Is there a Distress Risk Anomaly?

Pricing of Systematic Default Risk in the Cross Section of Equity Returns

Deniz Anginer and Çelim Yıldızhan*

March 27, 2017

Abstract

The standard measures of distress risk ignore the fact that firm defaults are correlated and that some defaults are more likely to occur in bad times. We use risk premium computed from corporate credit spreads to measure a firm's exposure to systematic variation in default risk. Unlike previously used measures, the credit risk premium explicitly accounts for the non-diversifiable component of distress risk. In contrast to prior findings in the literature, we find that stocks with higher systematic default risk exposures, have higher expected equity returns which are largely explained by the Fama-French risk factors. We confirm the robustness of these results by using an alternative systematic default risk factor for firms that do not have bonds outstanding.

JEL Classifications: G11, G12, G13, G14.

Keywords: Default risk, systematic default risk, credit risk, distress risk anomaly, bankruptcy, credit spread, asset-pricing anomalies, pricing of default risk, corporate bonds

* Deniz Anginer is a Financial Economist in the Development Research Group at the World Bank and can be reached at danginer@worldbank.org. Çelim Yıldızhan is an Assistant Professor of Finance at the Terry College of Business, University of Georgia, Athens, GA, 30602, and can be reached at celim@uga.edu. We would like to thank Alexander Barinov, Tobias Berg, Sugato Bhattacharyya, Dennis Capozza, Ilia Dichev, Stu Gillan, Jack He, Jens Hilscher, Sara Holland, Alex Hsu, Paul Irvine, Haitao Li, Jim Linck, Russell Lundholm, Harold Mulherin, Jeff Netter, Paolo Pasquariello, Bradley Paye, Annette Poulsen, Amiyatosh Purnanandam, Uday Rajan, Nejat Seyhun, Tao Shu, Tyler Shumway, Jeff Smith, Ralph Steuer, Ginger Wu, Julie Wu, Lu Zhang, seminar participants at the University of Michigan, University of Georgia, Virginia Tech, World Bank, University of Delaware, Southern Methodist University, University of Waterloo, Wilfrid Laurier University, University of Connecticut, Özyeğin Üniversitesi, Sabancı Üniversitesi, BlackRock, CFTC, Cornerstone Research, and the 37th EFA Annual Meeting for helpful discussion and guidance.

1. Introduction

A fundamental tenet of asset pricing is that investors should be compensated with higher returns for bearing systematic risk that cannot be diversified. As default risk remains a major source of potential large losses to equity investors, a number of recent papers have examined whether default risk is priced in the cross section of equity returns. Empirical work has focused on determining the probability of firms failing to meet their financial obligations using accounting and market-based variables and testing to see if estimated default probabilities are related to future realized returns. The existing empirical evidence contradicts theoretical expectations and suggests that firms with high default risk earn significantly lower average returns.[1]

The low returns on stocks with high default risk cannot be explained by Fama-French (1993) risk factors. Stocks with high distress risk tend to have higher market betas and load more heavily on size and value factors. This leads to significantly negative alphas for the high-minus-low default risk hedge portfolio and makes the anomaly even larger in magnitude. These empirical results provide a challenge to the standard risk-reward trade-off in financial markets and to the contention that small firms and value firms earn high average returns because they are financially distressed (Chan and Chen 1991; Fama and French 1996; Kapadia 2011).

In this paper, we argue that what matters for pricing is the non-diversifiable component of default risk. Figure 1, which plots the historical default rates on Moody's rated corporate issuers, suggests that default rates are highly dependent on the stage of

[1] See for example Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) for a discussion of this anomaly.

the business cycle. This casual analysis of the historical data suggests that there is an important systematic component of default risk and that the incidence of financial distress is correlated with macroeconomic shocks such as major recessions. Previous papers measure financial distress by determining firms' expected probabilities of default inferred from historical default data. This calculation ignores the fact that firm defaults are correlated and that some defaults are more likely to occur in bad times, and therefore fails to appropriately account for the systematic nature of default risk. Investors, however, would take into account the covariance of default losses from a company with the rest of the assets in their portfolio when pricing distress risk.[2]

Moreover, probability of default of a firm may not necessarily reflect its exposure to systematic default risk. In fact, George and Hwang (2010), in a theoretical model, show that firms with higher sensitivities to systematic default risk reduce their leverage in order to reduce their probabilities of default. This can lead to a negative relationship between default probabilities and systematic default risk exposures. It would not be correct to rank firms based on their default probabilities inferred from historical default data—as done in Dichev (1998), Campbell, Hilscher, and Szilagyi (2008), and others in this literature - when examining pricing implications of default risk, because such a ranking does not properly reflect firms' exposures to systematic default risk, the only type of default risk that should be rewarded with a premium.

[2] To illustrate this point, consider two portfolios of bonds with average default probabilities equal to 5% a year. Even though both portfolios have the same average default rate, one bond portfolio contains companies that are likely to experience defaults in good states of the world whereas the second portfolio contains companies that are likely to default in bad states of the world. The timing of the defaults would be as important in pricing these bond portfolios as their average default rates.

We use two approaches to measure a firm's exposure to the non-diversifiable portion of default risk. Our first measure is credit risk premia computed from corporate bond credit spreads. The fixed-income literature provides evidence of a significant risk premium component in corporate credit spreads, justifying our use of this measure as a proxy for firm exposure to systematic default risk.[3] It has been well-documented (Almeida and Philippon 2007; Berndt, Duffie, Ferguson and Schranz 2005; Hull, Predescu, and White 2004) that there is a substantial difference between the risk-adjusted probabilities (or risk-neutral, as commonly denoted in contingent claim pricing) inferred from bond prices and physical probabilities of default inferred from historical data. The difference between the two probabilities reflects the premia demanded by investors for being exposed to non-diversifiable default risk.

We compute credit spreads as the difference between the bond yield of a given firm and the corresponding maturity-matched treasury rate. We then compute credit risk premia by removing expected losses, taxes, and liquidity effects (Elton, Gruber, Agrawal and Mann 2001; Chen, Lesmond, and Wei 2007; Driessen and de Jong 2007) and using only the fraction of the spread that is due to systematic default risk exposure. Using credit risk premium sorted portfolios, we find that firms with higher exposures to

[3] The spread between corporate bond yields and maturity-matched treasury rates is too high to be fully captured by expected default and has been shown to contain a large risk premium for systematic default risk. See, for detailed analysis, Elton et al. (2001), Huang and Huang (2003), Longstaff et al. (2005), Driessen (2005), and Berndt et al. (2005).

systematic default risk have higher excess returns. This premium is economically and statistically subsumed by the Fama-French risk factors.[4]

Our second measure of systematic default risk exposure is computed for all firms in the CRSP-COMPUSTAT universe. First, we estimate the average default probability of all firms at each point in time and denote this average as the default risk factor. Then, we fit an AR (1) model to the default risk factor, and denote the residuals as innovations in the default factor. Finally, we compute systematic default risk betas for each firm by calculating the sensitivity of a firm's return to innovations in the default risk factor.

Using the systematic default risk beta, we first verify that it is significantly priced in the cross section of corporate bond risk premia. This finding ensures that the two systematic default risk measures used in this study are internally consistent and justifies our use of corporate bond risk premium as a measure of systematic default risk exposure. Second, we form portfolios by sorting all equities in the CRSP-COMPUSTAT sample based on their systematic default risk betas. Consistent with the bond sample results, we find that the portfolio with the highest systematic default risk exposure has higher returns than the lowest systematic default risk exposure portfolio. Moreover, we find that once we control for the Fama-French risk factors, the difference in returns between the highest and lowest systematic default risk portfolios becomes insignificant.

These results are consistent with basic structural models of default in which aggregate risk factors drive default probabilities as well as the returns on bonds and

[4] Our measure of systematic default risk exposure, calculated from credit spreads, limits the sample of firms to those that have issued corporate bonds. To ensure the robustness of our results, we show that when firms are ranked based on their physical default probabilities, as previously done in the literature, the distress anomaly is also observed in the Bond sample.

equities (Merton 1974; Campello, Chen and Zhang 2008). Since equity is a long call while debt is a short put option on the firm's assets, structural models propose that, if a firm's asset value is determined by a set of factors, such as the Market, SMB and HML factors, then the same set of factors should also determine the values of claims written on this asset. Similarly, since default occurs when asset value falls below the face value of debt, the same factors should also determine conditional default probabilities. A basic structural model, therefore, does not predict a separate risk factor to account for default risk, which is consistent with our findings.

In cross-sectional regressions we show that systematic default beta is positively priced on its own, but is subsumed by CAPM beta, size and value variables consistent with our time-series results. When systematic default beta and default probability are included together in cross-sectional regressions, they are both priced significantly, but both lose economic and statistical significance. These results indicate that systematic default beta partially explains the distress risk anomaly. This finding is consistent with the theoretical model in George and Hwang (2010) which shows that firms with low exposures to systematic distress risk choose high leverage and, as a result, have high default probabilities despite having low systematic default risk exposures.

We test and find empirical support for this notion that firms with high exposure to systematic default risk make capital structure choices to reduce their physical default probabilities. Adding changes in systematic default risk in the empirical models of Frank and Goyal (2003) and Rajan and Zingales (1995), we show that an increase (decrease) in systematic default risk exposure predicts reduced (higher) leverage in the next period.

Controlling for systematic default risk exposure reduces the distress risk anomaly, but the fact that the distress risk anomaly is not fully explained by systematic default exposures suggests that default probabilities may capture information about future returns distinct from systematic default exposure. One possible explanation for the remaining predictability of default probabilities may simply be due to an amalgamation of existing empirical regularities that the prior literature has uncovered. In particular, previous papers have shown that three stock characteristics—high idiosyncratic volatility, high leverage, and low profitability—are associated with high historical default rates. These are the same characteristics that are known to be associated with low expected future returns. Within the q-theory framework (Cochrane 1991; Liu, Whited and Zhang 2009), low profitability (more likely to default) firms have low expected future returns. Similarly, firms with high leverage (more likely to default) and high idiosyncratic volatility (more likely to default) have low expected future stock returns (Korteweg 2010; Dimitrov and Jain 2008; Penman, Richardson and Tuna 2007; Ang, Hodrick, Xing and Zhang 2009). In addition to the leverage channel which we examine in this paper, distress anomaly may be attributable to one or more of these previously documented return relationships.[5]

[5] There is a strong relationship between distress risk and these three stock characteristics. When we form quintile portfolios sorted on physical probabilities of default -computed using coefficients from Column 1 of Table 2-, idiosyncratic volatility increases monotonically from 2.5% for the lowest distress group to 4.5% for the highest distress group. Leverage increases from 0.22 for the lowest distress group to 0.61 for the highest distress group. Similarly, profitability for the lowest distress group is 1.2% and decreases monotonically to -1.1% for the highest distress group. The 3-factor alpha for the zero cost portfolio formed by going long high distress stocks and shorting low distress stocks is -1.078% per month, yet this premium decreases to -0.36% after controlling for leverage. When we control for idiosyncratic volatility, the return spread between high and low distress stocks reduces to -0.29%. Finally, controlling for profitability also reduces the spread to -0.29% per month, at the same time making it statistically insignificant.

Ours is not the first paper to study the relationship between default risk and equity returns. Dichev (1998) uses Altman's z-score and Ohlson's o-score to measure financial distress. He finds a negative relationship between default risk and equity returns for the 1981–1995 time period. In a related study, Griffin and Lemmon (2002), using the O-score to measure default risk, find that growth stocks with high probabilities of default have low returns. Using a comprehensive set of accounting and market-based measures, Campbell, Hilscher, and Szilagyi (2008, hereafter CHS) show that stocks with high risk of default deliver anomalously low returns. Garlappi, Shu, and Yan (2008), who obtain default risk measures from Moody's KMV, find results similar to those of Dichev (1998) and CHS (2008). They attribute their findings to the violation of the absolute priority rule. Vassalou and Xing (2004) find some evidence that distressed stocks, mainly in the small value group, earn higher returns.[6]

Avramov, Jostova, and Philipov (2007) show that the negative return for high default risk stocks is concentrated around rating downgrades. Chava and Purnanandam (2010) argue that the poor performance of high distress stocks is limited to the post-1980 period, when investors were positively surprised by defaults. When they use implied cost of capital estimates from analysts' forecasts to proxy for ex-ante expected returns, they find a positive relationship between default risk and expected returns. Campello, Chen, and

[6] Da and Gao (2010) argue that Vassalou and Xing's results are driven by one-month returns on stocks in the highest default likelihood group that trade at very low prices. They show that returns are contaminated by microstructure noise and that the positive one-month return is compensation for increased liquidity risk.

Zhang (2008) compute expected equity returns from corporate bonds spreads and use these returns to test asset pricing factors.[7]

Our paper contributes to the literature by constructing default risk measures that rank equities explicitly based on their exposures to systematic default risk rather than ranking firms based on their physical probabilities of default.

A concurrent paper by Friewald, Wagner, and Zechner (2014, hereafter FWZ) computes credit risk premia from credit default swaps (CDS's) and ranks equities based on this measure. There are significant differences in the samples used, both in terms of cross-section and time-series, in our paper and in that of FWZ (2014). These sample differences lead to different results and interpretations of the pricing of credit risk premia.

First, FWZ (2014) results are confined to a small subsample of the with actively traded CDSs. They do not find a significant distress anomaly in their CDS sample using physical default probabilities.[8] In our paper, we extract credit risk premia from a large cross-section of bonds over a 30 year time period. We alleviate sample selection concerns by showing that the distress anomaly exists for the sub-sample of firms with bonds, and by extending the analyses to the full CRSP universe by using an alternative systematic default risk measure for firms that do not have bonds outstanding. Second, FWZ (2014) paper is significantly limited in terms of the time frame it analyzes. Chava

[7] Our paper uses a similar methodology to back out credit risk premia from bonds. While Campello, Chen, and Zhang (2008) focus on testing the importance of standard asset pricing factors, our focus is on examining the relationship between credit risk premia and future realized stock returns.

[8] Since the focus of the literature has been on the 'distress risk anomaly, it is important to show that the anomaly exists in the smaller sample from which credit risk premia is computed. Otherwise, there is no anomaly to explain.

and Purnanandam (2010) stress the importance of looking at longer time-series when examining the pricing implications of default risk. FWZ (2014) find significant CAPM and 3-factor alphas to high credit risk premium portfolios for the time period between 2001 and 2010. In our analysis of the 1980 to 2010 time period, we find a statistically significant and positive difference only in the raw returns of high minus low credit risk premium portfolios. This difference is explained by the Fama-French risk factors, consistent with the simple structural models of credit risk.[9]

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 describes the physical default probability measure used in this study. Section 4 describes the use of credit spreads as a proxy for systematic default risk exposure. Section 5 contains asset pricing tests, in which equities are ranked based on their physical default probabilities and systematic default risk exposures constructed from bond credit spreads. Section 6 describes the construction and use of our alternative systematic default risk measure and extends the equity return analyses to the full CRSP-COMPUSTAT sample. Section 7 provides empirical evidence for George and Hwang's (2010) theoretical model by showing that an increase in systematic distress risk exposure predicts a reduction in leverage in the next period. Finally, Section 8 concludes.

2. Data

Corporate bond data used to compute the credit risk-premium in this study come from three separate databases: Lehman Brothers Fixed Income Database (Lehman) available

[9] We also find significant positive CAPM and 3-factor alphas for the post 2000 time period studied by FWZ (2014). This finding further reveals the importance of studying a longer time series in the analyses.

for the period 1974 to 1997, the National Association of Insurance Commissioners Database (NAIC) available for the period 1994 to 2006, and the Trade Reporting and Compliance Engine (TRACE) system dataset available for the period 2003 to 2010. We also use the Fixed Income Securities Database (FISD) for bond descriptions. Due to the small number of observations prior to 1980, we include only the period 1980 to 2010 in the analyses that follow. We match the bond information with firm-level accounting and price information obtained from COMPUSTAT and CRSP for the same time period. We exclude financial firms (SIC codes 6000–6999) from the sample. To avoid the influence of microstructure noise, we also exclude firms priced less than one dollar.

Our sample includes all U.S. corporate bonds listed in the above datasets that satisfy a set of selection criteria commonly used in the corporate bond literature.[10] We exclude all bonds that are matrix-priced (rather than market-priced) from the sample. We remove all bonds with equity or derivative features (i.e., callable, puttable, and convertible bonds), bonds with warrants, and bonds with floating interest rates. Finally, we eliminate all bonds that have less than one year to maturity.

For all selected bonds, we extract beginning of month credit spreads, calculated as the difference between the corporate bond yield and the corresponding maturity-matched treasury rate. There are a number of extreme observations for the variables constructed from the different bond datasets. To ensure that statistical results are not heavily influenced by outliers, we set all observations higher than the 99th percentile value of a given variable to the 99th percentile value. All values lower than the first percentile of

[10] See for instance Duffee (1999), Collin-Dufresne, Goldstein, and Martin (2001), and Avramov et al. (2007).

each variable are winsorized in the same manner. Using credit spreads we compute credit risk premia (*CRP*) as described in the next section. For each firm, we then compute a value-weighted average of that firm's *CRP*, using market values of the bonds as weights. There are 121,714 firm-months and 1,071 unique firms with *CRP* and corresponding firm-level accounting and market data. There is no potential survivorship bias in our sample as we do not exclude bonds of firms that have gone bankrupt or bonds that have matured.

We use hazard regressions using historical defaults to compute physical default probabilities. Corporate defaults between 1981 and 2010 are identified from the Moody's Default Risk Services' Corporate Default database, SDC Platinum's Corporate Restructurings Database, Lynn M. LoPucki's Bankruptcy Research Database, and Shumway's (2001) list of defaults. We choose 1981 as the earliest year for identifying defaults because the Bankruptcy Reform Act of 1978 is likely to have caused the associations between accounting variables and the probability of default to change. Furthermore, we have little corporate bond yield information prior to 1980. In all, we obtain a total of 1,290 firm defaults covering the period 1981–2010. We have complete accounting-based measures for 728 of these defaults. Of these 728 defaults, 118 also have corresponding corporate bond information. For the full CRSP-COMPUSTAT sample as well as for the subsample of firms that have bonds outstanding we use accounting and market-based variables used by CHS (2008) when predicting defaults. The variables we use are the following: *NIMTAAVG* is a geometrically declining average of past values of the ratio of net income to the market value of total assets; *TLMTA* is the ratio of total liabilities to the market value of total assets; *EXRETAVG* is a geometrically declining average of monthly log excess stock returns relative to the S&P 500 index; *SIGMA* is the standard deviation of daily stock returns over the previous three months; *RSIZE* is the log ratio of market capitalization to the market value of the S&P 500 index; *CASHMTA* is the ratio of cash to the market value of total assets; *MB* is the market-to-book ratio, *PRICE* is the log price per share truncated at $15 for shares priced above $15[11]; *DD is* the Merton (1974) "distance-to-default" measure, which is the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of the firm's asset value. These variables are described in detail in the Appendix.

The bond sample covers a small portion of the total number of companies, but a substantial portion in terms of total market capitalization. For instance, in the year 1997, the number of firms with active bonds in our sample constitutes about 4% of all the firms in the market. However, in terms of market capitalization, the dataset captures about 40% of aggregate equity market value in 1997. We compute summary statistics for default measures and financial characteristics of the companies in our bond sample and for all companies in CRSP. These results are summarized in Table 1. As not all companies issue bonds, it is important to discuss the limitations of our bond dataset. Not surprisingly, companies in the bond sample are larger and show a slight value tilt. They also have higher profitability, more leverage, and higher equity returns; they hold less cash and are less likely to default. There is, however, significant dispersion in size,

[11] This is following CHS (2008). Truncation in this setting means that firm observations with a price greater than $15 are set to $15.

market-to-book ratio, default probability, and credit spread values of firms in the bond sample. To ensure that our results are not driven by sample selection, in Section 5, we show that when firms are ranked based on physical default probabilities the distress anomaly is observed in the Bond sample. In Section 6, we extend the analyses to the CRSP/COMPUSTAT sample.

3. Physical Default Probabilities

There is a vast literature on modeling the probability of default. In this paper, we utilize dynamic models of default prediction (Shumway 2001; Chava and Jarrow 2004; CHS 2008), that avoid biases of static models by adjusting for potential duration dependence issues.[12] We compute physical default probabilities by estimating a hazard regression using the set of defaults described in the previous section. We use information available at the end of the calendar month to predict defaults 12 months ahead. Specifically, we assume that the probability of default in 12 months, conditional on survival in the dataset for 11 months, is given by:

$$PD_{i,t-1}\left(Y_{i,t-1+12} = 1 | Y_{i,t-2+12} = 0\right) = \frac{1}{1 + \exp\left(\beta X_{i,t-1}\right)} \tag{1}$$

where $Y_{i,t-1+12}$ is an indicator that equals one if the firm defaults in 12 months conditional on survival for 11 months. $X_{i,t-1}$ is a vector of explanatory variables available at the time of prediction. We use accounting and market-based variables used

[12] Altman (1968) and Ohlson (1980) are examples of such static models.

in CHS (2008) when predicting defaults. In addition we use Merton's distance to default measure that has been utilized in a number of previous studies.[13] All the variables included in the hazard regressions are described in detail in the Appendix. We use quarterly accounting variables lagged by two months and market variables lagged by one month to ensure that this information is available at the time of default prediction.

We run two sets of hazard regressions, one using the sample of firms in the Bond sample, and the other using all firms in the CRSP-COMPUSTAT sample. As mentioned earlier, to ensure that our results are not driven by sample selection, we construct physical default probabilities for the Bond sample using coefficients obtained from hazard regression-ns that use only the firms in the Bond sample. This ensures that the distress anomaly documented by the prior literature exists for the subset of firms that have bonds outstanding.

Table 2 reports the results from the hazard regressions. In the first column, we use the same covariates (*NIMTAAVG, TLMTA, EXRETAVG, SIGMA, RSIZE, CASHMTA, MB* and *PRICE*) used in CHS (2008) to predict corporate defaults. The sample includes all CRSP-COMPUSTAT firms for the 1980 to 2010 time period. As a comparison, we report the estimates from the CHS (2008) study in column 2. The coefficient estimates from these two regressions are very similar, suggesting that our default dataset, although smaller than the CHS (2008) default dataset, captures a significant portion of the

[13] Merton's (1974) structural default model treats the equity value of a company as a call option on the company's assets. The probability of default is based on the "distance-to-default" measure, which is the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of the firm's asset value. As "distance-to-default" increases, default probability decreases. There are a number of different approaches to calculating the distance-to-default measure. We follow CHS (2008) and Hillegeist et al. (2004) in constructing this measure, the details of which are provided in the appendix.

variation in firm defaults. In column 3, we limit the sample to firms with only bonds outstanding. Relative value (*MB*), liquidity position (*CASHMTA*), and share price (*PRICE*) are no longer statistically significant predictors of failure. In the bond sample, relatively larger firms are less likely to default, consistent with the full CRSP-COMPUSTAT sample. We also use Merton's distance to default (*DD*) measure as a predictor of defaults in the bond sample (reported in column 6). We obtain qualitatively similar results to those in the full CRSP-COMPUSTAT sample using our own set of defaults (reported in column 4) as well as when compared to CHS (2008) results (reported in column 5).

4. Using Corporate Spread to Measure Systematic Default Risk Exposure

There is now a significant body of research that shows that compensation for default risk constitutes a considerable portion of credit spreads.[14] We create our first systematic default risk exposure measure by extracting the credit risk premium component from the credit spreads. Although credit risk makes up a significant portion of corporate spreads, liquidity risk and taxes have also been shown to be important (Elton et al. 2001; Chen, Lesmond, and Wei 2007; Driessen and de Jong 2007). In computing the credit risk premium, we take into account expected losses, taxes, and liquidity effects, and use only

[14] Huang and Huang (2003), using the Longstaff-Schwartz (1995) model, find that distress risk accounts for 39%, 34%, 41%, 73%, and 93% of the corporate bond spread, respectively, for bonds rated AA, A, BAA, BA, and B. Longstaff, Mithal, and Neis (2005) use the information in credit default swaps (CDS) to obtain direct measures of the size of the default and non-default components in corporate spreads. They find that the default component represents 51% of the spread for AAA/AA-rated bonds, 56% for A-rated bonds, 71% for BBB-rated bonds, and 83% for BB-rated bonds. Blanco, Brennan, and Marsh (2005) and Zhu (2006) show significant similarity in the information content of CDS spreads and bond credit spreads with respect to default. They confirm, through co-integration tests, that the theoretical parity relationship between these two credit spreads holds as a long run equilibrium condition.

the fraction of the spread that is likely to be due to systematic default risk exposure. We follow Driessen and de Jong (2007), Elton et al. (2001), and Campello, Chen, and Zhang (2008) and compute the credit risk premium (*CRP*) for each bond *i* and month *t* as:

$$CRP_{i,t} = \left[\left(PD_{i,t} \times \left(1 - L_{i,t}\right) + \left(1 - PD_{i,t}\right)\right) \times \left(1 + CY_{i,t}\right)^{\tau}\right]^{\frac{1}{\tau}} - \left(1 + YG_{i,t}\right) - TX_{i,t} - LQ_{i,t} \quad (2)$$

In Equation (2), *PD* is the τ-year physical probability of default for firm *i* in month *t*.[15] *L* is the loss rate in the event of default. We follow Elton et al. (2001) and Driessen and de Jong (2007) and use historical loss rates reported in Altman and Kishore (1998) by rating category. The loss rates vary from 32% for AAA-rated firms to 62% for CCC-rated firms. *CY* is the τ-maturity corporate bond yield, and *YG* is the corresponding maturity-matched treasury yield. The equation assumes that all losses are incurred at maturity.

Because bond investors have to pay state and local taxes on bond coupons whereas treasury bond investors do not, we also remove this tax differential from the corporate yields. Expected tax costs, *TX*, are computed as: $\left[\left(1 - PD_{i,t}\right) \times Coupon_{i,t} + PD_{i,t} \times \left(1 - L_{i,t}\right)\right] \times TR$. The first part of this equation captures the coupon rate, *Coupon*,

[15] We compute physical default probabilities using the sample and variables from column 3 of Table 2. In computing physical default probabilities, we use quarterly accounting variables lagged by two months and market variables lagged by one month to ensure that this information is available at the beginning of the month over which physical default probabilities are measured. To compute cumulative physical default probabilities we form ten groups (similar to rating categories) based on estimated one year default probabilities. We then compute the one year transition matrix for the ten groups as in Moody's (2011). We also compute cumulative physical default probabilities for each group up to ten years. To compute cumulative physical default probabilities beyond ten years, we use the one year transition matrix assuming it remains constant. We obtain similar results if we use Moody's (2011) cumulative physical default probabilities and one year transition matrix.

conditional on no default. The second part captures the tax refund in the event of default. *TR* is the effective tax rate and following Elton et al. (2001) is set to 4.875%.

The recent literature emphasizes the role of liquidity risk in the pricing of corporate bonds (Driessen and de Jong 2007; Lin, Wang and Wu 2011; Downing, Underwood and Xing 2005). We explicitly account for the liquidity effect in credit spreads by computing liquidity risk premium for each bond in our dataset. The analysis follows Driessen and de Jong (2007) and is based on a linear multifactor asset pricing model in which expected corporate bond returns are explained by their exposure to market risk and liquidity risk factors.[16] We consider two types of liquidity risk, one originating from the equity market and another one originating from the treasury market. For the stock market, we use the liquidity innovations of Pastor and Stambaugh (2003); for the treasury market, we use changes in quoted bid-ask spreads on long-term treasury bonds.[17] We compute expected bond returns for 11 rating-maturity groups using equation (2), and use a cross-sectional regression to compute risk premium associated with liquidity innovations in the stock and treasury markets.[18] We then subtract the computed liquidity premium, *LQ*, from the corporate bond spreads with the corresponding rating and maturity. Since the cross-sectional variation in liquidity and tax effects is low by construction, we obtain similar results if we compute credit risk premia without taking into account liquidity and tax effects in the corporate bond spreads.

---

[16] As in Driessen and de Jong (2007) we also included changes in implied market volatility orthogonalized by market returns as an additional factor, and we obtained similar results.

[17] We thank Alex Hsu for providing the data on treasury bid-ask quotes.

[18] We refer to bonds with maturity greater than seven years as having "long maturity" and with maturity less than seven years as having "short maturity."

Our results are in line with the findings in the literature (Driessen and de Jong 2007; Elton et al. 2001; Campello, Chen and Zhang 2008). Figure 2 plots the computed expected losses, taxes, and liquidity premium against corporate spreads. In the rest of this paper, we use the portion of credit spreads that compensates for systematic default risk exposure, net of expected losses, taxes, and liquidity premium. We call this variable *CRP* (Credit Risk Premium).

It is possible that the *CRP* may contain risk premia that is not purely due to distress risk. For instance, if the stock and bond markets are integrated, traditional capital structure theory implies that a company's equity and credit premia will be linked and driven by the same aggregate risk factors. To the extent that the *CRP* contains premia unrelated to distress risk, they would be captured by the standard risk factors in the factor regressions we carry out in the next two sections.

5. Pricing of Distress Risk

5.1. Physical PD's and Equity Returns

In this section, we analyze the relationship between physical default probabilities and future stock returns using the full cross-section of firms in the CRSP-COMPUSTAT sample as well as using the firms that have bonds outstanding in the Bond sample. For the CRSP-COMPUSTAT sample we compute default probabilities using coefficients obtained from column 1 of Table 2.[19] For the Bond sample we compute default

[19] We obtain similar results using CHS coefficients computed on a rolling basis (we thank Jens Hilscher for providing this data), Merton's distance-to-default measure, Ohlson's o-score and Altman's z-score, which are not reported to save space.

probabilities using coefficients obtained from column 3 of Table 2. In computing these default probabilities, we use quarterly accounting variables lagged by two months and market variables lagged by one month to ensure that this information is available at the beginning of the month over which default probabilities are measured. We sort stocks in the full CRSP-COMPUSTAT sample into deciles each month from 1981 through 2010 according to their physical default probabilities, and compute value-weighted returns for each portfolio. If a delisting return is available, we use the delisting return; otherwise, we use the last available return in CRSP.

We repeat the same analyses for stocks that have bonds outstanding. We construct physical default probabilities in the Bond sample using coefficients obtained from hazard regressions using the bond sample. This analysis ensures that the distress risk anomaly observed in the full CRSP-COMPUSTAT sample also exists for the bond sample when firms are ranked using physical default probabilities. We compute value-weighted returns for these decile portfolios on a monthly basis and regress the portfolio return in excess of the risk-free rate on the market (*MKT*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors, to compute CAPM, 3 and 4 factor alphas.

In Panel A of Table 3, we report returns for the ten decile portfolios and the return difference between the top and bottom deciles for the CRSP-COMPUSTAT sample. Our results are consistent with those obtained in previous studies. Stocks in the highest default risk portfolio have significantly lower returns. The difference in returns between the highest and lowest default risk portfolios is -1.18% per month. The alphas from the market and the 3- and 4-factor models are economically and statistically significant. The monthly 4-factor alpha for the zero cost portfolio formed by going long on stocks in the highest default risk decile, and short on stocks in the lowest default risk decile is -0.83% per month.

Portfolio return analyses that utilize historical default probabilities calculated using coefficients from the bond sample are reported in Panel B of Table 3. The results are weaker for the bond sample, but still economically and statistically significant. Using firms that have credit spread information, the monthly 4-factor alpha for the zero cost portfolio formed by going long on stocks in the highest default risk decile and short on stocks in the lowest default risk decile is -0.49%. Distressed stocks load positively on the size and value factors.

As a robustness check, we also compute risk adjusted returns per unit of distress risk for the bond sample as well as for the CRSP-COMPUSTAT sample. One reason that the distress anomaly is smaller in the bond sample is that the companies in the highest distress decile in the CRSP-COMPUSTAT sample have higher default probabilities than the stocks in the highest distress decile in the bond sample. To take into account the differences in default probabilities, we follow CHS (2008) and regress the return of each long-short portfolio onto the differences in log default probabilities including no intercept in the regression. The coefficients from this regression would provide us with a distress premium per unit of log default probability. We use long-short distress portfolio returns adjusted for the Fama–French three-factor model. The coefficient estimate on the log default probability is 6.492 (t-stat = 5.02) for the CRSP-COMPUSTAT sample and 5.657 (t-stat = 3.24) for the bond sample, suggesting that per unit of log default probability, the distress effect is similar in the CRSP-COMPUSTAT and Bond samples. These results are in contrast to FWZ (2014) who do not find physical default probabilities to be negatively priced in their sample of firms with actively traded CDS contracts.

The analyses in this section show that using physical default probabilities computed in the Bond sample and the CRSP-COMPUSTAT sample produces results similar to those of CHS (2008) and others in the literature. The distress anomaly persists in our Bond sample when we use physical probabilities of default to rank firms.

5.2 Credit Risk Premia and Equity Returns

In this section, we examine how *CRP*s (credit risk premia) are related to future realized equity returns.[20] We sort stocks into deciles from 1981 to 2010, using *CRPs* in the previous month. We compute value-weighted returns for each portfolio and update the portfolios each month. As before, if a delisting return is available we use the delisting return; otherwise we use the last available return in CRSP. We report returns for the ten decile portfolios, and the return difference between the top and bottom deciles in Table 4.

Our results challenge those obtained in the previous studies. Using *CRP*s as a measure of systematic default risk exposure, the difference in raw returns between the highest and lowest default risk portfolios is 0.521% per month and statistically significant. The 4-factor monthly alpha for a portfolio formed by going long on stocks in the highest default risk exposure portfolio and short on stocks in the lowest default risk

[20] We also analyzed how *SPREADs* (credit spreads) are related to future realized equity returns. The returns on portfolios sorted on *SPREAD*s and *CRP*s have very similar returns. Furthermore, the differences in raw returns between the highest and lowest default risk portfolios are very similar whether firms are sorted on *SPREAD* or *CRP*.

exposure portfolio is -0.005% and statistically insignificant when we use *CRP* as our measure of systematic default risk exposure.

There is a positive relationship between *CRP* and excess equity returns, and the return of the high-minus-low excess spread portfolio is statistically significant. CAPM and multi-factor regressions show that alphas are subsumed in all *CRP* portfolios, suggesting that variation in systematic default risk exposure is captured by the market, size and value factors. Exposures to the market, size and value factors almost monotonically increase with *CRP* and are statistically significant for the high minus low *CRP* hedge portfolio suggesting that these factors are intimately related to systematic default risk exposure. As mentioned earlier, these results are consistent with structural models of default in which aggregate risk factors drive default probabilities as well as the returns on bonds and equities (Merton 1974; Campello, Chen and Zhang 2008).

Ranking stocks on their physical default probabilities inferred from historical data, as done in Dichev (1998), CHS (2008), and others, implicitly assumes that high default probability stocks also have high exposures to the systematic component of default risk. Using *CRP*, we explicitly rank firms based on their exposures to the systematic component of default risk and we find no evidence of systematic default risk being negatively priced.

6. Alternative Measure of Systematic Default Risk

6.1 Measuring Systematic Default Beta

We now extend the analysis of Section 5.2 to the full CRSP-COMPUSTAT sample to ensure the robustness of our results. In particular, we identify a measure of systematic default risk exposure that can be calculated for all firms regardless of whether they have bonds outstanding.

We assume that historical default probabilities have a single common factor and use the mean cross-sectional default probability to proxy for this common factor. The assumption of a single factor is a good approximation as we find that the first principal component explains more than 70% of the variation in default probabilities. The first principal component and the mean default probability have a correlation greater than 0.90 and are significantly higher during and after recessions.[21]

We fit an AR (1) model on a rolling window of 48 months to the average default probability and use the residuals as innovations. We regress firm returns on these innovations over 48-month rolling windows to compute loadings on the innovations in average default probability. We refer to the loading on the innovation as *SYSDEFBETA*, systematic default risk beta.[22]

[21] We follow Hilscher and Wilson (2017) and first shrink the size of the cross-section by assigning each firm-month to a rating-month group and calculate equal-weighted average 12-month cumulative default probabilities for each rating-group. This leaves us with a panel of 17 ratings groups with 360 months of data. Forming industry groups rather than ratings groups yields similar results.

[22] Our measure of systematic default risk beta (SYSDEFBETA) is different from Hilscher and Wilson's (2017), who measure a firm's SYSDEFBETA as the sensitivity of its physical default probability (PD) to the median PD of all firms. As an anonymous referee points out a risk exposure captures how the asset (equity) return is exposed to a specific risk factor, hence per his suggestion we use excess equity return as our dependent variable and innovation in average default probability as our independent variable.

6.2 Default Risk Beta and Credit Spreads

In this sub-section, we analyze the relationship between our measure of credit risk premium calculated in Section 4 and systematic default risk beta. We show that systematic default risk beta ($SYSDEFBETA$) can explain the cross-sectional variation in credit risk premia in corporate bonds.

Table 5 summarizes Fama-MacBeth cross-sectional regression results when monthly credit risk premium (in %) is regressed on lagged systematic default risk beta ($SYSDEFBETA$ as calculated in equation 5) and firm characteristics that are related to credit risk. In all regression specifications, we control for two bond characteristics: average issue amount (*OAMT*) and average time to maturity (*TTM)* of a firm's outstanding bonds. Furthermore, in all regression specifications we also control for the Standard & Poor's (S&P) rating (*RATING*) assigned to the firm. We control for the firm's credit risk estimated by the market using three alternative specifications. Our first proxy for the firm's credit risk is Merton's distance to default (*DD*). We use physical default probability (*PD*) as the second alternative specification. Finally, we use a specification that does not impose any structure directly control for firm characteristics that are associated with credit risk for the third alternative specification. In doing so, we control for return volatility (*SIGMA*), profitability (*NIMTAAVG*), leverage (*TLMTA*), amount of liquid assets (*CASHMTA*), market-to-book ratio (*MB*), and relative size of the firm (*RSIZE)*. The *t*-statistics for the slopes are based on the time series variability of the estimates, incorporating a Newey-West (1987) correction with four lags to account for possible autocorrelation in the estimates.

In column (1), we control for the bond offering amount, time to maturity, and firm rating. In column (2), we control for the bond offering amount, time to maturity, firm rating and Merton's distance to default. In column (3), we control for the bond offering amount, time to maturity, firm rating and the physical probability of default. In column (4), we control for the bond offering amount, time to maturity, firm rating and the stock characteristics that have been shown to be important determinants of credit risk by CHS (2008). In all specifications the loading on the systematic default risk beta, $SYSDEFBETA$, is positive and statistically significant.

The impact of $SYSDEFBETA$ on spreads is also economically significant. Results in column 4 of Table 5 suggest that moving from the 75th percentile systematic default risk beta firm ($SYSDEFBETA$ = *.298*) to the 95th percentile firm ($SYSDEFBETA$ = *.854)* leads to an increase of 37 basis points in bond risk premium after controlling for all parameters known to influence credit spreads.

The results suggest that systematic default risk exposure is an important driver of the credit risk premium in corporate bond spreads. *CRP*, our measure of exposure to systematic default risk computed from corporate bond spreads, and systematic default risk beta ($SYSDEFBETA$) are comparable proxies for exposure to systematic default risk.

6.3 Pricing of Systematic Default Risk in the CRSP-COMPUSTAT Sample

The systematic default risk beta described in the previous section allows us to test whether systematic default risk is priced in the full cross-section of the CRSP-COMPUSTAT sample. We use the same portfolio analysis approach described in Section

5. In particular, we sort stocks into deciles each month from January 1981 through December 2010 according to their systematic default risk betas (*SYSDEFBETA*) obtained at the beginning of the previous month. We then calculate the value-weighted decile portfolio returns for all stocks on a monthly basis and regress the portfolio return in excess of the risk-free rate on the market (*MKTRF*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors. In Table 6, we report regression results for all the decile portfolios along with the top decile minus bottom decile hedge portfolio.

Results in Table 6, which are obtained from the CRSP-COMPUSTAT sample, are similar to those reported in Table 4, which are obtained using the bond sample. Table 4 shows that the highest *CRP* decile portfolio earns on average 52 basis points more per month compared to the lowest *CRP* decile portfolio. Similarly, Table 6 shows that the highest systematic default risk beta decile portfolio in the full CRSP-COMPUSTAT sample earns 60 basis points more per month compared to the lowest systematic default risk beta decile portfolio. This result is significant at the 10% level. Once we control for the market factor, as well as the Fama-French size and value factors the statistical significance of the hedge portfolio return disappears, supporting the Fama and French (1992) conjecture that size and value premiums may be related to systematic distress risk.

Exposures to the market, size and value factors are statistically significant for the high minus low *SYSDEFBETA* hedge portfolio. Nevertheless, we only observe a strong monotonic pattern in the exposure to the value factor, suggesting perhaps the value factor is more correlated with innovations in the systematic default risk factor compared to the market and size factors. Exposure to the market factor is largely constant across

SYSDEFBETA portfolios, except for a sharp increase for the highest systematic default risk exposure stocks, while exposure to the size factor is U-shaped as it is higher for high systematic default risk and low systematic default risk portfolios alike but smaller in between. Overall, the results in this sub-section lend further support to our findings using the bond sample.

6.4 Cross-sectional Pricing of PD and SYSDEFBETA

In this sub-section, we conduct cross-sectional analyses to confirm our earlier findings based on the analysis of portfolio returns in the time-series. In particular, we run Fama-MacBeth regressions of excess equity returns on systematic default betas (*SYSDEFBETA*), physical default probabilities (*PD*) and firm characteristics. The results are reported in Table 7.

In column (1) of Table 7, regressing excess returns on physical default probabilities (*PD*), we find that the loading on *PD* is -3.733 and statistically significant. In column (2), regressing excess returns on the systematic default risk exposure measure (*SYSDEFBETA*), we find a statistically significant positive loading of 2.23, verifying our earlier results that the systematic component of default risk is priced in the cross-section of equity returns.

In column (3) of Table 7 we include both *PD* and *SYSDEFBETA* and find that the loading on PD is -0.871 and statistically significant and that the loading on *SYSDEFBETA* is positive (1.892) and also statistically significant. Controlling for *SYSDEFBETA* reduces the loading on *PD* economically, from -3.733 to -0.871, as well as statistically, from a t-statistic of 4.74 to 1.99, indicating that *SYSDEFBETA* partially reduces the significance distress risk anomaly, but does not eliminate it. This finding is consistent with the model in George and Hwang (2010) which shows that firms with low exposures to systematic distress risk choose high leverage and, as a result, have high default probabilities despite having low systematic default risk exposures.

In column (4), we further control for firm characteristics such as size, book-to-market, momentum and CAPM-beta that are associated with expected returns, and find that the default risk anomaly persists economically and statistically. Finally, in column (5) regressing excess returns on *SYSDEFBETA* as well as size, book-to-market, momentum and CAPM-beta, we verify earlier findings presented in Table 6 that characteristics associated with known risk factors largely subsume the premium for systematic default risk exposure.

7. Systematic Default Risk Exposure and Leverage

George and Hwang (2010) offer a specific mechanism for how the distress risk anomaly may arise. Their theoretical model suggests that firms with high exposures to systematic distress risk may lower their physical default probabilities by choosing low levels of leverage in an attempt to reduce distress costs. This in turn may lead one to classify risky (safe) firms as safe (risky) and yield a negative risk premium on *PD*. Cross-sectional regressions in section 6 reveal that controlling for systematic default risk exposure reduces the distress risk anomaly, lending partial support to George and Hwang

(2010). In this section, we empirically verify that an increase in systematic distress risk exposure predicts a reduction in leverage in the next period.

In Table 8, following the empirical model in Frank and Goyal (2003) and Rajan and Zingales (1995), we investigate what happens to financial leverage when exposure to systematic default risk changes. In particular, we regress changes in leverage (Δ*Leverage*) on changes in systematic default risk beta (Δ*SYSDEFBETA*) and changes in credit risk premium (Δ*CRP*), controlling for changes in profitability (Δ*NIMTA*), market-to-book ratio (Δ*MB*), the log of total sales (Δ*LogSALE*), tangibility of assets (Δ*TANG*) and firm fixed effects.

In column (1) of Table 8 we report baseline results confirming the findings in Frank and Goyal (2003) and Rajan and Zingales (1995). In columns (2) and (3) we add changes in credit risk premium and changes in systematic default risk beta, respectively, as additional covariates. Using both measures we find that there is a statistically and economically strong negative relationship between changes in systematic default risk exposure and changes in financial leverage. In addition to providing empirical support to the theoretical predictions in George and Hwang's (2010), these results also support the basic premise of our paper that when assessing the default risk premium in the cross section of equity returns one should use exposure to systematic default risk and not the physical probability of default.[23]

[23] In unreported results, we sort stocks annually and put them into ten groups based on changes in systematic default risk beta (*SYSDEFBETA*) and changes in credit risk premium (*CRP*). We then compute average changes in leverage over the next year. The results indicate that firms which see an increase in their systematic default risk exposure reduce their leverage and their physical default probabilities in the next period in both samples, consistent with the regression analyses.

8. Conclusion

In this paper, we argue that what matters for pricing is the non-diversifiable component of default risk. The prior literature measures financial distress by computing firms' expected probabilities of default inferred from historical default data. This calculation ignores the fact that firm defaults are correlated and that some defaults are more likely to occur in bad times and fails to appropriately account for the systematic nature of default risk. We use credit risk premia obtained from corporate credit spreads as well as an alternative measure that captures the sensitivity of equity returns to innovations in average default probability to proxy for a firm's exposure to systematic default risk.

We find that stocks that have higher credit risk premia have higher expected equity returns. Consistent with structural models of default, we also show that the premium to a high minus low systematic default risk hedge portfolio is largely explained by the market, size and value factors, suggesting that sensitivities to three well known risk factors capture most of the variation in systematic default risk exposure.

The empirical results in the paper also lend support to the George and Hwang (2010) hypothesis that firms with higher sensitivities to systematic default risk make capital structure choices that reduce their overall physical probabilities of default. We find that changes in systematic distress risk exposure predict changes in leverage in the next period offering a partial explanation for the anomalous results previously documented in the literature.

APPENDIX

Here we explain the details of the variables used to compute the physical probability of default (*PD*) and the Merton distance-to-default (*DD*) measure. We use quarterly accounting data from COMPUSTAT and monthly market data from CRSP. Book equity, *BE* is defined as in Davis, Fama, and French (2000). We adjust total value of assets, *TA* by the difference between the market equity (*ME*) and book equity (*BE*): $MTA_{i,t} = TA_{i,t} + 0.1 * (ME_{i,t} - BE_{i,t})$. *NIMTAAVG* is a geometrically declining average of past quarterly values of the ratio of net income to adjusted total assets: $NIMTAAVG_{t-1,t-12} = \frac{1-\emptyset^3}{1-\emptyset^{12}} \left(NIMTA_{t-1,t-3} + \ldots . + \emptyset^9 NIMTA_{t-10,t-12}\right)$. *EXRETAVG* is a geometrically declining average of monthly log excess stock returns relative to the S&P 500 index: $EXRETAVG_{t-1,t-12} = \frac{1-\emptyset}{1-\emptyset^{12}} \left(EXRET_{t-1,} + \ldots . + \emptyset^{11} EXRET_{t-12}\right)$. The weighting coefficient is set to $\emptyset = 2^{-1/3}$, such that the weight is halved each quarter. *TLMTA* is the ratio of total liabilities to adjusted total assets. *SIGMA* is the standard deviation of daily stock returns over the previous three months. *SIGMA* is coded as missing if there are fewer than five observations. *RSIZE* is the log ratio of market capitalization to the market value of the S&P 500 index. *CASHMTA* is the ratio of the value of cash and short-term investments to the value of adjusted total assets. *PRICE* is the log price per share truncated from above at $15. All variables are winsorized using a 1/99 percentile interval in order to eliminate outliers.

We follow CHS (2008) and Hillegeist, Keating, Cram, and Lunstedt (2004) to compute the Merton's distance-to-default measure. Market value of equity is modeled as a call option on the company's assets: $V_E = V_A e^{-dT} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-dT}) V_A$ with $d_1 = \left(\log\left(\frac{V_A}{X}\right) + \left(r - d + \frac{s_A^2}{2}\right) T\right) / \left(s_A \sqrt{T}\right)$ and $d_2 = d_1 - s_A \sqrt{T}$. V_E is the market value of firm equity. V_A is the value of the firm's assets. X is the face value of debt maturing at time T. r is the risk-free rate, and d is the dividend rate expressed in terms of V_A. s_A is the volatility of the value of assets, which is related to equity volatility, s_E, through the following equation: $s_E = (V_A e^{-dT} N(d_1) s_A)/V_E$.

We simultaneously solve the above two equations to find the values of V_A and s_A. We use the market value of equity for V_E and short-term plus one-half long-term book debt to proxy for the face value of debt X. s_E is the standard deviation of daily equity returns over the past three months. T equals one year, and r is the one-year treasury bill rate. The dividend rate, d, is the sum of the prior year's common and preferred dividends, obtained from COMPUSTAT divided by the market value of assets. We use the Newton method to simultaneously solve the two equations above. For starting values for the unknown variables we use $V_A = V_E + X$, and $s_A = s_E \times V_E/(V_E + X)$. Once we determine asset values, V_A, we then compute asset returns as in Hillegeist et al. (2004): $m_t = max\left[\left(V_{A,t} + d - V_{A,t-1}\right)/V_{A,t-1}, r\right]$. Because expected returns cannot be negative, if asset returns are below zero, they are set to the risk-free rate.[24] Merton's distance to default is finally computed as: $DD = log\left(\frac{V_A}{X}\right) + \left(m - d - \frac{s_A^2}{2}\right) T / \left(s_A \sqrt{T}\right)$.

[24] We obtain similar results if we use a 6% equity premium instead of asset returns as in CHS (2008).

References

Almeida, H., and T. Philippon. 2007. "*The Risk-Adjusted Cost of Financial Distress*." *Journal of Finance 62*(6): 2557–2586.

Altman, E. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *Journal of Finance* 23(4): 589–609.

Altman, Edward I., and Vellore M. Kishore. 1998. "Defaults and Returns on High Yield Bonds: Analysis through 1997." Working paper, NYU Salomon Center.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time Series Effects." *Journal of Financial Markets* 5(1): 31–56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaozan Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance* 61: 259–299.

Ang A., R. Hodrick, Y. Xing, and X. Zhang. 2009. "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence." *Journal of Financial Economics* 91: 1–23.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov. 2009. "Credit Ratings and the Cross-Section of Stock Returns." *Journal of Financial Markets* 12(3): 469–499.

Avramov, Doron, Gergana Jostova, and Alexander Philipov. 2007. "Understanding Changes in Corporate Credit Spreads." *Financial Analysts Journal* 63(2): 90–105

Bakshi, G., D. Madan, and F. Zhang. 2006. "Investigating the Role of Systematic and Firm-Specific Factors in Default Risk: Lessons from Empirically Evaluating Credit Risk Models." *Journal of Business* 79: 1955–1988.

Barberis, Nicholas, and Ming Huang. 2001. "Mental Accounting, Loss Aversion, and Individual Stock Returns." *Journal of Finance* 56: 1247–1292.

Berndt, A., R. Douglas, D. Duffie, M. Ferguson, and D. Schranz. 2005. "Measuring Default Risk Premia from Default Swap Rates and EDFs." *Working paper,* Stanford University.

Bharath, Sreedhar, and Tyler Shumway. 2008. "Forecasting Default with the KMV Merton Model." *Review of Financial Studies* 21(3): 1339–1369.

Blanco, R., S. Brennan, and I. W. Marsh. 2005. "An Empirical Analysis of the Dynamic Relationship between Investment Grade Bonds and Credit Default Swaps." *Journal of Finance* 60: 2255–2281.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam. 1998. "Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns." *Journal of Financial Economics* 49: 345–373.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008. "In Search of Distress Risk." *Journal of Finance* 63: 2899–2939.

Campbell, John Y., and Glen B. Taksler. 2003. "Equity Volatility and Corporate Bond Yields." *Journal of Finance* 58: 2321–2350.

Campello, M., L. Chen, and L. Zhang, 2008. "Expected Returns, Yield Spreads, and Asset Pricing Tests." *Review of Financial Studies* 21: 1297–1338.

Carhart, Mark. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52(1): 57–82.

Chan, K. C., and Nai-fu Chen. 1991. "Structural and Return Characteristics of Small and Large Firms." *Journal of Finance* 46: 1467–1484.

Chava, Sudheer, and Robert A. Jarrow, 2004. "Bankruptcy prediction with Industry Effects." *Review of Finance* 8: 537–569.

Chava, Sudheer, and A. Purnanandam. 2010. "Is Default Risk Negatively Related to Stock Returns?" *Review of Financial Studies* 23: 2523–2559.

Chen, L., D. A. Lesmond, and J. Wei. 2007. "Corporate Yield Spreads and Bond Liquidity." *Journal of Finance* 62:, 119–149.

Chernih, Andrew, S. Vanduffel, and L. Henrard. 2006. "Asset Correlations: A Literature Review and Analysis of the Impact of Dependent Loss Given Defaults." Working paper.

Cochrane, John H. 1991. "Production-based Asset Pricing and the Link between Stock Returns and Economic Fluctuations." *Journal of Finance* 46:, 209–237.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin, 2001. "The Determinants of Credit Spread Changes." *Journal of Finance* 56: 2177–2207.

Conrad, Jennifer, Nishad Kapadia, and Yuhang Xing. 2012. "What explains the distress risk puzzle: death or glory?" Working paper, UNC Chapel Hill and Rice University.

Da, Zhi, and Pengjie Gao, 2010. “Clientele Change, Liquidity Shock, and the Return on Financially Distressed Stocks.” *Journal of Financial and Quantitative Analysis* 45: 27–48.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers. 1997. “Measuring Mutual Fund Performance with Characteristic-Based Benchmarks.” *Journal of Finance* 52(3): 1035–1058.

Das, Sanjiv R., Darrell Duffie, Nikunj Kapadia, and Leandro Saita. 2007. “Common Failings: How Corporate Defaults Are Correlated.” *Journal of Finance* 72(1): 93–117.

Dichev, Ilia D. 1998. “Is the Risk of Bankruptcy a Systematic Risk?” *Journal of Finance* 53(3): 1131–1147.

Dimitrov, Valentin, and P. Jain, 2008. “The Value-Relevance of Changes in Financial Leverage beyond Growth in Assets and GAAP Earnings.” *Journal of Accounting, Auditing & Finance* 23: 191–222.

Downing, Chris, Shane Underwood, and Yuhang Xing. 2005. “Is Liquidity Risk Priced in the Corporate Bond Market?” Working paper, Rice University.

Driessen, J. 2005. “Is Default Event Risk Priced in Corporate Bonds?” *Review of Financial Studies* 18(1): 165–195.

Driessen, J., and Frank de Jong. 2007. “Liquidity Risk Premia in Corporate Bond Markets.” *Management Science* 53(9): 1439–1451.

Duffee, Gregory. 1999. “Estimating the Price of Default Risk.” *Review of Financial Studies* 12: 197– 226.

Duffie, Darrell, and Kenneth J. Singleton. 1995. “Modeling Term Structures of Defaultable Bonds.” Working paper, Stanford Graduate School of Business.

Duffie, Darrell, and Kenneth J. Singleton. 1997. “An Econometric Model of the Term Structure of Interest-Rate Swap Yields.” *Journal of Finance* 52: 1287–1321.

Duffie, D., L. Saita, and K. Wang. 2007. “Multi-Period Corporate Default Prediction with Stochastic Covariates.” *Journal of Financial Economics* 83(3): 635–665.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann. 2001. “Explaining the Rate Spread on Corporate Bonds.” *Journal of Finance* 56(1): 247–277.

Eom, Young Ho, Jean Helwege, and Jing-Zhi Huang. 2004. "Structural Models of Corporate Bond Pricing: An Empirical Analysis." *Review of Financial Studies* 17: 499–505.

Falkenstein, Eric G. 1996. "Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings." *Journal of Finance* 51: 111–135.

Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *Journal of Finance* 47(2): 427–465.

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33: 3–56.

Fama, Eugene F., and Kenneth R. French. 1996. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance* 51: 55–84.

Fama, Eugene F., and James D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81: 607–636.

Ferguson, Michael F., and Richard L. Shockley. 2003. "Equilibrium Anomalies." *Journal of Finance* 58: 2549–2580.

Frank, Murray Z., and Vidhan K. Goyal. 2003. "Testing the pecking order theory of capital structure." *Journal of Financial Economics* 67: 217–248.

Friewald, Nils, Christian Wagner and Josef Zechner. 2014. "The Cross-Section of Credit Risk Premia and Equity Returns." *Journal of Finance* 69: 2419–2469.

Garlappi, Lorenzo, Tao Shu, and Hong Yan. 2008. "Default Risk, Shareholder Advantage, and Stock Returns." *Review of Financial Studies* 21(6): 2743–2778.

George, Thomas J., and Hwang, Chuan-Yang. 2010. "A Resolution of the Distress Risk and Leverage Puzzles in the Cross Section of Equity Returns." *Journal of Financial Economics* 96: 56–79.

Gompers, P., and A. Metrick. 2001. "Institutional Investors and Equity Prices." *Quarterly Journal of Economics* 116: 229–259.

Griffin, John M., and Michael L. Lemmon. 2002. "Book-to-Market Equity, Distress Risk, and Stock Returns." *Journal of Finance* 57:, 2317–2336.

Hasbrouck, Joel. 2005. "Trading Costs and Returns for US Equities: The Evidence from Daily Data." Unpublished paper, Leonard N. Stern School of Business, New York University.

Hillegeist, Stephen A., Elizabeth Keating, Donald P. Cram, and Kyle G. Lunstedt. 2004. "Assessing the Probability of Bankruptcy." *Review of Accounting Studies* 9: 5–34.

Hilscher, Jens, and Wilson, M. 2017. "Credit Ratings and Credit Risk." *Management Science* Forthcoming.

Hong, H., T. Lim, and J. C. Stein. 2000. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance* 55: 265–295.

Huang, Jing-Zhi, and Ming Huang. 2003. "How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk?" Working paper, Pennsylvania State University.

Hull, J., M. Predescu, and A. White. 2004. "The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements." *Journal of Banking and Finance* 28(11): 2789–2811.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48(1): 35–91.

Jones, Charles M., and Matthew Rhodes-Kropf. 2003. "The Price of Diversifiable Risk in Venture Capital and Private Equity." Working paper, Columbia University.

Kapadia, Nishad. 2011. "Tracking Down Distress Risk." *Journal of Financial Economics* 102: 167–182.

Korteweg, Arthur. 2010. "The Net Benefits to Leverage." *Journal of Finance* 65: 2137–2170.

Li, E. X., D. Livdan, and L. Zhang. 2007. "Anomalies." *Review of Financial Studies* 22(11): 4301–4334.

Lin, Hai, Junbo Wang, and Chunchi Wu. 2011. "Liquidity Risk and the Cross-Section of Expected Corporate Bond Returns." *Journal of Financial Economics* 99: 628–650.

Lintner, John. 1965. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics* 47: 13–37.

Liu, Laura Xiaolei, Toni M. Whited, and Lu Zhang. 2*009*. "Investment-Based Expected Stock Returns." *Journal of Political Economy 117*(6): *1105–1139.*

Longstaff, F., S. Mithal, and E. Neis. 2005. "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit–Default Swap Market." *Journal of Finance* 60(5): 2213–2253.

Longstaff, Francis A., and Eduardo S. Schwartz. 1995. "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt." *Journal of Finance* 50(3): 789–821.

Malkiel, Burton G., and Yexiao Xu. 2002. "Idiosyncratic Risk and Security Returns." Working paper, University of Texas at Dallas.

Merton, Robert C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance* 29: 449–470.

Merton, Robert C. 1987. "A Simple Model of Capital Market Equilibrium with Incomplete Information." *Journal of Finance* 42: 483–510.

Nagel, Stefan. 2005. "Short Sales, Institutional Investors and the cross-section of Stock Returns." *Journal of Financial Economics* 78: 277–309.

Newey, Whitney, and Kenneth West. 1987. "A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55:, 703–708.

Ohlson, James A. 1980. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Accounting Research* 18: 109–131.

Pastor, Lubos, and Robert F. *Stambaugh*. 2003. "Liquidity risk and expected stock returns." *Journal of Political Economy* 111: 642--685

Pastor, Lubos, and Pietro Veronesi. 2003. "Stock Valuation and Learning about Profitability." *Journal of Finance* 58(5): 1749–1790.

Penman, S., S. Richardson, and I. Tuna. 2007. "The Book-to-Price Effect in Stock Returns: Accounting for Leverage." *Journal of Accounting Research* 45: 427–467.

Rajan, Raghuram, and Luigi Zingales. 1995. "What do we know about capital structure? Some evidence from international data." *Journal of Finance* 50: 1421-1460.

Roll, R. 1984. "A Simple Measure of the Bid-Ask Spread in an Efficient Market." *Journal of Finance* 39: 1127–1140.

Saita, L. 2006. "The Puzzling Price of Corporate Default Risk." Working Paper, Stanford University.

Sharpe, William F. 1964. “Capital Asset Prices: A Theory of Market Equilibrium.” *Journal of Finance* 19: 425–442.

Shumway, Tyler. 2001. “Forecasting Bankruptcy More Accurately: A Simple Hazard Model.” *Journal of Business* 74: 101–124.

Vassalou, Maria, and Yuhang Xing. 2004. “Default Risk in Equity Returns.” *Journal of Finance* 59: 831–868.

Zhang, Lu. 2007, March. “Discussion: ‘In Search of Distress Risk.’” Conference on Credit Risk and Credit Derivatives, Federal Reserve Board, Washington, D.C

Zhu, Haibin. 2006. “An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market.” *Journal of Financial Services Research* 29:211–235.

Zmijewski, Mark E. 1984. “Methodological Issues Related to the Estimation of Financial Distress Prediction Models.” *Journal of Accounting Research* 22: 59–82.

Table 1: Summary Statistics

Table 1 reports summary statistics for firm characteristics and distress measures for companies in the CRSP sample (left panel) and the bond sample (right panel). *MB* is the market-to-book ratio, and *ME* is market capitalization in millions of dollars. *CASHMTA* is the ratio of cash to the market value of total assets. *EXRETAVG* is a geometrically declining average of monthly log excess stock returns relative to the S&P 500 index. *NIMTAAVG* is a geometrically declining average of past values of the ratio of net income to the market value of total assets. *TLMTA* is the ratio of total liabilities to the market value of total assets, and *RSIZE* is the log ratio of market capitalization to the market value of the S&P 500 index. *IDIOVOL* is the standard deviation of regression errors obtained from regressing daily excess returns on the Fama and French (1993) factors. *TOTVOL* is the standard deviation of daily stock returns over the previous twelve months. *PRICE* is the log price per share truncated at $15. *PD* is the physical probability of default reported as a percentage. *DD* is the Merton distance to default measure. The Appendix describes how these variables are calculated. P25, P50, and P75 represent 25th, 50^{th,} and 75th percentiles, respectively. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	CRSP Sample					Bond Sample					
Variables	Mean	STD	P25	P50	P75	Mean	STD	P25	P50	P75	Difference
MB	1.983	1.466	0.900	1.533	2.644	1.794	1.131	0.999	1.486	2.268	0.189***
ME	1,273.8	5,713.0	20.7	91.8	271.6	5,327.7	17,251.1	417.5	1,297.2	3,811.6	-4,053.4***
CASHMTA	0.091	0.091	0.024	0.070	0.114	0.050	0.058	0.010	0.028	0.070	0.041***
EXRETAVG	-0.010	0.043	-0.034	-0.006	0.018	-0.001	0.030	-0.017	0.000	0.016	-0.008***
NIMTAAVG	0.003	0.015	-0.001	0.005	0.012	0.008	0.008	0.003	0.008	0.012	-0.005***
TLMTA	0.413	0.282	0.159	0.374	0.643	0.536	0.229	0.360	0.535	0.708	-0.123***
RSIZE	-10.708	1.604	-11.907	-10.790	-9.617	-8.031	1.160	-8.724	-7.701	-7.113	-2.677***
IDIOVOL	0.035	0.027	0.018	0.028	0.044	0.018	0.010	0.012	0.015	0.020	0.018***
TOTVOL	0.037	0.028	0.020	0.030	0.046	0.020	0.010	0.014	0.018	0.023	0.017***
PRICE	2.116	0.705	1.646	2.431	2.708	2.635	0.263	2.708	2.708	2.708	-0.519***
PD * 100	0.081	0.155	0.021	0.039	0.078	0.043	0.067	0.020	0.031	0.048	3.762***
DD	7.094	39.000	2.906	5.024	8.177	8.384	5.856	5.063	7.518	10.643	-1.290***

Table 2: Default Prediction

Table 2 reports results from hazard regressions of the default indicator on the predictor variables. The data are constructed such that all of the predictor variables are observable 12 months before the default event. *NIMTAAVG* is a geometrically declining average of past values of the ratio of net income to the market value of total assets. *TLMTA* is the ratio of total liabilities to the market value of total assets. *EXRETAVG* is a geometrically declining average of monthly log excess stock returns relative to the S&P 500 index. *SIGMA* is the standard deviation of daily stock returns over the previous three months. *RSIZE* is the log ratio of market capitalization to the market value of the S&P 500 index. *CASHMTA* is the ratio of cash to the market value of total assets. *MB* is the market-to-book ratio; *PRICE* is the log price per share truncated at $15, and *DD* is Merton's distance to default. These variables are described in detail in the Appendix. Results under "All Firms" are estimates computed using the full CRSP-COMPUSTAT sample of defaults with available accounting information. Results under "CHS Sample" show the estimates CHS (2008) report in their paper. Results under "Firms with Bonds" are estimates computed using the sample of defaults from companies that have issued bonds with available accounting information. Absolute values of *z-statistics* are reported in parentheses below coefficient estimates. McFadden pseudo R^2 values are reported for each regression. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample Period:	1981–2010	1963–2003	1981–2010	1981–2010	1981–2010	1981–2010
Lag (Months)	12	12	12	12	12	12
NIMTAAVG	-21.989***	-20.260***	-18.308***			
	(10.33)	(18.09)	(2.74)			
TLMTA	2.188***	1.420***	1.503***			
	(16.84)	(16.23)	(2.76)			
EXRETAVG	-7.871***	-7.13***	-6.241**			
	(10.28)	(14.15)	(2.13)			
SIGMA	1.461***	1.410***	1.774***			
	(11.19)	(16.49)	(5.17)			
RSIZE	-0.063***	-0.045**	-0.614***			
	(4.21)	(2.09)	(7.28)			
CASHMTA	-1.516***	-2.130***	-1.064			
	(7.85)	(8.53)	(1.21)			
MB	0.085***	0.075***	0.127			
	(2.63)	(6.33)	(0.91)			
PRICE	-0.167*	-0.058	-0.017			
	(1.74)	(1.40)	(0.95)			
DD				-0.356***	-0.345***	-0.460***
				(17.18)	(33.73)	(8.07)
CONSTANT	-9.718***	-9.160***	-13.844***	-3.401***	Not	-2.634***
	(18.12)	(30.89)	(8.90)	(48.52)	Reported	(11.10)
Observations	993,560	1,565,634	54,551	993,560	1,565,634	54,551
Defaults	728	1968	118	728	1968	118
Pseudo R^2	0.134	0.114	0.156	0.083	0.066	0.129
Sample Type	All Firms in CRSP-COMPUSTAT	CHS Sample, CHS (2008)	Firms with Bonds	All Firms in CRSP-COMPUSTAT	CHS Sample, CHS (2008)	Firms with Bonds

Table 3: Distress Portfolio Returns Sorted on Physical Default Probabilities

Table 3 reports the time series averages of excess returns as well as CAPM, Fama-French 3-factor and Carhart 4-factor alphas for distress risk portfolios. We sort stocks into deciles each month from January 1981 to December 2010 according to their physical default probabilities, obtained at the beginning of the previous month, calculated using the hazard coefficients computed in the full CRSP-COMPUSTAT sample (Panel A) as well as in the bond sample (Panel B). We compute the value-weighted returns for these decile portfolios and calculate portfolio returns in excess of the risk-free rate on a monthly basis. We report the regression coefficients the on the market (*MKT*), size (*SMB*) and value (*HML*) factors in both panels for the respective decile portfolios as well as the high-minus-low distress risk hedge portfolio. The factors are obtained from Ken French's website. Absolute values of *t*-statistics are reported in parentheses below their respective coefficient estimates. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Monthly Equity Returns For Default Risk Portfolios in the full CRSP-COMPUSTAT sample

Physical PD's constructed with coefficients from Column (1) of Table 2

	Excess Ret	CAPM alpha	3-factor alpha	4-factor alpha	MKT	SMB	HML
Low	0.608**	0.166	0.433***	0.096	0.879***	0.109**	-0.462***
	(2.01)	(0.99)	(2.86)	(0.72)	(23.63)	(2.17)	(8.05)
2	0.569**	0.095	0.090	0.022	0.898***	0.110***	-0.141***
	(2.55)	(1.51)	(1.42)	(0.36)	(54.84)	(4.66)	(-2.72)
3	0.534**	0.092	0.034	0.043	1.033***	0.116***	-0.071***
	(2.51)	(1.48)	(0.55)	(0.69)	(60.30)	(4.66)	(-2.75)
4	0.553*	-0.059	-0.168**	-0.075	1.170***	0.249***	0.069**
	(1.92)	(-0.70)	(-2.06)	(-0.96)	(54.03)	(7.90)	(2.13)
5	0.496	-0.175	-0.279***	-0.167*	1.252***	0.367***	-0.021
	(1.54)	(-1.64)	(-2.73)	(-1.69)	(45.85)	(9.24)	(-0.84)
6	0.385*	-0.112	-0.157	0.056	1.254***	0.389***	0.013
	(1.70)	(-0.79)	(-1.19)	(0.47)	(36.52)	(9.37)	(0.32)
7	0.408*	-0.089	-0.224*	-0.043	1.245***	0.458***	0.031
	(1.68)	(-0.65)	(-1.77)	(-0.37)	(41.65)	(10.52)	(0.68)
8	0.308	-0.371***	-0.476***	-0.280***	1.171***	0.358***	0.027
	(0.92)	(-2.73)	(-3.99)	(-2.61)	(36.10)	(7.57)	(0.55)
9	0.200	-0.596**	-0.653***	-0.375***	1.425***	0.920***	0.053
	(0.44)	(-2.17)	(-2.67)	(-2.85)	(23.64)	(12.44)	(0.58)
High	-0.576	-1.216***	-1.509***	-0.736***	1.511***	0.923***	0.430***
	(1.19)	(3.87)	(5.29)	(3.24)	(21.63)	(9.82)	(3.99)
High-Low	-1.184**	-1.382***	-1.942***	-0.832***	0.632***	0.814***	0.892***
	(2.34)	(2.96)	(4.68)	(2.64)	(5.69)	(10.96)	(6.25)

Panel B: Monthly Equity Returns For Default Risk Portfolios in the Bond sample							
Physical PD's constructed with coefficients from Column (3) of Table 2							
	Excess Ret	CAPM alpha	3-factor Alpha	4-factor Alpha	MKT	SMB	HML
Low	0.825***	0.382**	0.385**	0.271*	0.891***	-0.274***	0.003
	(3.05)	(2.29)	(2.36)	(1.65)	(22.27)	(5.18)	(0.05)
2	0.425*	0.152*	0.165*	0.103	0.913***	-0.271***	0.030
	(1.96)	(1.68)	(1.67)	(1.42)	(35.69)	(-8.17)	(0.88)
3	0.551**	0.119	0.078	0.070	0.935***	-0.183***	0.160***
	(2.43)	(1.18)	(0.85)	(0.67)	(44.08)	(-5.91)	(5.00)
4	0.502*	0.077	-0.079	-0.139	0.986***	-0.121***	0.280***
	(1.88)	(0.75)	(-0.86)	(-1.54)	(46.41)	(-3.91)	(8.77)
5	0.575**	0.053	-0.173	-0.113	1.153***	-0.069**	0.369***
	(1.99)	(0.37)	(-1.45)	(-1.15)	(50.71)	(-2.10)	(10.78)
6	0.524	0.027	-0.225	-0.153	1.219***	-0.038	0.445***
	(1.59)	(0.17)	(-1.45)	(-1.21)	(50.42)	(-1.09)	(12.24)
7	0.776**	0.001	-0.204**	-0.065	1.275***	-0.039	0.496***
	(2.41)	(0.01)	(-2.08)	(-0.45)	(46.04)	(-0.96)	(11.90)
8	0.489	-0.089	-0.284**	-0.168	1.372***	-0.010	0.519***
	(1.35)	(-0.54)	(-2.24)	(-1.06)	(46.84)	(-0.23)	(11.77)
9	0.184	-0.105	-0.349***	-0.196	1.387***	0.106	0.476***
	(0.45)	(-0.83)	(-3.34)	(-0.91)	(38.78)	(1.03)	(5.13)
High	0.318	-0.323	-0.694***	-0.217	1.437***	0.009	0.685***
	(0.82)	(1.36)	(3.19)	(1.15)	(26.89)	(0.13)	(8.39)
High-Low	-0.507*	-0.705***	-1.079***	-0.487**	0.546***	0.284***	0.682***
	(1.66)	(2.60)	(3.83)	(1.97)	(7.89)	(3.10)	(6.45)

Table 4: Monthly Equity Returns for Credit Risk Premium Portfolios

In Table 4, we report time series averages of excess returns as well as CAPM, Fama-French 3-factor and Carhart 4-factor alphas for distress risk portfolios. Each month from January 1981 through December 2010, we sort stocks into 10 portfolios based on their bond credit risk premia (CRP) at the beginning of the previous month. We compute the value-weighted returns for these decile portfolios and calculate portfolio returns in excess of the risk-free rate on a monthly basis. We report the regression coefficients the on the market (*MKT*), size (*SMB*) and value (*HML*) factors for all the decile portfolios as well as the high-minus-low distress risk hedge portfolio. The factors are obtained from Ken French's website. Absolute values of *t*-statistics are reported in parentheses below their respective coefficient estimates. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Equity Returns in Credit Risk Premia Portfolios							
	Excess Ret	CAPM alpha	3-factor alpha	4-factor alpha	MKT	SMB	HML
Low	0.463*	-0.074	-0.021	0.01	0.890***	-0.319***	0.020
	(1.65)	(0.52)	(0.17)	(0.08)	(27.51)	(9.29)	(0.47)
2	0.489**	0.048	0.026	-0.000	0.971***	-0.287***	0.017
	(2.19)	(0.45)	(0.24)	(-0.20)	(41.48)	(-8.35)	(0.48)
3	0.552**	-0.033	0.006	0.001	0.909***	-0.131***	0.050
	(2.31)	(-0.25)	(0.05)	(0.99)	(37.17)	(-3.66)	(1.35)
4	0.568**	-0.053	-0.116	0.000	0.978***	-0.105***	0.046
	(2.29)	(-0.39)	(-0.86)	(0.28)	(36.24)	(-2.66)	(1.12)
5	0.574**	0.095	0.020	-0.001	1.022***	-0.066*	0.190***
	(2.29)	(0.68)	(0.14)	(-0.75)	(39.59)	(-1.73)	(4.84)
6	0.608***	0.069	0.092	0.002	1.032***	0.004	0.281***
	(2.66)	(0.47)	(0.62)	(1.56)	(35.49)	(0.09)	(6.36)
7	0.619*	0.063	0.004	-0.000	1.114***	0.157***	0.419***
	(1.73)	(0.54)	(0.04)	(-0.21)	(35.73)	(3.43)	(8.86)
8	0.621**	-0.012	-0.053	0.002	1.217***	0.192***	0.324***
	(2.21)	(-0.10)	(-0.46)	(1.12)	(31.57)	(5.15)	(5.54)
9	0.795**	0.054	0.015	-0.000	1.239***	0.231***	0.575***
	(2.45)	(0.49)	(0.14)	(-0.15)	(29.70)	(5.00)	(8.39)
High	0.984***	0.325	-0.193	0.005	1.28***	0.157***	0.715***
	(2.58)	(1.33)	(0.93)	(0.02)	(22.83)	(2.63)	(9.62)
High-Low	0.521**	0.399	-0.172	-0.005	0.391***	0.476***	0.695***
	(1.98)	(1.50)	(0.75)	(0.02)	(6.32)	(7.25)	(8.49)

Table 5: Pricing of Systematic Default Risk Beta in the Cross Section of Credit Spreads

In Table 5, we run monthly Fama-MacBeth (1973) regressions of credit risk premium (in %) on default risk prediction variables used in CHS 2008, firm rating and systematic default risk beta. Our sample period covers January 1981 to December 2010. We report Fama-MacBeth regression coefficients as well as their corresponding Newey-West (1987) corrected *t*-statistics in parentheses. Credit risk premium are calculated in month *t+1* as the difference between the corporate bond yield and the corresponding maturity-matched treasury rate minus expected losses, liquidity compensation, and tax compensation. *SYSDEFBETA* is the firm's systematic default risk exposure and calculated as the sensitivity of its equity return in excess of the risk free rate to innovations in the mean default probability of all firms in the CRSP-COMPUSTAT sample. SYSDEFBETA is calculated over the *t-48* to *t-1* time frame on a rolling basis. *SIGMA, NIMTAAVG, TLMTA, CASHMTA, MB, RSIZE, RATING,* and *DD* are all calculated at time *t*. These variables are described in detail in Table 2. *OAMT* is the market value of debt at the time of its issuance in millions of dollars, and *TTM* is the time to maturity of debt in years. *PD* is the physical probability of default reported as a percentage. Absolute values of *t*-statistics are reported in parentheses below coefficient estimates. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) Credit Risk Premium	(2) Credit Risk Premium	(3) Credit Risk Premium	(4) Credit Risk Premium
SYSDEFBETA	1.989***	1.493***	1.276***	0.673***
	(8.26)	(7.45)	(8.57)	(4.13)
OAMT	-0.592	-1.190**	-1.403***	0.103
	(0.13)	(2.50)	(4.40)	(0.43)
TTM	1.082***	1.221***	1.054***	0.098***
	(4.81)	(6.88)	(5.96)	(4.71)
RATING	1.438***	1.308***	1.050***	0.092***
	(15.80)	(14.40)	(21.73)	(17.47)
DD		-1.191***		
		(9.50)		
$PD^{*}10^{6}$			0.577***	
			(7.31)	
SIGMA				0.308***
				(14.78)
NIMTAAVG				-0.355***
				(9.62)
TLMTA				0.315***
				(4.15)
CASHMTA				-1.031***
				(4.71)
MB				0.013
				(0.08)
RSIZE				-0.459***
				(13.69)
Constant	-2.508**	1.165***	0.959	-3.552***
	(2.15)	(7.63)	(1.00)	(16.07)

Table 6: Equity Returns for Systematic Default Risk Beta Portfolios

In Table 6, we report time series averages of excess returns as well as CAPM, Fama-French 3-factor and Carhart 4-factor alphas for distress risk portfolios. We sort all stocks in the CRSP-COMPUSTAT sample into deciles each month from January 1981 through December 2010 according to their systematic default risk betas—*SYSDEFBETAs*—obtained at the beginning of the previous month. *SYSDEFBETA* is the firm's systematic default risk exposure and calculated as the sensitivity of its equity return in excess of the risk free rate to innovations in the mean default probability of all firms in the CRSP-COMPUSTAT sample. We compute the value-weighted returns for these decile portfolios and calculate portfolio returns in excess of the risk-free rate on a monthly basis. We report the regression coefficients on the market (*MKT*), size (*SMB*) and value (*HML*) factors for all the decile portfolios as well as the high-minus-low distress risk hedge portfolio. The factors are obtained from Ken French's website. Absolute values of *t*-statistics are reported in parentheses below coefficient estimates. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Equity Returns in SYDEFBETA Portfolios							
	Excess Return	CAPM alpha	3-factor Alpha	4-factor Alpha	MKT	SMB	HML
Low	0.405	-0.469**	-0.180	-0.064	1.126***	0.391***	-0.424***
	(1.03)	(2.10)	(0.92)	(0.92)	(22.03)	(6.18)	(5.63)
2	0.448	-0.274**	-0.254**	-0.182**	1.103***	0.062	-0.026
	(1.49)	(2.23)	(2.02)	(2.02)	(33.70)	(1.54)	(0.53)
3	0.586**	-0.520	-0.151	-0.105*	1.069***	-0.174***	0.138***
	(2.23)	(0.53)	(1.66)	(1.66)	(45.20)	(5.92)	(3.97)
4	0.575**	-0.340	-0.181*	-0.010**	1.050***	-0.157***	0.217***
	(2.26)	(0.33)	(1.92)	(1.92)	(42.94)	(5.17)	(6.02)
5	0.770***	0.183*	0.002	0.002	1.009	-0.133***	0.248***
	(3.21)	(1.88)	(0.24)	(0.24)	(46.13)	(4.88)	(7.69)
6	0.829***	0.231**	0.003	0.006	1.064***	-0.141***	0.307***
	(3.27)	(2.07)	(0.30)	(0.30)	(43.43)	(4.65)	(8.51)
7	0.727***	0.127	-0.007	0.001	1.0549***	-0.090**	0.301***
	(2.77)	(0.98)	(0.56)	(0.56)	(33.70)	(2.33)	(6.53)
8	0.854***	0.219	0.005	0.038	1.072***	0.100**	0.277***
	(3.07)	(1.57)	(0.38)	(0.38)	(29.98)	(2.26)	(5.27)
9	0.880***	0.136	0.004	0.082	1.195***	0.171***	0.227***
	(2.73)	(0.83)	(0.03)	(0.03)	(27.94)	(3.23)	(3.60)
High	1.03**	0.061	0.006	0.182	1.393***	0.676***	0.154*
	(2.33)	(0.25)	(0.03)	(0.03)	(23.81)	(9.32)	(1.79)
High-Low	0.598*	0.530	0.186	0.246	0.267***	0.285***	0.579***
	(1.84)	(1.61)	(0.57)	(0.57)	(3.13)	(2.70)	(4.61)

Table 7: Cross-sectional Pricing of PD and SYSDEFBETA

In Table 7, we run monthly Fama-MacBeth (1973) regressions of returns in excess of the market (in %) on physical probability of default calculated as in CHS 2008 as well as on systematic default risk beta. Our sample period covers January 1981 to December 2010. We report Fama-MacBeth regression coefficients as well as their corresponding Newey-West (1987) corrected *t*-statistics in parentheses. *Excess return* is the equity return of the firm minus the risk-free rate calculated in month *t+1*. *PD* is the physical probability of default at time *t* and is reported as a percentage. *SYSDEFBETA* is the firm's systematic default risk beta (failure beta) at time *t* and is calculated as the sensitivity of its equity return in excess of the risk free rate to innovations in the mean default probability of all firms in the CRSP-COMPUSTAT sample. *SYSDEFBETA* is calculated over the *t-48* to *t-1* time frame on a rolling basis. *CAPM Beta* is the sensitivity of a stock's excess return to the market risk premium at time *t* as predicted by the Capital Asset Pricing Model. *CAPM Beta* is also calculated over the *t-48* to *t-1* time frame. *log BM* is the log of book-to-market ratio and is calculated as in Daniel and Titman (2006). *Momentum* is the cumulative return in the past twelve-to-two-month period. *log ME* is the logarithm of market capitalization. Absolute values of *t*-statistics are reported in parentheses below coefficient estimates. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) Excess Return	(2) Excess Return	(3) Excess Return	(4) Excess Return	(5) Excess Return
PD	-3.733***		-0.871**	-2.286***	
	(-4.74)		(1.99)	(-3.60)	
SYSDEFBETA		2.230**	1.892*		0.810
		(2.08)	(1.78)		(1.10)
CAPM Beta				0.007	0.047
				(0.05)	(0.26)
log BM				0.180***	0.120*
				(4.22)	(1.70)
Momentum				0.791***	0.590***
				(3.48)	(3.41)
log ME				-0.075*	-0.232***
				(-1.79)	(-3.37)
Constant	1.285***	1.427***	1.148***	1.71***	2.697***
	(4.61)	(4.72)	(4.19)	(6.30)	(5.83)

Table 8: Impact of Systematic Default Risk Exposure on Leverage

Table 8 reports regression results where the dependent variable is the year over year change in leverage (Δ*Leverage*), computed in year t. The independent variables are also year over year changes, computed in year t-1. *NIMTA* measures profitability and is computed as the ratio of net income to the market value of total assets. *MB* is the market-to-book ratio. *LogSALE* is the log of total sales. *TANG* measures tangibility of assets. Credit risk premium (*CRP*) is the difference between the corporate bond yield and the corresponding maturity-matched treasury rate minus expected losses, liquidity compensation, and tax compensation. *SYSDEFBETA* is the firm's systematic default risk beta (failure beta) at time *t* and is calculated as the sensitivity of its equity return in excess of the risk free rate to innovations in the mean default probability of all firms in the CRSP-COMPUSTAT sample. The regression includes firm fixed effects. Robust standard errors adjusted for firm-level clustering are reported below coefficient estimates. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) ΔLeverage	(2) ΔLeverage	(3) ΔLeverage
ΔNIMTA	-0.217^{***}	-0.209^{***}	-0.462^{***}
	(0.035)	(0.052)	(0.139)
ΔMB	-0.004^{***}	-0.004^{***}	-0.007^{***}
	(0.001)	(0.001)	(0.002)
ΔLogSALE	0.012^{***}	0.013^{***}	0.022^{***}
	(0.002)	(0.003)	(0.008)
ΔTANG	-0.019^{***}	-0.017^{***}	-0.086^{***}
	(0.005)	(0.007)	(0.016)
LEVERAGE	-0.399^{***}	-0.367^{***}	-0.361^{***}
	(0.006)	(0.007)	(0.018)
ΔSYSDEFBETA		-0.028^{**}	
		(0.012)	
ΔCRP			-0.579^{***}
			(0.140)
Constant	0.160^{***}	0.160^{***}	0.180^{***}
	(0.002)	(0.002)	(0.009)
Firm FE	Yes	Yes	Yes
Observations	46,747	46,747	4,552
R-squared	0.279	0.282	0.277

Figure 1: Historical Corporate Default Rates
This figure plots the historical default rates on Moody's rated corporate issuers. The data are from Moody's Investor Services. Grey areas indicate NBER recessions.

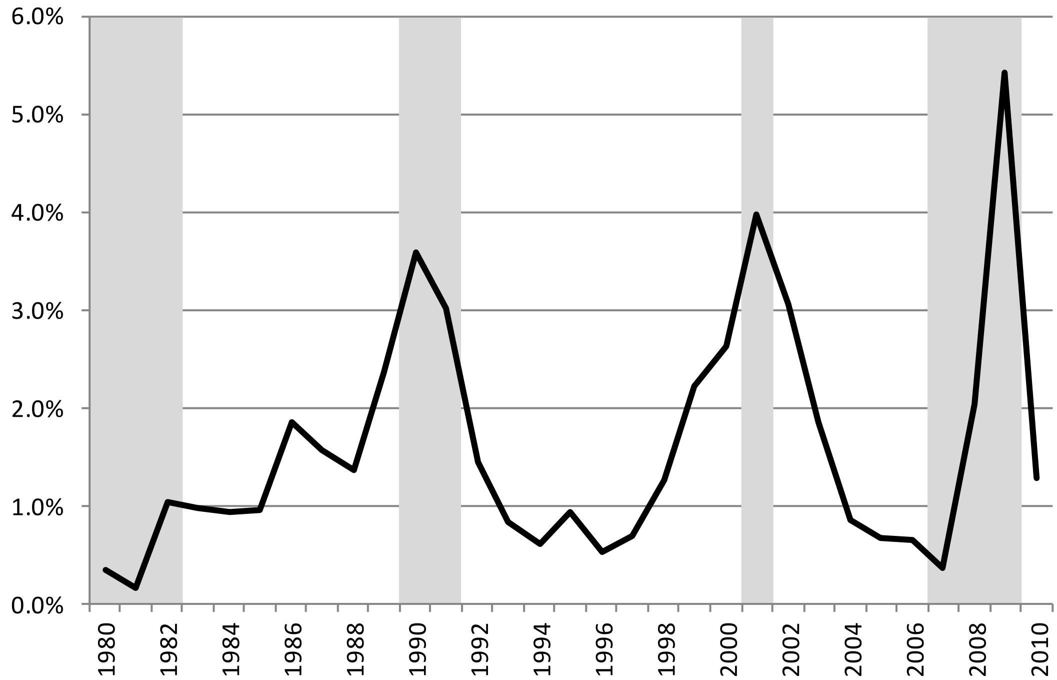

Figure 2: Components of Corporate Spreads

This figure plots the expected losses, taxes, and liquidity premium components of corporate spreads. The estimation of these components is described in Section 4. Bonds with maturity greater than seven years are referred to as having "long maturity" and bonds with maturity less than seven years are referred to as having "short maturity."