.350***	0.662***	0.515***
	(7.14)	(3.77)	(3.08)	(1.74)	(0.51)	(0.05)	(1.19)	(1.60)	(2.94)	(3.19)	(5.05)	(4.90)
CMA	0.016	-0.001	-0.056	-0.000	-0.011	0.024	-0.036	-0.059	-0.035	0.003	-0.013	-0.024
	(0.17)	(0.01)	(1.06)	(0.00)	(0.19)	(0.30)	(0.34)	(0.47)	(0.27)	(0.02)	(0.06)	(0.12)
RMW	-0.054	0.066	0.106***	0.108***	0.104*	0.054	0.039	0.006	0.048	0.117	0.171	0.077
	(0.58)	(1.16)	(3.62)	(2.62)	(1.83)	(0.92)	(0.61)	(0.09)	(0.51)	(0.91)	(0.84)	(0.46)
Adj R-sq	0.8941	0.9424	0.9554	0.9536	0.9419	0.9320	0.9275	0.8997	0.8809	0.8131	0.3452	0.3341
	Panel C: Regression Coefficients for Price>$5 Using Cut-offs from Price>$1 Sample											
Alpha	0.002*	0.002*	0.002***	0.002*	0.003***	0.003***	0.003**	0.002	-0.000	-0.003	-0.005	-0.003
	(1.91)	(1.91)	(3.30)	(1.92)	(2.77)	(2.83)	(2.12)	(1.17)	(0.07)	(0.92)	(1.31)	(1.16)
MKTRF	0.855***	1.008***	0.993***	1.035***	1.067***	1.064***	1.112***	1.157***	1.217***	1.302***	0.448***	0.329***
	(21.87)	(37.67)	(41.59)	(41.15)	(26.96)	(31.95)	(26.33)	(22.39)	(17.38)	(9.58)	(2.82)	(2.85)
SMB	0.396***	0.392***	0.539***	0.592***	0.658***	0.712***	0.735***	0.723***	0.777***	0.883***	0.488*	0.437**
	(6.48)	(10.15)	(15.22)	(14.11)	(12.95)	(11.64)	(10.87)	(8.75)	(7.45)	(4.21)	(1.97)	(2.42)
HML	-0.298***	-0.123***	-0.081**	-0.058	0.011	0.119*	0.187**	0.339***	0.417***	0.748***	1.045***	0.793***
	(6.92)	(3.60)	(2.20)	(1.42)	(0.20)	(1.75)	(2.30)	(3.95)	(3.70)	(4.83)	(6.24)	(6.35)
CMA	0.023	-0.015	-0.052	-0.002	-0.026	-0.126	-0.115	-0.151	-0.162	-0.413	-0.436	-0.292
	(0.26)	(0.25)	(1.02)	(0.04)	(0.29)	(1.09)	(0.89)	(1.16)	(0.95)	(1.59)	(1.37)	(1.21)
RMW	-0.044	0.076*	0.123***	0.111**	0.038	-0.025	0.006	-0.017	0.042	-0.290	-0.246	-0.140
	(0.48)	(1.97)	(3.22)	(2.18)	(0.59)	(0.32)	(0.07)	(0.16)	(0.32)	(1.12)	(0.77)	(0.61)
Adj R-sq	0.9059	0.9515	0.9554	0.9525	0.9325	0.9284	0.9095	0.8888	0.8295	0.6796	0.3062	0.3398

Table 6: Regression Results for Distress-Sorted Portfolios Using Different Price Cut offs

This table reports the regression results for portfolios formed on deciles of distress. The dependent variable is the value-weighted excess return over the risk-free rate. Panel A reports the results for stocks with a share price of no less than $1 per share. Panel B similarly excludes stocks with prices of less than $5 per share. Panel C uses the same decile cut offs as Panel A, but removes stocks priced less than $5 per share. Portfolios are rebalanced monthly in response to updated failure probabilities during January 2001 to November 2018. The columns labelled LS9010 and LS8020 contain the spreads between the top and bottom decile (quintile) of distress. The regression model implemented is:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1\left(R_{m,t} - R_{f,t}\right) + \beta_2 REG_t + \beta_3 RIA_t + \beta_4 RME_t + \beta_5 ROE_t + \epsilon_{i,t}.$$

Where $\left(R_{m,t} - R_{f,t}\right)$ REG, RIA, RME and ROE are the factors of Hou, Mo, Xue, and Zhang (2018). Coefficients are reported first with the absolute value of their t-statistic reported underneath in parentheses. T-statistic are obtained using heteroskedastic-robust standard errors following White (1980).*,**,*** respectively denote significance at 10%, 5% and 1%.

Portfolios	1	2	3	4	5	6	7	8	9	10	ls9010	ls8020
Coefficient								Panel A: Regression Coefficients for Price>$1				
Alpha	0.001	0.002**	0.003***	0.003***	0.005***	0.006***	0.007***	0.009***	0.013***	0.020***	0.019***	0.015***
	(1.20)	(2.01)	(4.53)	(3.84)	(4.49)	(5.08)	(5.11)	(4.80)	(5.04)	(6.12)	(5.54)	(4.91)
MKTRF	0.920***	0.987***	0.910***	0.915***	0.945***	0.902***	0.924***	0.922***	0.895***	0.845***	-0.076	-0.084
	(42.87)	(36.60)	(42.68)	(33.60)	(28.87)	(24.08)	(21.05)	(14.48)	(10.01)	(8.27)	(0.71)	(0.82)
REG	0.056	-0.020	-0.004	-0.064	-0.146*	-0.097	-0.018	-0.013	-0.156	-0.188	-0.244	-0.190
	(1.21)	(0.42)	(0.08)	(1.07)	(1.68)	(1.22)	(0.22)	(0.12)	(1.07)	(0.86)	(1.07)	(1.04)
RIA	-0.255***	-0.165***	-0.213***	-0.132***	-0.122*	-0.108	-0.063	0.023	0.011	0.289	0.544**	0.360
	(6.00)	(3.31)	(4.78)	(2.63)	(1.80)	(1.25)	(0.68)	(0.16)	(0.06)	(1.24)	(2.18)	(1.57)
RME	0.268***	0.374***	0.529***	0.594***	0.667***	0.738***	0.794***	0.797***	0.816***	0.724***	0.456***	0.449***
	(8.71)	(13.87)	(18.97)	(19.24)	(19.51)	(19.39)	(18.75)	(15.92)	(11.30)	(5.90)	(3.83)	(4.89)
ROE	0.183***	0.074*	-0.079**	-0.146***	-0.208***	-0.411***	-0.519***	-0.701***	-0.872***	-1.291***	-1.475***	-1.210***
	(5.08)	(1.69)	(2.01)	(3.16)	(3.07)	(5.19)	(6.93)	(6.57)	(5.83)	(5.41)	(5.70)	(5.84)
Adj R-sq	0.9435	0.9560	0.9584	0.9608	0.9560	0.9542	0.9473	0.9288	0.8788	0.8119	0.6043	0.6094
						Panel B: Regression Coefficients for Price>$5						
Alpha	0.001	0.002**	0.002***	0.003***	0.003***	0.005***	0.007***	0.009***	0.011***	0.019***	0.019***	0.014***
	(1.04)	(2.18)	(2.67)	(4.16)	(4.08)	(4.65)	(6.05)	(6.99)	(8.77)	(11.28)	(9.70)	(8.62)
MKTRF	0.912***	0.976***	0.949***	0.900***	0.923***	0.948***	0.873***	0.910***	0.884***	0.840***	-0.071	-0.082*
	(41.11)	(39.42)	(38.50)	(38.87)	(33.18)	(35.41)	(24.04)	(24.04)	(22.99)	(16.15)	(1.25)	(1.69)
REG	0.080	-0.046	0.020	-0.061	-0.083	-0.116	-0.160**	-0.091	-0.012	-0.141	-0.221*	-0.093
	(1.64)	(0.85)	(0.45)	(0.97)	(-1.29)	(1.33)	(2.13)	(1.04)	(-0.14)	(1.21)	(-1.71)	(0.91)
RIA	-0.272***	-0.157***	-0.210***	-0.139***	-0.132**	-0.095**	-0.083	-0.043	0.058	0.332***	0.604***	0.409***
	(6.38)	(3.01)	(4.77)	(2.79)	(2.48)	(1.97)	(1.01)	(0.52)	(0.67)	(2.97)	(4.77)	(3.78)
RME	0.255***	0.378***	0.431***	0.565***	0.611***	0.656***	0.738***	0.735***	0.794***	0.794***	0.539***	0.478***
	(8.42)	(10.99)	(18.13)	(18.59)	(18.48)	(18.67)	(21.03)	(17.76)	(17.17)	(11.87)	(7.57)	(8.53)
ROE	0.202***	0.124***	-0.002	-0.074	-0.118**	-0.141**	-0.283***	-0.352***	-0.476***	-0.650***	-0.852***	-0.726***
	(5.07)	(2.63)	(0.04)	(1.61)	(2.38)	(2.49)	(4.30)	(4.66)	(7.45)	(5.19)	(5.68)	(6.68)
Adj R-sq	0.9380	0.9497	0.9586	0.9578	0.9564	0.9531	0.9556	0.9424	0.9355	0.8971	0.6637	0.6707
						Panel C: Regression Coefficients for Price>$5 Using Cut-offs from Price>$1 Sample						
Alpha	0.001	0.002**	0.003***	0.003***	0.004***	0.005***	0.005***	0.004***	0.004**	0.004	0.003	0.003
	(1.20)	(1.99)	(4.39)	(3.74)	(4.19)	(4.91)	(3.95)	(3.69)	(2.34)	(1.20)	(0.84)	(1.13)
MKTRF	0.920***	0.987***	0.913***	0.920***	0.952***	0.910***	0.950***	0.968***	1.004***	0.971***	0.050	0.034
	(42.89)	(36.45)	(43.65)	(34.40)	(29.57)	(28.13)	(24.42)	(24.04)	(16.86)	(10.94)	(0.51)	(0.45)
REG	0.056	-0.022	-0.005	-0.067	-0.163*	-0.100	-0.029	-0.004	-0.197	-0.493*	-0.549**	-0.362*
	(1.21)	(0.47)	(0.08)	(1.11)	(1.84)	(1.35)	(0.40)	(0.05)	(1.53)	(1.92)	(2.03)	(1.95)
RIA	-0.255***	-0.165***	-0.208***	-0.128***	-0.117*	-0.087	-0.043	0.174*	0.245*	0.278	0.532**	0.471***
	(6.00)	(3.29)	(4.68)	(2.60)	(1.76)	(1.16)	(0.54)	(1.97)	(1.92)	(1.32)	(2.29)	(2.72)
RME	0.268***	0.372***	0.530***	0.592***	0.670***	0.752***	0.810***	0.818***	0.822***	0.941***	0.673***	0.561***
	(8.71)	(13.73)	(18.94)	(19.19)	(19.93)	(21.01)	(19.94)	(17.47)	(12.12)	(6.41)	(4.47)	(5.41)
ROE	0.183***	0.074*	-0.072*	-0.128***	-0.171***	-0.372***	-0.413***	-0.544***	-0.544***	-1.047***	-1.230***	-0.924***
	(5.08)	(1.69)	(1.84)	(2.83)	(2.61)	(5.53)	(6.82)	(6.88)	(3.64)	(3.49)	(3.82)	(3.94)
Adj R-sq	0.9435	0.9557	0.9583	0.9605	0.9569	0.9587	0.9527	0.9457	0.9008	0.7925	0.5681	0.6101

Table 7: Results for Firms Having Low Prices Per Share

This table reports the results for the stocks that are excluded from the previous analysis due to having a price per share is less than $5. Panel A reports the average monthly excess returns over the risk-free rate, alongside the average firm size, average probability of default (PD), and the average number of firms contained within each portfolio. Panel B reports the regression alphas and adjusted R-squared values from the Fama and French (2015) Five-Factor model, as well as the Q-Factor model of Hou, Mo, Xue, and Zhang (2018). The sample period covers January 2001-November 2018, for a total of 215 firm-month observations. Only the returns of the upper four decile4 of distress risk are reported, because the lower deciles have too few firms for statistically reliable testing. Coefficients are reported first with the absolute value of their t-statistic reported underneath in parentheses. T-statistic are obtained using heteroskedastic-robust standard errors following White (1980).*,**,*** respectively denote significance at 10%, 5% and 1%.

Portfolios	1	2	3	4	5	6	7	8	9	10
Price Panel A: Characteristics for Firms with Low Share Prices										
Excess							0.021***	0.024***	0.024***	0.027***
Returns							(4.33)	(4.61)	(4.57)	(4.73)
Size							11.8127	11.6765	11.4200	10.7979
Firms	1	1	2	3	6	13	27	57	113	203
PD	0.002%	0.004%	0.005%	0.007%	0.009%	0.013%	0.020%	0.036%	0.079%	0.531%
Panel B: Regression Results for Firms with Low Share										
Portfolios	7	8	9	10			7	8	9	10
	FF Five-Factor Model						Q-Factor Model			
Alpha	0.017***	0.018***	0.018***	0.019***			0.019***	0.020***	0.020***	0.023***
	(5.78)	(6.11)	(5.47)	(5.59)			(6.16)	(6.12)	(5.82)	(6.97)
R-Squared	0.6475	0.7199	0.7174	0.6719			0.6840	0.7518	0.7832	0.7870

Table 8: Characteristics of Size-Distress Sorted Portfolios

This table reports the value weighted excess returns and characteristics of portfolios independently sorted on size and distress. Portfolios are rebalanced monthly in response to updated failure probabilities. The left side of the table reports for the sample filtering at $1 per share and the right column reports for the sample that filters at $5 per share after sorting at $1 per share. Panel A reports the average excess returns over the monthly risk-free rate. The column and row labelled "Difference" contains the difference in returns between high and low quintiles distress, and small and high quintiles of size. The distress quintile is reported along the top and the size quintile is reported on the left. Panel B reports the average number of firms held in a portfolio each month. Panel C and Panel D report the average size and failure probabilities (PD) of these portfolios, respectively.*,**,*** respectively denote significance at 10%, 5% and 1%.

Size Quintile	Price>$1						Price>$5 Stocks, Price>$1Cutoffs					
	PD Quintile						PD Quintile					
	Panel A: Excess Returns											
	1	2	3	4	5	Difference	1	2	3	4	5	Difference
Small	0.018***	0.014***	0.016***	0.018***	0.023***	0.006*	0.018***	0.013***	0.014***	0.012***	0.010**	-0.008
2	0.013***	0.012***	0.013***	0.014***	0.016***	0.003	0.013***	0.012***	0.012***	0.012***	0.006	-0.006*
3	0.010***	0.010***	0.010**	0.011**	0.016**	0.006	0.010***	0.011***	0.010**	0.010**	0.010*	0.000
4	0.007**	0.008**	0.009**	0.010*	0.020**	0.012**	0.008**	0.009**	0.009**	0.009*	0.017**	0.009
Large	0.006**	0.007**	0.009**	0.007	0.004	-0.001	0.006**	0.007**	0.009**	0.007	-0.005	-0.011
Difference	0.012***	0.007**	0.007***	0.011***	0.019**	0.007	0.012***	0.006*	0.004	0.005	0.015	0.003
	Panel B: Number of Firms											
Small	5	12	48	136	326		5	11	39	93	89	
2	13	53	136	187	136		13	52	129	158	75	
3	50	143	161	124	47		51	142	159	117	34	
4	136	186	130	59	13		136	186	129	57	9	
Large	322	130	51	19	4		321	130	51	18	3	
	Panel C: Average Size											
Small	11.0937	11.1353	11.0717	10.9351	10.5663		11.0860	11.1383	11.1086	10.9893	10.8191	
2	12.3958	12.3669	12.3176	12.2543	12.1818		12.3919	12.3669	12.3200	12.2669	12.2139	
3	13.4034	13.3467	13.2824	13.2475	13.2091		13.3990	13.3425	13.2789	13.2486	13.2138	
4	14.4148	14.3341	14.2795	14.2355	14.2114		14.4101	14.3299	14.2753	14.2284	14.1966	
Large	16.4552	15.7825	15.6100	15.4961	15.5524		16.4522	15.7802	15.6094	15.4920	15.4972	
	Panel D: Average PD											
Small	0.003%	0.005%	0.011%	0.029%	0.354%		0.003%	0.005%	0.011%	0.028%	0.121%	
2	0.002%	0.005%	0.011%	0.027%	0.170%		0.002%	0.005%	0.011%	0.026%	0.103%	
3	0.002%	0.005%	0.010%	0.026%	0.127%		0.002%	0.005%	0.010%	0.026%	0.094%	
4	0.002%	0.005%	0.010%	0.025%	0.115%		0.002%	0.005%	0.010%	0.024%	0.091%	
Large	0.002%	0.005%	0.010%	0.023%	0.115%		0.002%	0.005%	0.010%	0.023%	0.089%	

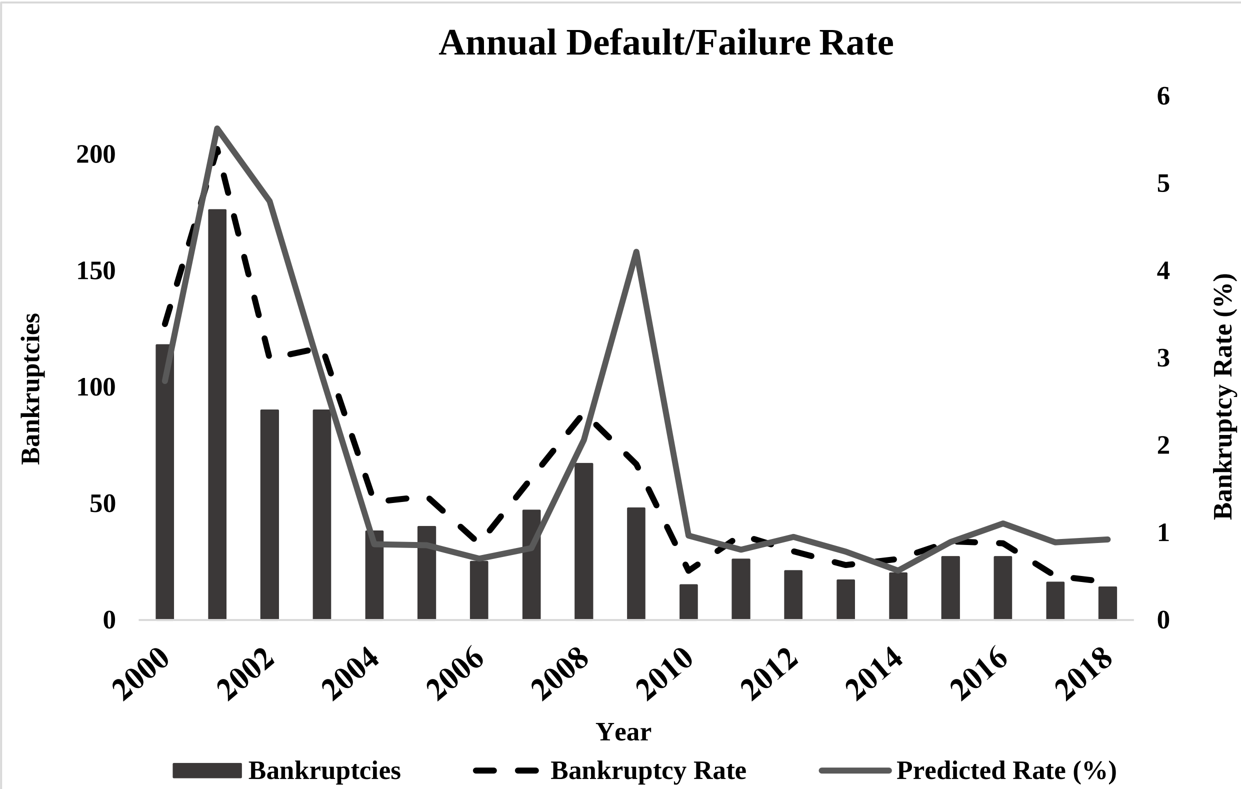

Figure 1: Predicted Versus Observed Failure Rates

This figure plots the number of observed defaults (bars) alongside the predicted (solid line) and the observed (dotted line) default rates, in percent. The predicted failure rate is estimated using the variables in Column 4 of Table 3 (i.e. excluding macroeconomic variables). The number of failures is on the left Y-axis, and the failure rate is on the right Y-axis.