Bankruptcy and the Size Effect

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Abstract

The size effect and distress risk have both presented puzzles in modern finance. In this paper, we build on the methodology of Campbell et al (2008) and Shumway (2001) to consider potential time variation in pricing behavior of size and distress. We adjust this methodology in two ways. First, we allow for sample differences, documenting the importance of regime shifts in the size effect. Second, we use a broader definition of distress that focuses on delisting instead of bankruptcy alone, and examine differences in financial and non-financial firms. We find that with our delisting definition, distressed firms do not earn low returns, which reverses the Campbell et al (2008) distress anomaly. In a linear factor model, the premium for distress risk switches from positive to negative, and prices out the Fama-French factors during the early part of the sample.

Keywords: Bankruptcy; Distress Risk; Financial Firms; Regime Shift; Sample Selection; Size Effect

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1 Background and Motivation

The recent financial crisis and its aftershocks provide a powerful motive to re-examine the pricing performance of financial models. In particular, this performance has been shown to vary over time. In this paper we focus on two crisis-related factors, size and distress. The size effect has been linked to financial distress by researchers, but the debate has thus far proved inconclusive. In one of the first papers in this debate, Chan and Chen (1991) document that small firm portfolios often comprise marginal firms, whose higher exposure to distress risk contributes to a higher return. However, these results are challenged by more recent research findings. Dichev (1998) uses the Z- and O-Scores of Altman (1968) and Ohlson (1980) to rank securities into decile portfolios. The author finds that firms with higher bankruptcy risk do not earn higher average returns since 1980. This finding contradicts the results of Chan and Chen (1991), casting doubt on whether exposure to distress risk is systematic. In similar vein, Campbell et al (2008) document that financially distressed stocks deliver anomalously low returns. Therefore, the authors conclude that bankruptcy risk is unlikely to be a source of the size effect.

1.1 Motivation

One important piece of information is missing in the above debate: the size effect is all but non-existent during the sample periods of Dichev (1998) and Campbell et al (2008). As shown in Table 1, from 1980 to 1995 the annualized monthly average of the Fama-French SMB factor (FF-SMB) is only 0.26%, far below its long term (1926-2009) average of 2.84%. Even in the slightly longer sample of Campbell et al (2008), from 1981 to 2003,[1] the SMB average is still only 1.31%. When we tighten the definition of “small" and “big" stocks to the top and bottom decile size portfolios, the return differential between small and big firms becomes larger. Again in Table 1, the second line (Decile SMB) shows a *negative* size effect of -2.92 for 1980-1995. This is in contrast to the full-sample size effect of 7.06. While the magnitudes in Table 1 may be economically significant, the large standard deviations indicate that the size effect is statistically insignificant.

In other literature, the existence of the size effect has been debated by a number of authors. Horowitz et al. (2000) show that the size effect disappeared during 1980-1996. Given that

[1] Campbell et al (2008) have bankruptcy data from 1963 to 2004, and analyze the returns on distress risk-sorted portfolios from 1981 to 2003, see their Table VI on page 2920.

the size effect mostly stems from small firms having better performance in January each year (Keim (1983), Reinganum (1983)), it is easy to exploit this anomaly by purchasing small stocks in December and reaping the expected benefit a month after (Booth et al. (2000)). However, as shown in Figure 1, the size effect does not seem to evolve around its mean but rather shows regime shifts. In particular, the size effect disappears in the 1980s and most of the 1990s, but re-emerges in recent years. Moreover, the same scenario has happened before, as small firms under-performed big firms during the 1950s, and in the late 1960s to early 1970s. Thus, according to these preliminary results, the size effect appears to have the following characteristics: it holds over the long run, and may have shorter-run regime shifts.

The possibility of these regime shifts does not automatically discredit the size effect as a risk factor. The market return, for example, also shows shifts in regimes (Chen (2009)). Thus, a finding of no relation between distress probability and subsequent realized returns does not rule out linkages between distress and the size effect.

1.2 Contribution of our Paper

Our research has three main contributions. First, in light of the above considerations, we re-examine the impact of distress risk with a longer sample period which allows us to discern regime shifts. We also use the Fama and MacBeth (1973) regression framework to investigate risk premia. Second, we use a flexible methodology that allows for regimes, and therefore we improve on the methodology of existing bankruptcy probability models. Such existing models (Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008)) illustrate that a dynamic logit model usually performs better than the traditional class of fixed-parameter models based on Z-Score or O-Score. However, Campbell et al. (2008) still document a discrepancy between the actual and projected probabilities.[2] The discrepancy is not completely random but rather shows a persistent pattern of error. If distress probability is indeed linked to the size effect, then the existence of periods where size effect is absent should have an impact on the implied bankruptcy probability. We explore such issues in Section 4. Third, we use a more general definition of distress that accounts for delisting instead of bankruptcy alone, compare our results to existing work based on much shorter samples. Finally, using a linear factor framework of the CAPM augmented with distress, we conduct

[2]See Figure 1 of Campbell et al. (2008).

asset pricing tests on the subsamples. These tests provide evidence of regime shifts in the sign of distress risk premia and in the appropriateness of a distress-based factor model.

The rest of the paper is organized as follows. Section 2 outlines empirical models for integrating analysis of distress and the size effect. Section 3 discusses our data and comparative results. Section 4 presents our empirical results on predicting distress and estimating the price of distress risk with regime shift models. Section 5 concludes.

2 Modelling Distress and Time-Varying Size Effects

2.1 Distress Probability Model

The first step of this paper is to examine whether a regime shift of SMB in year t may be linked to market and accounting data in year $t-1$. To accomplish this, we utilize a hazard model of Shumway (2001). This framework is a preliminary approach designed to give us a broad indication as to potential links between the size effect and the probability of distress. If some explanatory variables show different sensitivities during different SMB regimes, there might be unobserved linkages between distress risk and the size effect. Moreover, performance of the distress probability model can be evaluated by the difference between the actual and projected probabilities.[3] As an econometrician with full knowledge of the sample's SMB regimes, one can tackle this issue in two steps. First, one can account for regimes in SMB with a dummy variable, which can be used in a logit model to see whether this enhances predictability. Second, if predictability obtains, one can then implement information about the regime in a formal econometric model. We now outline a basic empirical framework to accomplish these steps.

A standard dynamic logit model is as follows:

$$\text{Prob}(Y_{it} = 1|\Im_{t-1}) = \frac{1}{1+\exp(-\alpha - \beta x_{i,t-1})}, \tag{1}$$

where Y_{it} is the distress dummy equal to 1 when the firm i goes bankrupt and 0 otherwise, and $\Im_{t-1}$ represents all information available up to time $t-1$. $x_{i,t-1}$ includes all accounting and market information of firm i at time $t-1$ which can predict the bankruptcy event at

[3]This is in similar spirit to Figure 1 in Campbell et al. (2008).

time t. We examine whether the distress probability can be improved by including the ex post SMB regime dummy D_t, so that

$$\text{Prob}(Y_{it} = 1|\Im_{t-1}) = \frac{1}{1+\exp(-\alpha - \beta x_{i,t-1} - \gamma D_t x_{t-1})}, \tag{2}$$

The dummy variable D_t in equation (2) is generated from the regime of SMB. It can be derived from monthly SMB with a Markov switching model.[4] If the smoothed probability of the low SMB regime is greater than 0.5 for a particular month, then we categorize SMB_t as falling in this regime. If the majority of months in a year fall ina low SMB regime, then the dummy variable takes the value 1, and 0 otherwise.

Evidently D_t is not a valid real-time predictor for investors and econometricians, since it represents information that is unavailable before observing the realization of y_{it}. Therefore, equation (2) can only suggest which explanatory variables have differential ties to SMB in different economic regimes. Such results provide information on potential linkages between distress probability and the size effect, which may then be used to improve predictive power of the empirical model.

2.2 A Longer run Perspective on Distress Risk and the Size Effect

In order to examine whether distress risk is systematic and related to the size effect, it is not enough merely to calculate subsequent portfolio returns following evaluation of distress risk. We have to first control for the sample selection problem noted in the Introduction and in Table 1. We therefore re-examine the association between distress risk and subsequent realized returns over a longer period than in existing studies. We track *long-term performance* of portfolios sorted on distress risk, from the 1950s to 2009. This alleviates the sample selection bias problem in Dichev (1998). Subsequently, we examine the relation between distress and other popular risk factors. Here we use the Fama and MacBeth (1973) approach described in more detail in Section 4.

Lu (2009) documents that the size premium of small firms is a short term effect, lasting only a few years. We use a similar approach to examine the performance of firms according to their distress probabilities. This approach can show whether distress risk is a persistent risk source that sticks to a firm longer than other risk factors. According to Fama and French (2007), firms often jump to other size or book-to-market ratio groups, so frequent

[4]See the appendix for more details of the model and parameter estimation.

rebalancing can help exploit the excess return which can be retrieved from these two trading strategies. Our work therefore addresses the interesting question of whether disress probability exhibits similar behavior.

3 Data and Comparative Results

3.1 Selection of variables

Given the variety of literature on distress, we take some time to explain our decisions on which variables to include, both regressands and regressors.

Regressands: Definition of Distress. In order to expand our sample period to earlier years, we have to select a proper regressand y_{it} for distress, because most bankruptcy databases do not date back before 1980. In the database compiled by Professor Lynn LoPucki of UCLA Law School, a total of 882 firms have filed for bankruptcy under chapter 7 or chapter 11, from 1980 to March 2010. Other authors who use similar definitions of bankruptcy all hand-collect their own data. Shumway (2001) collects data from *Wall Street Journal Index*, the *Capital Changes Reporter* and the *Compustat Research File*. His sample period is from 1962 to 1992, with 300 bankruptcies in total. Furthermore, Chava and Jarrow (2004) analyze the SDC Database and SEC filings, which in total contain 1461 bankruptcies between 1962 and 1999. Campbell et al. (2008) use the database of Chava and Jarrow (2004) and add a broader failure indicator which records all the above criteria, along with firms being delisted for financial reasons.[5]

In order to capture a broad enough definition of distress for our larger sample, we use the approach of Dichev (1998). That is, we choose firms which have been delisted because of poor performance as our sample for "failed" firms. From the view of portfolio management, a firm is as good as bankrupt when it has been delisted because of poor performance. We analyze firms with CRSP delisting code in the 400 and 500 classes.[6]

Explanatory variables. Based on previous research, we select the following explanatory variables which are either market variables or accounting variables.

[5] In footnote 4 on page 2903 Campbell et al. (2008) mention that typical financial reasons to delist a stock include failure to maintain minimum market capitalization or stock price, file financial statements, or pay exchange fees. Nonfinancial reasons include mergers and minor delays in filing financial statements.

[6] A CRSP delisting code in the 400 class means the firm is being liquidated. The 500 class indicates the firm is being delisted because of poor performance.

1. NI/TA: net income to total assets, a.k.a. return on assets. This variable is used by Zmijewski (1984) and Shumway (2001). Compustat mnemonics: NI/AT.

2. TL/TA: total liability to total assets. This variable is used by Zmijewski (1984) and Shumway (2001), and bears a similar meaning to ME/TL in Altman (1968). Compustat mnemonics: LT/AT.

3. CA/CL: current assets to current liability, also called current ratio. This variable is used by Zmijewski (1984) to capture short term default probability. Compustat mnemonics: ACT/LCT.

4. $Rsize$: the logarithm of each firm's size relative to the total size of all firms at the same time. Campbell et al. (2008) use a similar measure, with the total size of S&P 500 firms in the denominator. This variable is derived from the firm's June price and shares outstanding, so we only include firms with those data in the CRSP tape.

5. $r_{i,t-1} - r_{m,t-1}$: the return on the firm in the previous year in excess of the market return. It is used in Shumway (2001) and Campbell et al. (2008). This is derived from CRSP.[7]

6. $Sigma$: the volatility of the stock return in the previous year. This market data is used in both Shumway (2001) and Campbell et al. (2008).[8]

There are other variables that we considered. For example, Campbell et al. (2008) find that the $PRICE$ of a stock is a good indicator whether it is in danger to default. They therefore winsorize all the prices above \$15 and use this as an explanatory variable. Campbell et al. (2008) also include $CASHMTA$, the ratio of a company's cash and short-term assets to the market value of its assets as a measure of liquidity. One other popular variable is $SALE/TA$, which indicates a firm's turnover ability. Shumway (2001) also include a firm's age as an independent variable, but he finds no evidence that it relates to the bankruptcy probability, so we follow Campbell et al. (2008) and exclude it from our list of candidates.

[7] If some observations are missing, Shumway (2001) substitutes the missing returns with the market return and then cumulates monthly returns from that year. However, this approach could be misleading when a firm was first listed in the last few months of the year. Even if the firm garners a large excess return, this effect will be diluted when cumulating monthly returns into annual returns.

[8] Shumway (2001) regresses each firm's monthly return of firms in the previous year on the monthly return of the market for the same year, then records the standard deviation of the residual. If a firm does not have 12 observations for the regression, the bankruptcy event data is dropped from the sample for that year. This approach reveals the idiosyncratic volatility after adjusting for the market risk. Campbell et al. (2008) use monthly data to construct their bankruptcy probability model, and use daily stock returns from the previous 3 months to compute return volatility.

Choice of Methodology for Predicting Distress There are two approaches we could take to explore our research question, that of Campbell et al (2008) and that of Shumway (2001). These two models differ mainly in their sampling frequency. Campbell et al. (2008) use quarterly accounting data along with monthly stock data to construct their explanatory variables and model. By contrast, Shumway (2001) works with annual accounting data to predict the probability of bankruptcy of each firm.

After extensive exploratory work, we opt for the Shumway (2001) model for the following reasons. First, the model incorporates annual data and thus makes annual predictions of financial failure. This aligns better with the usual practice of annually-rebalanced portfolios. Although Campbell et al. (2008) consider the 12 month horizon of prediction for each firm in distress, the estimation of distress probability is contingent on survival up to the 11th month. Second, the quarterly accounting data in COMPUSTAT from early years of the sample are of very poor quality, which would leave us a much smaller data pool for portfolio formation in the next stage. Specifically, with the Campbell et al. (2008) model, there are fewer than 1,000 firms per month before 1975, while we have at least 1,000 firm-years even a decade earlier (after 1965) with the Shumway (2001) model. Third, quarterly financial statements, although conveying data more frequently than annual reports, still do not relay important and up-to-date information on a monthly basis. Furthermore, the definition of "short-term" in financial statements usually has a time span of a year in mind. Therefore we feel that using annual data as in Shumway (2001) works well for the current research design.

In light of the above reasons, we estimate the probability of a firm's financial distress with its annual accounting data, which are always at least 6 months leading to the end of June.[9] If a firm gets delisted for a financial reason from July of year t to June of year $t+1$, the distress dummy of this firm will be assigned to 1 for year t, and 0 otherwise. The market data of firms are also used as explanatory variables. Firm size is determined by the market capitalization in the end of June. We divide it by the sum of the market capitalization of all NYSE, AMEX, and NASDAQ firms and then take the natural logarithm. Excess returns and firm volatility are all calculated with monthly stock returns a year before the end of June in year t.

Potential Data Issues A potential challenge in the distress probability model is that we have to sacrifice a lot of observations because some firms on CRSP tapes do not have

[9] That is, all the accounting data to be used to predict the financial distress event from July of year t to June of year $t+1$ are known before the end of December of year $t-1$).

corresponding COMPUSTAT data in certain years. The financial statements of small firms in COMPUSTAT tend to have poorer quality. Therefore it is natural for small firms to have lower coverage than large firms after combining CRSP and Compustat databases, which is an essential procedure for estimating the dynamic logit model. Figure 2 shows the loss of observations in the model.

Table 2 compares returns on 10 size portfolios from 1963 to 2009. The portfolios in Panel A include all available firms on CRSP tapes with market capitalization in June and share code of 10 or 11. Panel B shows size portfolios for firms that are on both CRSP and COMPUSTAT. These returns are slightly higher than all firms on CRSP, in the above panel. The overall pattern is nonetheless very similar. In general, smaller firms have higher returns during the course of the past 5 decades.

3.2 Summary Statistics

Table 3 presents summary statistics of the explanatory variables of all firms and of firms delisted in the following years. The first panel shows full-sample results. The second panel illustrates statistics of firms delisted in the following year, and the third panel displays the statistics of healthy firms. In addition to the variables we used in the Shumway (2001) model, we include a few others for comparison. $CASHTA$ is the cash and short-term investment to total assets ratio, and CR is the current ratio, the ratio of current assets and current liabilities. These two variables are used to capture short-term liquidity of a firm. MB is the market-to-book equity ratio of a firm. $CASHTA$ and MB are also used in Campbell et al. (2008).[10]

Most of the minimum and maximum values of the variables are the same across different panels because we winsorize all variables at 1% and 99% levels to mitigate the impact of extreme values. It is clear that failure firms have lower profitability ($NITA$), higher leverage ($TLTA$), worse stock performance ($ExRET$ and $Sigma$), and are smaller ($RSize$). They also have poorer liquidity (CR) and lower book-to-market equity ratio (BM). The ratio of the cash and short-term investments to total assets ($CASHTA$) is somewhat ambiguous. However, this is not an issue for our study because this variable, like BM and CR, does not have good explanatory power.

[10]Campbell et al. (2008) use $CASHMTA$, which adjusts the book value of total assets in the denominator with the market value of equity. In the data description, they define $CASHMTA$ as "a company's cash and short-term assets to the market value of its assets." For this definition to be feasible, the term short-term assets must refer to short-term investment.

3.3 Comparative Results

In order to place our approach firmly in the existing literature, we compare our results to those of Campbell et al (2008) and Shumway (2001), using our broader definition of distress Although we choose the Shumway (2001) model over

Comparison to Campbell et al (2008). We do our estimation with the sample of Campbell et al. (2008) model, using our less restrictive definition of the dummy variable for financial distress. The results are presented in Table 4. Evidently all variables are significant in the logistic regression. The most striking difference between our results and those of Campbell et al. (2008) is the coefficient of $RSize$. It is generally believed that smaller firms, other things being equal, usually run higher risks of bankruptcy. However, Campbell et al. (2008) find this coefficient to be positive (i.e. bigger firms have higher distress risk) yet non-significant. The only difference between two datasets is the choice of dependent variable. We use the broader definition of financial distress as firms being delisted for liquidations or for financial reasons.[11] If a firm goes bankrupt in a certain month or year, it must get delisted, but not the other way round. The distressed firm-month variable in Campbell et al. (2008) is thus a subset of our data. Our approach may therefore capture more marginal firms than they do, which ensures the correct sign of $RSize$ in our logistic regression. Thus, using our approach yields a reversal of the Campbell et al (2008) anomalously low returns for distressed stocks.

Comparison to the Shumway (2001) Model. With more observations in recent years and the inclusion of NASDAQ firms, our findings are still very similar to those of Shumway (2001). We present our comparative results in Table 5. Following Shumway (2001), volatility $Sig2$ is the square root of the average of CAPM residuals. Theoretically, this is a good measure of idiosyncratic risk.[12] The results show that all variables are significant. Moreover, all variables have a negative impact on distress risk except for $TLTA$ and $Sigma$, which is intuitive. The estimates of $TLTA$, $Sigma$, and $Rsize$ are quite close to their counterparts in the previous Table, which is reassuring.

[11]These reasons include insufficient number of shareholders or the price fell below acceptable level. In general, we choose firms with CRSP delisting code in 400's and 500's and assign 1 to the year they are delisted, and 0 otherwise.

[12]A potential challenge is that the CAPM beta is calculated with the returns from past 12 months only. During such a short period of time, the betas might not reveal the market risk each firm is bearing very well. The residual of the regression, therefore, consists not only the idiosyncratic risk but also the part of the mismeasured market risk as well. An alternative, due to Campbell et al, is to take the square root of the average of sum of squared stock returns, which contains both systematic and idiosyncratic risks. However, these two measures are strikingly similar, with a correlation higher than 0.90.

4 Empirical Results with SMB Regimes

As shown in the previous section and discussed in the Introduction, the size effect is not always intact during much of the 1980s and 1990s, although it existed before (Horowitz et al. (2000)). We therefore use a Markov regime-switching model to capture such shifts in SMB. In this framework, we work backward to see whether distress probability can be better evaluated if we factor in regime shifts of SMB. This exercise is valuable because it may help explain the source of higher returns to small firms over the long run, discussed in the Introduction. For example, if distress risk is such a source of the size effect, we could also see changes in estimated distress probability which stem from the SMB regimes.

In order to implement this insight, we augment the Shumway (2001) model by multiplying explanatory variables with a dummy variable D, and estimate a logistic regression. This dummy variable equals 1 if there is a high SMB regime in the predicting period, and 0 otherwise. The results are presented in Table 6. The notation $\times D_t$ indicates that a regressor is multiplied by the SMB dummy variable. Evidently, all cross-product terms have opposite signs from the original variables, and the dummy variable is significant with a positive sign. Leverage ($TLTA \times D_t$) and idiosyncratic risk ($Sigma \times D_t$) do not show significant differences between different SMB regimes, but the others do. This means the predictability of firms being in distress next year is lower for all regressors if the coming year is in the high SMB regime. For example, the coefficient on excess returns is negative (-1.27) without the dummy, but switches to positive (0.2624) with the dummy. Since both coefficients are significant, it suggests the importance of accounting for regimes. Consequently, our framework indicates an important direction for empirical research. In particular, it shows existence of a time-varying relation between the size effect and distress probability that has been previously neglected.

4.1 Predicting the Probability of Delisting

It is always a challenge to test predictive power of a distress risk model because the realized bankruptcies or delistings are small relative to the full sample. One method used by many studies is to sort observations into different groups according to their corresponding failure probability, then examine whether the observations of bankrupt firm-years show up in the riskier group.

Table 7 compares the Shumway (2001) logit model and the Shumway model plus an SMB dummy in the first two columns. We form 10 portfolios each year according to the firm's failure probability (the probability it is going to be delisted in the following year). Portfolio 1 consists of the firms with the highest failure probabilities. Portfolio 10 includes firms with the least likelihood to be delisted for financial reasons. If the model predicts delisting properly, we would see failing firms extensively in the first few portfolios. Although the SMB dummy proves to be significant in the logit model estimation, its impact on the failure probabilities is small. The first two columns are essentially the same.

The third column shows portfolios formed by the Z-score of Altman (1968), which has been used by practitioners to assess credit risks for several decades. Apparently it is out-performed by the dynamic logit models. The last column modifies the static approach of Altman (1968) by using the original Z-score variables in a dynamic logit model. The performance is better than the static Z-score of Altman (1968), but the improvement is limited. Corroborating the results of Shumway (2001) and Campbell et al. (2008), the inclusion of market data is essential to the predictability power of the logit model.[13]

4.2 Double Sorting

In order to implement our model, we construct 25 portfolios by double-sorting firms according to size and failure probability. First we sort firms into five size groups according to market capitalization relative to the NYSE quintile breakpoints. Then we further sort firms within each size group to 5 different portfolios based on their failure probabilities. All portfolios are constructed in June of each year and weighted according to their current market capitalization.[14]

Table 8 shows average portfolio returns and standard deviations. In Panel A we find a similar pattern to that of Campbell et al. (2008), namely, high risk firms have a lower average return than low risk firms after controlling for size. However, the difference (see the row labeled "High-Low") is far less significant than the results of Campbell et al. (2008).

In Panel B and C we separate the portfolio returns according to SMB regimes. In Panel B we calculate average returns and standard deviation of returns on each portfolio with

[13]Note that the last two rows illustrate the number of delisting firms and the total observations. Since the quality of accounting data in COMPUSTAT is not consistent to all firms and all variables, the more accounting variables we include, the more likely we will see missing variables in some observations.

[14]This is a standard approach, used for example in Table VII of Campbell et al. (2008).

samples from high SMB years.[15] We pay special attention to the largest and smallest size groups. Large-cap and small-cap firms all report positive spreads between high risk and low risk firms, as theory would predict. The return differential between high and low failure probability portfolios turns negative like other groups, and of all times when SMB falls in the low value regime. Most of the risk spreads are statistically insignificant.

In sum, we find as in Campbell et al. (2008) that distressed firms underperform the market. However, this result is not statistically significant. The size effect is linked to financial distress only through the correlation between firm size and distress probability.

4.3 Results for Non-Financial vs Financial Firms

In light of recent financial events, it is important to understand whether there is a differential between financial and non-financial firms. We therefore include in our study a consideration of financial versus non-financial firms. This is relevant also from a research perspective, since some researchers do not include financial firms in asset pricing study because they behave very differently in certain areas. For example, financial firms typically have higher leverage, and this is usually an important variable in modelling distress probabilities.

Non-Financial Firms. Table 10 presents summary statistics for all non-financial firms in our sample. The first panel displays results for all firms. The second panel shows data for firms which are in distress at some point in the following year. The third panel reports the information of firms that are healthy at least for the following year. The statistics appear quite close to those of the full sample. We list the statistics of the book-to-market ratio and the current ratio, but they are not used in the logit model because of low explanatory power.[16]

The variable that is most affected by regimes is leverage ($TLTA$), in terms of standard deviation. However, these parameters are of the same sign and similar magnitude as the ones in the full sample estimation. This corroborates our results for the sample of all firms. During high SMB regimes, the marginal effect on distress probability is lower for all variables. $TLTA$ and $Sig2$ are again not significantly different during different regimes.

[15] The list of high SMB years: 1963-67, 1974-82, 1999-04, for a total of 20 years. There are 26 low SMB years in our sample. These years are identified with annual SMB and a Markov regime-switching model, described in the Appendix.

[16] The book-to-market ratio has a p-value greater than 0.05 but less than 0.10 for all firms and non-financial firms.

Table 9 examines sample variation in distressed firms, with regard to their respective failure probability portfolios. Evidently the logit model on either all firms or only non-financial firms gives very similar results. We also verify again that the explanatory variables used in Altman (1968)'s Z-score are outperformed by the Shumway (2001) model.

We examine the double-sorting results in Table 12. This table is comparable to Table 8, except that we exclude financial firms (SIC code 6000-6999). To present the significance of differences between high- and low-risk portfolios within size groups, we calculate the t-value as follows:

$$t = \frac{\overline{R_H - R_L}}{s(R_H - R_L)/\sqrt{n}}$$

In such case, only the risk spreads between the highest and lowest risk quintile portfolios from the biggest and the smallest size groups are significant when SMB falls in the low regime. In most of the cases the difference is not significant, which is contrary to the findings of Campbell et al. (2008).

Financial Firms. Table 13 presents results on the Shumway (2001) model for financial firms. Interestingly, financial leverage, or the capital structure, does not statistically affect the distress probability of the financial industry. Other than that, the rest of the explanatory variables have the same sign as other publicly listing firms.

Financial firms are usually assumed to have higher debt/asset ratio than other firms by nature. However, we find that that healthy financial firms have in fact higher debt/asset ratio than distressed firms. The summary statistics of explanatory variables are in Table 14. Distressed firms comprise 301 firms, compared to more than 20,000 for healthy firms. We also conduct double-sorting for financial firms. The resultant portfolios are in Table 15. Because the number of financial firms is much lower than the non-financial firms, we limit the number of size portfolios to only 2: big and small size portfolios. For the same reason, the number of distress probability portfolios is limited to 3 for each size group. We have 6 portfolios in total to keep the number of firms in each portfolios above 20 most of the time. The return differential High-Low is statistically insignificant in both regimes and for the full sample.

4.4 The Pricing of Distress Risk

We now estimate the price of distress risk. Following the approach of Fama and Macbeth (1973), we run time-series regressions of 10-by-10 size and distress probability portfolios to obtain 100 sets of risk loadings:

$$(R_{it} - R_{ft}) = \alpha_i + \sum_k \beta_{ik} f_{kt} + \varepsilon_{it} \qquad t = 1, \ldots, T, \tag{3}$$

where $i = 1, \ldots, 100$ represent different portfolios, f_t includes the excess market return (in CAPM), or excess market return, SMB and HML (in the Fama-French 3 factor model.)

We sort securities in the end of June each year by their respective market capitalization and distress probability to form 100 portfolios for the test. The first step is to divide securities into 10 size groups according to NYSE breakpoints. We then sort firms within each size group with their distress probability and form 10 portfolios with equal number of firms. In the second stage we use these loadings to run a cross-sectional regression in each month. The dependent variable is the realized excess return on 100 test portfolios, and the independent variables are the corresponding risk loadings measured in the first stage.

$$(R_{it} - R_{ft}) = \sum_k \beta_{ik} \lambda_{kt} + s_{it} \gamma_t + \alpha_{it} \qquad i = 1, \ldots, 100 \text{ for each } t, \tag{4}$$

For each month we obtain a set of risk prices λ_t and γ_t. The choice of the distress risk measure in the cross-sectional regression is the weighted odds ratio of firms in the portfolio, $\log(P_{it}/(1 - P_{it}))$. We use the market capitalization in the end of each month to construct the weights. Therefore P_{it} represents the distress probability of the portfolio.[17] We run one time-series regression for each portfolio.

There are only a few firms in some portfolios in early years, so we also calculate the risk loadings with sum beta approach to alleviate the thin-trading problem. That is, we regress the test portfolio return on the factors and lagged factors. Therefore, equation (3) can be written as

$$(R_{it} - R_{ft}) = \alpha_i + \sum_k \beta^1_{ik} f_{kt} + \sum_k \beta^2_{ik} f_{kt-1} + \varepsilon_{it} \qquad t = 1, \ldots, T. \tag{5}$$

The risk loadings used in equation (4) are the sum of β^1 and β^2.

[17] We use annual accounting data to estimate the distress probability, so P_{it} of each firm is unchanged over the 12 month period from July of year t to June of year $t+1$. The market capitalization of each firm changes on the daily basis, so the weight of each firm (and hence, the distress probability) in the portfolio changes every month.

We estimate λ_k and γ as the average of the cross-sectional regression estimates, such that

$$\hat{\lambda}_k = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{kt}, \qquad \hat{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t. \tag{6}$$

The variance of these variables should account for the fact that the time series are serially correlated, so we estimate Newey and West (1987) standard deviations.

The price of risk estimates are in Table 16. The results from sum beta approach and the traditional beta approach are very similar. Panel A shows results without an intercept. Surprisingly, the odds ratio is insignificant except in the Fama-French 3-factor model. Panel B shows results with an intercept term. The odds ratio is always unpriced. However, when the odds ratio is added to the Fama French model, it removes significance of the intercept term. Thus, inclusion of the odds ratio appears to reduce pricing error.[18][19]

GMM Results for Linear Factor Model. Finally, we construct a distress factor based on portfolio return differentials as in Fama and French (1993). We first present correlations, then analyze risk premia and asset pricing tests in the context of a linear factor model. In accordance with our reasoning from Section 1, we split the sample into two regimes, which reflect potentially different behavior of the size effect.[20]

Correlations are displayed in Table 17. Interestingly, our distress factor has a negative correlation with HML over the entire sample, but this masks a switch from positive (0.1632) to negative (-0.2481) over the two samples. Furthermore, the distress factor's correlation with SMB decreases from 0.9140 to 0.7641 over the samples. This provides suggestive evidence on structural change in the factors, which we explore further below.

Table 18 presents risk premia and formal GMM-based asset pricing tests, in the linear factor model framework. Let us examine the estimated risk premia in Panel B. In this panel, the most striking finding is that for the CAPM-Distress Risk model, the Distress premium

[18] One major difference between models in Panel A and Panel B is we force the α_{it} term in equation (4) to absorb all the pricing error, especially those from α_i in equation (3). These unexplained errors can be absorbed by the intercept term present in Panel B.

[19] We also try a 60-month rolling window approach to estimate time-series regressions in order to get time-varying betas. The results are similar to those in the previous Table 16, and available from the authors, upon request.

[20] The first part of the data is from 1963.7 to 1982.6, and the second is from 1982.7 to 2009.6. This division reflects the periods before and after the size effect was well publicized: a plausible range for this period is from the time of a primary article on size, Banz (1981), to the time of the June 1983 *Journal of Financial Economics* issue devoted to the size effect. It is fair to say that the size effect was made well known in early 1980s, and some researchers argue that this effect has subsequently disappeared. We considered the years 1981, 1982, and 1983. We chose 1982 because it features the largest dispersion of SMB returns.

switches sign from the first period (1.26%) to the second period (-1.17%). A similar result obtains in the Fama-French model augmented with a Distress factor.

Formal asset pricing tests on the exposure portfolios are presented in Panel C, Model Diagnostics. J-stat is the Hansen (1982) test of over-identifying restrictions. HJ Dist is the distance metric of Hansen and Jagannathan (1997), which measures the maximum annualized pricing error for each model. Large p-values for the J-statistic and HJ distance indicate that the particular model fits well. The Delta-J test of Newey and West (1987) examines whether SMB and HML have additional ability to explain asset prices, relative to each alternative model.[21] Small p-values for the Delta-J test indicate that addition of SMB and HML improves model fit. The J-test has large p-values, indicating that we cannot reject any of the models. Returning to Panel C, the HJ-distance only has large p-values for the early sample, for each model. This indicates that we can only accept the models during the period 1963-1982, or alternatively, after 1982 we cannot accept any of the models considered. Turning to the Delta-J test, the small p-values in the late sample indicate that SMB and HML improve the fit of a model of CAPM augmented with Distress. However, for the early sample, the p-value of 0.07 indicates that Distress is statistically superior to a model with SMB and HML, at conventional significance levels.

To summarize, the distress factor earns a significant positive premium only in the first part of the sample. Moreover, the CAPM augmented with the Distress factor can plausibly price out SMB and HML in the early sample. This is interesting since the early sample is when SMB was large. Taken together, our results indicate striking differences between the two sample regimes.

5 Conclusions

The recent financial crisis has shown that distress risk is a serious matter in both the financial and real economy. In this paper we show that it is important to account for regime switches in the risk factors. Building on the work of Dichev (1998), Shumway (2001), and Campbell et al. (2008), we analyze the link between distress and the size effect. We also account for possible differences between financial and non-financial firms. Importantly, we find that the distress anomaly of Campbell et al (2008) is removed when we use a broader definition of distress, which allows for delisting. We have two additional results. First, we

[21]For more details on these tests, see Cochrane (2001).

control for sample selection, documenting the importance of regime shifts in the size effect. Second, we estimate the premium for distress risk in two ways, using both the odds of distress and a distress risk factor based on return differentials. In the odds ratio approach, the price of distress risk is generally not significant. In the factor approach, distress risk earns a significant positive premium and can plausibly price out SMB and HML in the first part of the sample.

More broadly, our results indicate instability in the premia for risk factors, as well as fragility of anomalies related to distress risk. These findings suggest that the risk of distress could be profitably modelled in a regime switching framework. Understanding the ramifications of this more flexible approach to modelling risk premia may be a valuable direction for future research.

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6 Appendix

6.1 Regime-Switching Model on SMB

We model the expected mean and variance of SMB via a two state Markov-switching model, so the state variable S_t, which governs the regime shift, takes a value of 1 or 2. When $S_t = 1$, ($S_t = 2$) the expected mean of SMB_t is high (low). The basic model is

$$y_t = \mu_k + \sigma_k \varepsilon_t \qquad \varepsilon_t \sim N(0,1). \tag{7}$$

where y_t represents SMB_t, μ_k and σ_k are state-dependent mean and standard deviation of SMB_t. k=1 or 2, which identifies the state SMB_t is in at time t. The state variable S_t is assumed to follow a 2-state first-order Markov process with fixed transition probabilities as follows:

$$\begin{aligned} p &= \Pr(S_t = 1|S_{t-1} = 1) \\ 1-p &= \Pr(S_t = 2|S_{t-1} = 1) \\ q &= \Pr(S_t = 2|S_{t-1} = 2) \\ 1-q &= \Pr(S_t = 1|S_{t-1} = 2) \end{aligned} \tag{8}$$

The mean and variance of SMB are determined by the current state, and the state variable S_t is independent of information beyond one period's lag. SMB_t in each state is assumed to follow the normal distribution, with parameters of the distribution function only contingent on the state k, so

$$f(y_t|S_t = k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(\frac{-(y_t - \mu_k)^2}{2\sigma_k^2}\right)$$

for $k = 1,2$. The log-likelihood function is

$$\ln \mathscr{L}(y_1, y_2, \ldots, y_T; \theta) = \sum_{t=1}^{T} \ln[\Pr(S_t = 1) f(y_t|S_t = 1) + \Pr(S_t = 2) f(y_t|S_t = 2)] \tag{9}$$

We estimate the regime probability $\Pr(S_t = k)$ with the recursive representation of Gray (1996):

$$\begin{aligned} \Pr(S_t = 1) \quad = \quad & (1-q)\left[\frac{f(y_{t-1}|S_{t-1} = 2)\Pr(S_{t-1} = 2)}{f(y_{t-1}|S_{t-1} = 1)\Pr(S_{t-1} = 1) + f(y_{t-1}|S_{t-1} = 2)\Pr(S_{t-1} = 2)}\right] \\ & + p\left[\frac{f(y_{t-1}|S_{t-1} = 1)\Pr(S_{t-1} = 1)}{f(y_{t-1}|S_{t-1} = 1)\Pr(S_{t-1} = 1) + f(y_{t-1}|S_{t-1} = 2)\Pr(S_{t-1} = 2)}\right] \end{aligned} \tag{10}$$

where lowercase p and q are transition probabilities defined in (8) and $\Pr(S_t = 2) = 1 - \Pr(S_t = 1)$.

Table 1: Return Differentials between Portfolios of Small and Big firms

	1980-1995	1981-2003	1926-2009
F-F SMB	0.26	1.31	2.84
	(8.17)	(11.70)	(11.56)
Decile SMB	−2.92	0.87	7.06
	(13.38)	(17.76)	(26.49)

Standard deviations are in parentheses.

Figure 1: The return differentials and probability of SMB regimes
The figure shows the difference in returns between the first and the 10th decile size portfolios and the smoothed probability of the high small stock premium regime. Panel A shows the annual portfolio return difference between small and big stocks. The smoothed inference of the high SMB regime is shown in Panel B. The shaded area indicates the contraction period during US business cycles.

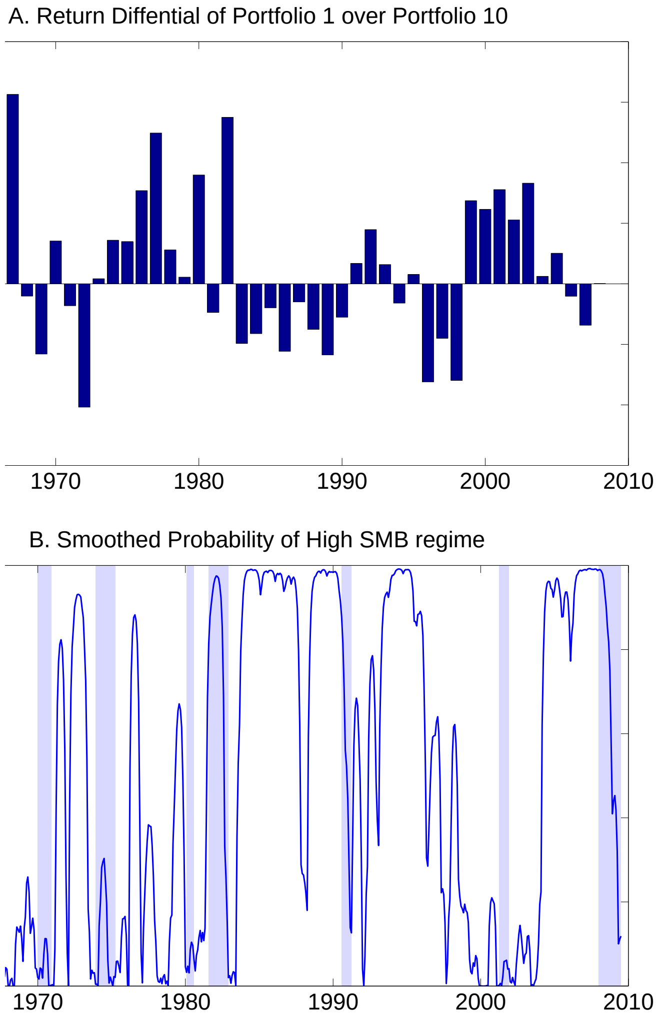

Figure 2: Percentage of observations lost in each size portfolio.

The figure shows the percentage of observations lost in each portfolio after combining CRSP database and the dynamic logit model, which uses both CRSP and COMPUSTAT data. The denominator is the total number of firms of each size portfolio with CRSP data only. Small firms usually have a higher “missing" rate than large firms because the quality of their accounting data is poorer. Size1 means the size portfolio with the largest firms, and Size10 is the size portfolio consists of the smallest firms. Portfolio breakpoints are determined by all NYSE firms on CRSP tape according to their June market capitalization (ME). NASDAQ and AMEX firms are inserted to each portfolio according to their June ME and the breakpoints.

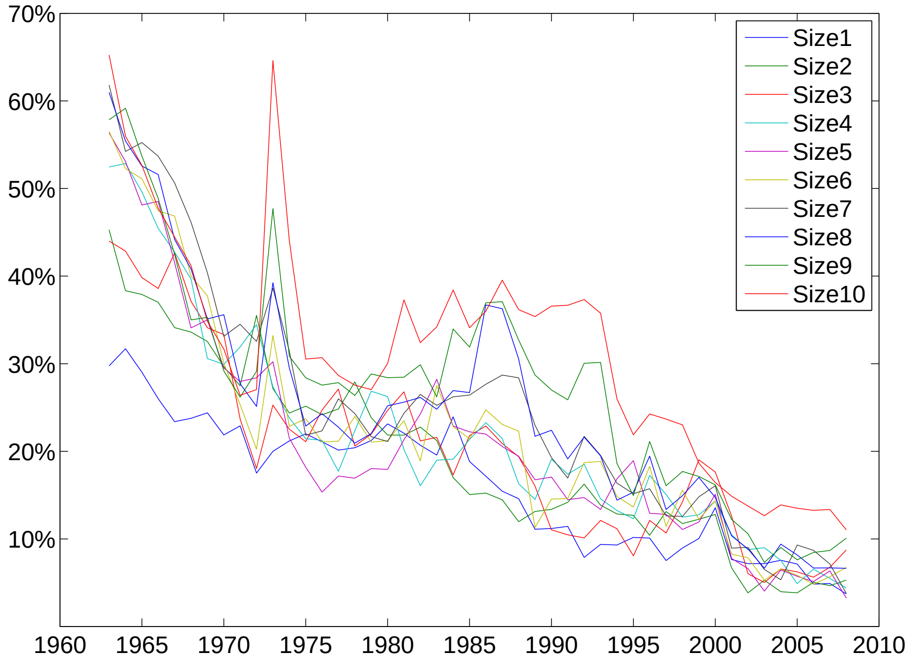

Table 2: Comparison of size portfolio returns between portfolios sorted with firms on CRSP tape or firms on both CRSP and COMPUSTAT tapes. These data are reported in monthly frequency

Panel A: All NYSE, AMEX and NASDAQ listed Firms

Variable	Mean	Std Dev	Minimum	Maximum
Size1	0.0083	0.0428	-0.1976	0.1807
Size2	0.0098	0.0467	-0.2246	0.1799
Size3	0.0103	0.0505	-0.2403	0.1903
Size4	0.0111	0.0518	-0.2572	0.2181
Size5	0.0106	0.0531	-0.2621	0.2061
Size6	0.0117	0.0560	-0.2809	0.2524
Size7	0.0117	0.0588	-0.2954	0.2479
Size8	0.0118	0.0601	-0.2889	0.2535
Size9	0.0113	0.0633	-0.3015	0.2843
Size10	0.0120	0.0647	-0.2894	0.2957

Panel B: Firms with Bankruptcy Probability Information

Variable	Mean	Std Dev	Minimum	Maximum
Size1	0.0084	0.0427	-0.1938	0.1870
Size2	0.0101	0.0466	-0.2189	0.1850
Size3	0.0107	0.0502	-0.2368	0.1973
Size4	0.0111	0.0517	-0.2603	0.2131
Size5	0.0108	0.0528	-0.2585	0.2096
Size6	0.0122	0.0559	-0.2865	0.2551
Size7	0.0122	0.0581	-0.2879	0.2531
Size8	0.0126	0.0599	-0.3004	0.2542
Size9	0.0123	0.0639	-0.3143	0.2963
Size10	0.0131	0.0659	-0.3037	0.3031

Table 3: Summary statistics of explanatory variables under different distress conditions. All variables are winsorized at 1% and 99% levels of the full dataset. Here we include CASHTA, BM, CR, but they are not used in the logit model.

Panel A: All Observations

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	166434	-0.0053	0.1861	-1.0656	0.2510
TLTA	166434	0.5280	0.2482	0.0499	1.1574
ExRET	166434	1.0200	0.4883	0.1693	3.0682
RSize	166434	-10.6028	2.0015	-14.8387	-5.7508
Sigma	166434	0.1446	0.0910	0.0301	0.5508
CASHTA	165247	0.1479	0.1903	0.0005	0.8741
BM	163317	0.7901	0.7140	-0.7993	3.8470
CR	143388	2.8579	2.8017	0.3252	19.5520

Panel B: Firms in Distress the Following Year

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	4585	-0.2548	0.3479	-1.0656	0.2510
TLTA	4585	0.6233	0.2872	0.0499	1.1574
ExRET	4585	0.6131	0.4891	0.1693	3.0682
RSize	4585	-13.2283	1.3448	-14.8387	-5.9060
Sigma	4585	0.2491	0.1256	0.0301	0.5508
CASHTA	4585	0.1581	0.2171	0.0005	0.8741
BM	4533	0.7366	1.0193	-0.7993	3.8470
CR	4189	2.2899	3.0047	0.3252	19.5520

Panel C: Firms in Healthy Condition the Following Year

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	161849	0.0017	0.1743	-1.0656	0.2510
TLTA	161849	0.5253	0.2465	0.0499	1.1574
ExRET	161849	1.0315	0.4833	0.1693	3.0682
RSize	161849	-10.5284	1.9666	-14.8387	-5.7508
Sigma	161849	0.1417	0.0880	0.0301	0.5508
CASHTA	160662	0.1477	0.1894	0.0005	0.8741
BM	158784	0.7916	0.7033	-0.7993	3.8470
CR	139199	2.8750	2.7936	0.3252	19.5520

Table 4: Results of Campbel et al Model Estimation

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-16.7924	0.3834	1918.6342	<.0001
NIMTAAVG	-30.6854	1.2232	629.3002	<.0001
TLMTA	1.5468	0.063	603.2093	<.0001
EXRETAVG	-3.5426	0.4749	55.6585	<.0001
Sigma	0.3896	0.0547	50.754	<.0001
RSize	-0.7906	0.0288	751.8166	<.0001
CASHMTA	-0.8489	0.1834	21.4247	<.0001
MB	0.2414	0.00746	1046.2596	<.0001
PRICE	-0.8621	0.0355	590.9697	<.0001

Table 5: Shumway Model with all firms available

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-13.4489	0.189	5063.4687	<.0001
NITA	-1.1662	0.0548	453.1463	<.0001
TLTA	1.5278	0.0603	642.265	<.0001
ExRET	-1.1782	0.0435	732.6389	<.0001
Sigma	3.5775	0.1474	588.9153	<.0001
RSize	-0.7635	0.0137	3089.7731	<.0001

Table 6: Shumway Model with SMB dummy.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-13.8858	0.2493	3102.671	<.0001
Dum	1.0676	0.3853	7.6796	0.0056
NITA	-1.2528	0.0681	338.6526	<.0001
TLTA	1.5479	0.0748	428.5006	<.0001
ExRET	-1.2726	0.0588	468.8030	<.0001
Sigma	3.7817	0.1955	374.1542	<.0001
RSize	-0.802	0.0181	1964.8444	<.0001
NITA $\times D_t$	0.2745	0.1153	5.6698	0.0173
TLTA $\times D_t$	-0.0847	0.1274	0.4423	0.5060
ExRET $\times D_t$	0.2624	0.0871	9.0846	0.0026
Sigma $\times D_t$	-0.1223	0.3047	0.1613	0.6880
RSize $\times D_t$	0.1025	0.0280	13.3834	0.0003

Table 7: Comparison of different models

Port	Shumway (2001) Logit Model	Shumway (2001) Logit Model w/ SMB Dummy	Zscore	Altman Logit
1	3055	3049	1316	1728
2	700	709	531	650
3	321	318	354	268
4	155	159	277	184
5	118	119	224	246
6	88	84	178	203
7	66	67	177	133
8	44	42	189	128
9	27	27	243	109
10	11	11	244	84
No. of Delisted firms	4585	4585	3733	3733
No. of total obs.	166434	166434	124162	124162

Table 8: Portfolios sorted by size and failure risk

Panel A. Full Sample

	Big	Size 2	Size 3	Size 4	Small
High Risk	0.0076	0.0083	0.0076	0.0083	0.0091
	(0.0565)	(0.0622)	(0.0656)	(0.0752)	(0.0930)
Failure Prob 2	0.0085	0.0103	0.0109	0.0120	0.0103
	(0.0486)	(0.0522)	(0.0541)	(0.0592)	(0.0791)
Failure Prob 3	0.0080	0.0102	0.0109	0.0126	0.0111
	(0.0479)	(0.0482)	(0.0513)	(0.0572)	(0.0701)
Failure Prob 4	0.0074	0.0101	0.0107	0.0129	0.0117
	(0.0452)	(0.0495)	(0.0515)	(0.0564)	(0.0617)
Low Risk	0.0086	0.0108	0.0121	0.0117	0.0129
	(0.0436)	(0.0592)	(0.0619)	(0.0625)	(0.0605)
High-Low	-0.0011	-0.0025	-0.0045	-0.0034	-0.0038
	(0.0388)	(0.0432)	(0.0433)	(0.0411)	(0.0557)

Panel B. High SMB regime

	Big	Size 2	Size 3	Size 4	Small
High Risk	0.0087	0.0118	0.0108	0.0154	0.0253
	(0.0558)	(0.0657)	(0.0667)	(0.0786)	(0.1053)
Failure Prob 2	0.0100	0.0146	0.0167	0.0171	0.0244
	(0.0475)	(0.0507)	(0.0528)	(0.0598)	(0.0857)
Failure Prob 3	0.0091	0.0132	0.0160	0.0202	0.0234
	(0.0487)	(0.0476)	(0.0495)	(0.0591)	(0.0743)
Failure Prob 4	0.0049	0.0139	0.0164	0.0190	0.0220
	(0.0483)	(0.0499)	(0.0509)	(0.0579)	(0.0634)
Low Risk	0.0067	0.0146	0.0171	0.0194	0.0224
	(0.0457)	(0.0627)	(0.0631)	(0.0642)	(0.0636)
High-Low	0.0020	-0.0028	-0.0063	-0.0040	0.0028
	(0.0433)	(0.0525)	(0.0483)	(0.0458)	(0.0623)

Panel C. Low SMB regime

	Big	Size 2	Size 3	Size 4	Small
High Risk	0.0067	0.0056	0.0051	0.0029	-0.0033
	(0.0571)	(0.0593)	(0.0649)	(0.0722)	(0.0803)
Failure Prob 2	0.0073	0.0070	0.0064	0.0080	-0.0005
	(0.0494)	(0.0531)	(0.0547)	(0.0585)	(0.0720)
Failure Prob 3	0.0072	0.0078	0.0070	0.0067	0.0016
	(0.0474)	(0.0485)	(0.0523)	(0.0551)	(0.0653)
Failure Prob 4	0.0093	0.0073	0.0063	0.0082	0.0038
	(0.0426)	(0.0492)	(0.0516)	(0.0548)	(0.0594)
Low Risk	0.0101	0.0079	0.0082	0.0059	0.0056
	(0.0419)	(0.0564)	(0.0607)	(0.0606)	(0.0571)
High-Low	-0.0035	-0.0023	-0.0032	-0.0030	-0.0089
	(0.0349)	(0.0345)	(0.0389)	(0.0372)	(0.0494)

Table 9: Comparison of different models.

	All Firms		Non-Financial Firms					
Port	Shumway Logit Model	PCT	Shumway Logit Model	PCT	Altman Var Logit Model	PCT	Zscore	PCT
1	3055	66.63	2641	65.88	1639	46.84	1250	35.72
2	700	15.27	654	16.31	598	17.09	529	15.12
3	321	7.00	284	7.08	249	7.12	306	8.75
4	155	3.38	140	3.49	210	6.00	247	7.06
5	118	2.57	106	2.64	192	5.49	214	6.12
6	88	1.92	75	1.87	180	5.14	164	4.69
7	66	1.44	47	1.17	122	3.49	165	4.72
8	44	0.96	30	0.75	124	3.54	178	5.09
9	27	0.59	24	0.60	106	3.03	214	6.12
10	11	0.24	8	0.20	79	2.26	232	6.63
	4585	100.00	4009	100.00	3499	100.00	3499	100.00

Table 10: Summary Statistics of explanatory variables, all non-financial firms

Panel A: All Observations

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	138745	-0.00893	0.203259	-1.15184	0.254766
TLTA	138745	0.48172	0.22439	0.049534	1.193983
ExRET	138745	1.017521	0.508374	0.162495	3.194179
RSize	138745	-10.4396	1.993704	-14.6836	-5.56507
Sigma	138745	0.15188	0.093112	0.033631	0.571001
CASHTA	137829	0.153786	0.197356	0.00039	0.884473
BM	135808	0.771061	0.724988	-0.88421	3.824365
CR	136385	2.854803	2.725819	0.334666	18.87261

Panel B: Firms in Distress the Following Year

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	4009	-0.27919	0.369839	-1.15184	0.254766
TLTA	4009	0.615368	0.289817	0.049534	1.193983
ExRET	4009	0.60556	0.494013	0.162495	3.194179
RSize	4009	-13.0629	1.322718	-14.6836	-5.68278
Sigma	4009	0.255185	0.12664	0.033631	0.571001
CASHTA	4009	0.158477	0.218841	0.00039	0.884473
BM	3960	0.707725	1.021368	-0.88421	3.824365
CR	3919	2.236349	2.785974	0.334666	18.87261

Panel C: Firms in Healthy Condition the Following Year

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	134736	-0.00089	0.190359	-1.15184	0.254766
TLTA	134736	0.477744	0.220914	0.049534	1.193983
ExRET	134736	1.029779	0.503661	0.162495	3.194179
RSize	134736	-10.3615	1.957094	-14.6836	-5.56507
Sigma	134736	0.148806	0.090131	0.033631	0.571001
CASHTA	133820	0.153645	0.196676	0.00039	0.884473
BM	131848	0.772964	0.714105	-0.88421	3.824365
CR	132466	2.8731	2.72189	0.334666	18.87261

Table 11: Estimation of Shumway model, non-financial firms

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-13.5198	0.2009	4527.704	<.0001
NITA	-1.1049	0.0548	406.2917	<.0001
TLTA	1.7502	0.0657	709.1715	<.0001
ExRET	-1.12	0.0463	586.115	<.0001
Sigma	3.1596	0.1586	396.785	<.0001
RSize	-0.7768	0.0148	2740.053	<.0001

Table 12: Portfolios sorted by size and failure risk, non-financial firms

Panel A. Full Sample

	Big	Size 2	Size 3	Size 4	Size 5
High Risk	0.0077	0.0081	0.0083	0.0083	0.0094
	(0.0531)	(0.0639)	(0.0690)	(0.0792)	(0.0938)
Failure Prob 2	0.0084	0.0099	0.0113	0.0121	0.0109
	(0.0464)	(0.0518)	(0.0562)	(0.0640)	(0.0847)
Failure Prob 3	0.0087	0.0104	0.0106	0.0122	0.0113
	(0.0471)	(0.0479)	(0.0529)	(0.0602)	(0.0749)
Failure Prob 4	0.0073	0.0099	0.0105	0.0124	0.0121
	(0.0448)	(0.0527)	(0.0540)	(0.0580)	(0.0664)
Low Risk	0.0087	0.0107	0.0117	0.0118	0.0125
	(0.0448)	(0.0616)	(0.0633)	(0.0646)	(0.0627)
High-Low	-0.0010	-0.0026	-0.0033	-0.0034	-0.0032
	(0.0383)	(0.0436)	(0.0431)	(0.0417)	(0.0552)

Panel B. High SMB regime

	Big	Size 2	Size 3	Size 4	Size 5
High Risk	0.0091	0.0112	0.0130	0.0160	0.0244
	(0.0574)	(0.0687)	(0.0718)	(0.0851)	(0.1047)
Failure Prob 2	0.0091	0.0145	0.0168	0.0188	0.0257
	(0.0457)	(0.0523)	(0.0560)	(0.0650)	(0.0951)
Failure Prob 3	0.0094	0.0133	0.0163	0.0192	0.0239
	(0.0496)	(0.0483)	(0.0520)	(0.0629)	(0.0809)
Failure Prob 4	0.0039	0.0137	0.0160	0.0189	0.0228
	(0.0479)	(0.0538)	(0.0535)	(0.0593)	(0.0703)
Low Risk	0.0068	0.0143	0.0163	0.0195	0.0220
	(0.0472)	(0.0666)	(0.0641)	(0.0660)	(0.0662)
High-Low	0.0024	-0.0031	-0.0033	-0.0035	0.0024
	(0.0455)	(0.0522)	(0.0474)	(0.0470)	(0.0595)

Panel C. Low SMB regime

	Big	Size 2	Size 3	Size 4	Size 5
High Risk	0.0065	0.0058	0.0048	0.0024	-0.0022
	(0.0495)	(0.0599)	(0.0666)	(0.0740)	(0.0828)
Failure Prob 2	0.0079	0.0064	0.0071	0.0069	-0.0005
	(0.0471)	(0.0512)	(0.0561)	(0.0628)	(0.0739)
Failure Prob 3	0.0081	0.0082	0.0061	0.0069	0.0017
	(0.0452)	(0.0475)	(0.0533)	(0.0575)	(0.0685)
Failure Prob 4	0.0099	0.0070	0.0062	0.0074	0.0038
	(0.0422)	(0.0517)	(0.0541)	(0.0565)	(0.0620)
Low Risk	0.0102	0.0079	0.0081	0.0058	0.0053
	(0.0428)	(0.0574)	(0.0626)	(0.0629)	(0.0588)
High-Low	-0.0036	-0.0021	-0.0034	-0.0034	-0.0075
	(0.0316)	(0.0357)	(0.0395)	(0.0372)	(0.0513)

Table 13: Estimation of Shumway model, financial firms

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-10.1012	0.6485	242.6329	<.0001
NITA	-3.5996	1.0809	11.091	0.0009
TLTA	-0.2326	0.2759	0.7111	0.3991
ExRET	-1.7458	0.1921	82.5879	<.0001
Sigma	8.0392	0.7306	121.0837	<.0001
RSize	-0.6591	0.0495	177.4241	<.0001

Table 14: Summary Statistics of explanatory variables, financial firms

Panel A: All Observations

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	20485	0.015963	0.037423	-0.1563	0.186411
TLTA	20485	0.830259	0.173737	0.133926	0.971224
ExRET	20485	1.04591	0.359443	0.26314	2.354572
RSize	20485	-8.72666	2.048475	-12.7093	-4.06394
Sigma	20485	0.094877	0.056167	0.02437	0.359719
CASHTA	20217	0.101728	0.115157	0.002077	0.625715
BM	20444	0.864317	0.547656	0.036893	3.450739
CR	1770	2.373825	2.572627	0.230239	18.08202

Panel B: Firms in Distress the Following Year

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	301	-0.02483	0.073507	-0.1563	0.186411
TLTA	301	0.764391	0.231594	0.133926	0.971224
ExRET	301	0.670708	0.413134	0.26314	2.354572
RSize	301	-11.189	1.572742	-12.7093	-5.31709
Sigma	301	0.18686	0.104406	0.02437	0.359719
CASHTA	301	0.135756	0.156692	0.002077	0.625715
BM	301	1.083676	0.908897	0.036893	3.450739
CR	54	2.676117	3.429431	0.230239	18.08202

Panel C: Firms in Healthy Condition the Following Year

Variable	N	Mean	Std Dev	Minimum	Maximum
NITA	20184	0.016572	0.036274	-0.1563	0.186411
TLTA	20184	0.831242	0.172545	0.133926	0.971224
ExRET	20184	1.051505	0.35561	0.26314	2.354572
RSize	20184	-8.68994	2.032312	-12.7093	-4.06394
Sigma	20184	0.093505	0.05396	0.02437	0.359719
CASHTA	19916	0.101213	0.114342	0.002077	0.625715
BM	20143	0.861039	0.539792	0.036893	3.450739
CR	1716	2.364312	2.541727	0.230239	18.08202

Table 15: Portfolios sorted by size and distress risk, Financial Firms

Panel A. Full Sample

	Big	Small
High Risk	0.0057	0.0101
	(0.0688)	(0.0876)
Mid Risk	0.0096	0.0132
	(0.0631)	(0.0626)
Low Risk	0.0087	0.0132
	(0.0620)	(0.0544)
High-Low	-0.0030	-0.0031
	(0.0420)	(0.0632)

Panel B. High SMB regime

	Big	Small
High Risk	0.0097	0.0224
	(0.0634)	(0.0950)
Mid Risk	0.0121	0.0193
	(0.0590)	(0.0590)
Low Risk	0.0088	0.0182
	(0.0580)	(0.0499)
High-Low	0.0009	0.0042
	(0.0400)	(0.0729)

Panel C. Low SMB regime

	Big	Small
High Risk	0.0027	0.0007
	(0.0725)	(0.0804)
Mid Risk	0.0077	0.0086
	(0.0661)	(0.0649)
Low Risk	0.0086	0.0094
	(0.0650)	(0.0574)
High-Low	-0.0059	-0.0087
	(0.0433)	(0.0541)

Table 16: Risk Premium Estimates. Panel A reports the price of risk estimated with no intercept term in the cross-sectional regression. Panel B displays the estimation with intercept term in the cross-sectional regression. We also present both sum beta on the left and tradition simple beta on the right. t-values are in the parentheses.

Panel A: No intercept in cross-sectional regression

	Sum Beta Approach					Simple Beta Approach			
	CAPM		FF3			CAPM		FF3	
MKTRF	0.0048	0.0031	0.0048	-0.0078	MKTRF	0.0051	0.0039	0.0048	-0.0102
	(2.27)	(1.20)	(2.31)	(-2.64)		(2.30)	(1.16)	(2.38)	(-2.94)
SMB			0.0020	0.0053	SMB			0.0022	0.0062
			(1.37)	(3.46)				(1.40)	(3.62)
HML			-0.0024	0.0025	HML			-0.0030	0.0027
			(-1.12)	(1.22)				(-1.47)	(1.28)
ODDS		-0.0003		-0.0016	ODDS		-0.0002		-0.0018
		(-1.31)		(-5.32)			(-0.70)		(-5.21)

Panel B: Intercept term included in cross-sectional regression

	Sum Beta Approach					Simple Beta Approach			
	CAPM		FF3			CAPM		FF3	
Intercept	0.0062	0.0174	0.0154	0.0063	Intercept	0.0081	0.0163	0.0160	0.0043
	(2.11)	(3.37)	(5.26)	(1.00)		(2.28)	(3.38)	(5.04)	(0.68)
MKTRF	-0.0003	-0.0048	-0.0099	-0.0091	MKTRF	-0.0020	-0.0057	-0.0105	-0.0109
	(-0.08)	(-1.53)	(-2.93)	(-2.92)		(-0.44)	(-1.73)	(-2.89)	(-3.15)
SMB			0.0014	0.0039	SMB			0.0015	0.0052
			(0.98)	(1.76)				(0.93)	(2.69)
HML			-0.0004	0.0010	HML			-0.0007	0.0018
			(-0.20)	(0.52)				(-0.38)	(0.71)
ODDS		0.0008		-0.0010	ODDS		0.0006		-0.0014
		(1.81)		(-1.34)			(1.28)		(-1.85)

Table 17: The correlation coefficients between factors

A. Full Sample (1963-2009)

	SMB	HML	DISTRESS
MKTRF	0.3015	-0.3342	0.2438
SMB		-0.2490	0.8222
HML			-0.0996

B. 1963-1982

	SMB	HML	DISTRESS
MKTRF	0.4625	-0.2854	0.3608
SMB		-0.0380	0.9140
HML			0.1632

C. 1982-2009

	SMB	HML	DISTRESS
MKTRF	0.2033	-0.3618	0.1774
SMB		-0.3722	0.7641
HML			-0.2481

The correlation coefficients between factors in different sample periods are shown in this table.

Table 18: GMM Estimation of Competing Models

	CAPM			CAPM and Distress Risk			FF-3 Model			FF-3 and Distress Risk		
	Full	1963-82	1982-09	Full	1963-82	1982-09	Full	1963-82	1982-09	Full	1963-82	1982-09
A. Coefficient:												
CONST	1.00	1.00	1.01	1.00	1.02	1.04	1.05	1.07	1.06	1.05	1.09	1.06
t-value	(154.57)	(200.39)	(94.50)	(140.59)	(56.01)	(69.40)	(50.58)	(34.44)	(35.35)	(48.71)	(27.51)	(35.17)
MKTRF	-1.58	-1.39	-1.63	-1.47	-0.12	-2.13	-3.25	-1.29	-4.41	-3.26	-0.92	-4.35
t-value	(-1.66)	(-1.13)	(-1.32)	(-1.52)	(-0.09)	(-1.82)	(-2.88)	(-0.95)	(-2.67)	(-2.87)	(-0.64)	(-2.64)
SMB							-1.19	-4.20	2.43	-1.02	-10.90	1.37
t-value							(-0.84)	(-1.72)	(1.26)	(-0.34)	(-1.23)	(0.45)
HML							-7.33	-8.65	-7.48	-7.30	-10.20	-7.47
t-value							(-4.00)	(-3.06)	(-2.92)	(-3.81)	(-3.03)	(-2.92)
DISTRESS				-0.59	-2.92	2.64				-0.10	3.11	0.85
t-value				(-0.88)	(-2.76)	(2.69)				(-0.07)	(0.75)	(0.48)
B. Premium:												
MKTRF	0.0032	0.0027	0.0034	0.0034	0.0033	0.0029	0.0039	0.0023	0.0046	0.0039	0.0021	0.0043
t-value	(1.66)	(1.13)	(1.32)	(1.73)	(1.37)	(1.18)	(1.82)	(0.92)	(1.57)	(1.80)	(0.80)	(1.43)
SMB							0.0009	0.0045	-0.0040	0.0009	0.0049	-0.0044
t-value							(0.64)	(2.17)	(-2.29)	(0.65)	(2.30)	(-2.31)
HML							0.0046	0.0054	0.0059	0.0046	0.0055	0.0059
t-value							(3.29)	(2.79)	(3.29)	(3.25)	(2.83)	(3.29)
DISTRESS				0.0039	0.0126	-0.0117				0.0033	0.0107	-0.0081
t-value				(1.23)	(2.96)	(-2.42)				(0.88)	(2.38)	(-1.43)
C. Model Diagnostics:												
J-Stat	44.50	23.75	42.78	43.87	20.79	39.88	35.04	16.33	37.42	35.03	15.85	37.09
p-value	(0.00)	(0.42)	(0.01)	(0.00)	(0.53)	(0.01)	(0.03)	(0.75)	(0.02)	(0.02)	(0.73)	(0.01)
HJ Dist	0.35	0.39	0.51	0.35	0.36	0.51	0.30	0.31	0.49	0.30	0.29	0.48
p-value	(0.00)	(0.06)	(0.00)	(0.00)	(0.15)	(0.00)	(0.00)	(0.45)	(0.00)	(0.00)	(0.53)	(0.00)
Delta-J				0.64	3.31	8.98						
p-value				(0.43)	(0.07)	(0.00)						

D. Factor Statistics:

	Full Sample	1963-1982	1982-2009
MKTRF (*t*-value)	4.65 (0.66)	1.59 (1.01)	6.80 (0.88)
SMB (*t*-value)	2.99 (0.47)	5.63 (0.71)	1.13 (0.62)
HML (*t*-value)	4.82 (0.43)	6.02 (0.60)	3.97 (0.60)
DISTRESS (*t*-value)	0.94 (1.01)	8.16 (1.50)	-4.15 (1.36)

This table reports results of asset pricing tests on our sample. Robust p-values are in round brackets. The J-test is the over-identifying restriction test of Hansen (1982). HJ-distance refers to the distance metric of Hansen and Jagannathan (1997). The delta-J test of **?** assesses whether the inclusion of HML and SMB improves model fit. A small p-value for the delta-J test indicates that additional factors improve model fit.

The distress risk factor is the return difference between a high risk portfolio and low risk portfolio. We sort all firms in June each year according to their respective distress risk and form 5 quintile portfolios with same number of firms in each of them. The portfolios with top 20% and bottom 20% of distress risk probabilities are used to calculate the distress risk factor. All portfolios are value weighted.

The sample period is from July 1963 to June 2009. We further divide the sample into two subperiods, July 1963 to June 1982 and July 1982 to June 2009.