Is there a Distress Risk Anomaly? Pricing of Systematic Default Risk in the Cross Section of Equity Returns

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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 that proxy for a firm's physical probability of default, credit spreads proxy for a risk-adjusted default probability and thereby explicitly account for the non-diversifiable component of distress risk. In contrast to prior findings in the literature, we find that stocks that have higher credit risk premia, that is stocks with higher systematic default risk exposures, have higher expected equity returns which are largely explained by the market factor. We confirm the robustness of these results by using an alternative systematic default risk factor for firms that do not have bonds outstanding. Consistent with the theoretical result in George and Hwang (2010), we also show that firms react to increases in their systematic default risk exposures by reducing their leverage, leading to lower physical probabilities of distress. Our results show no evidence of firms with high systematic default risk exposure delivering anomalously low returns.

JEL Classifications: G11, G12, G13, G14.

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

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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 a systematic risk and whether it is priced in the cross section of equity returns. From a theoretical perspective, default risk can be a priced factor if a firm's capital asset pricing model (CAPM) beta does not fully capture default-related risk. 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.[2]

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).

We argue that the anomalous results documented in the literature are due to incorrectly measuring systematic default risk. Figure 1, which plots the historical default

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

rates on Moody's rated corporate issuers, suggests that default rates are highly dependent on the stage of 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, will take into account the covariance of default losses from a company with the rest of the assets in their portfolio when pricing distress risk.[3]

We use credit risk premium computed from corporate credit spreads to proxy for a firm's exposure to the non-diversifiable portion of default risk. 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.[4] 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 (or risk-neutral, as commonly designated in contingent claim pricing) and physical probabilities of default. Ranking stocks based on their physical default probabilities inferred from historical default data—as done in

[3] 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.

[4] 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).

Dichev (1998), Campbell, Hilscher, and Szilagyi (2008), and others in this literature—implicitly assumes that stocks with high physical probabilities of default also have high exposures to systematic variation in default risk. George and Hwang (2010) show that a firm's physical probability of default does not necessarily reflect its exposure to systematic default risk. In fact, George and Hwang (2010) show that firms with higher sensitivities to systematic default risk make capital structure choices that reduce their physical probabilities of distress. It is therefore not correct to rank firms based on their physical default probabilities when pricing financial distress, 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.

Moreover, previous papers have shown that three stock characteristics—high idiosyncratic volatility, high leverage, and low profitability—are associated with high historical default rates. However, 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). It is not clear if the distress anomaly is at least partially 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

We take a different approach and use a market-based measure, credit risk premium computed from corporate credit spreads, to proxy for systematic default risk exposure. We compute credit spreads as the difference between the bond yield of the firm and the corresponding maturity-matched treasury rate. We then compute credit risk premium 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. This measure offers two distinct advantages over others that have been used in the literature. First, unlike stock characteristics used to measure default risk, which may reflect information about future returns unrelated to distress risk, credit spreads reflect the market consensus view of the credit risk of the underlying firm. Second, credit spreads contain risk premium for systematic default risk, and are a proxy for the market-implied risk-adjusted probability of default. Using credit risk premia sorted portfolios, we find that firms with higher exposures to systematic default risk have higher expected equity returns. This premium is subsumed by the market factor, as predicted by structural models of default and rational asset pricing theory, and is further reduced economically and statistically by the Fama-French risk factors.

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. To further alleviate sample selection issues, we extend the

spread between high and low distress stocks reduces to -0.29%. Finally, controlling for profitability reduces the spread to -0.29% per month, making it statistically insignificant.

analysis to the full CRSP-COMPUSTAT sample. We compute a measure of systematic default risk exposure for all firms regardless of whether they have bonds outstanding. We assume a single factor structure for default risk and measure a firm's systematic default risk exposure as the sensitivity of its default probability to the common factor. We refer to the common factor as the systematic default risk factor, and the sensitivity of a firm's default probability to the common factor as its systematic default risk beta. First, we verify that systematic default risk beta is significantly priced in the cross section of corporate bond risk premia, justifying our use of corporate bond risk premium as a measure of systematic default risk exposure. This relationship is robust to controlling for bond ratings, physical default probabilities, accounting variables, market variables, and structural model parameters. Second, we form decile 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 equity returns than the lowest systematic default risk exposure portfolio. Moreover, we find that once we control for the market factor, the difference in returns between the highest and lowest systematic default risk portfolios becomes insignificant.

In our analyses of the sample of firms with bonds outstanding and of the full CRSP-COMPUSTAT sample, we find no evidence of firms with high systematic default risk exposure delivering anomalously low equity returns. These results are consistent with the basic 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).

Our systematic default risk measure allows us to test the George and Hwang (2010) hypothesis that firms with low exposures to systematic distress risk choose high leverage and, as a result, have high physical default probabilities despite having low systematic default risk exposures. We find empirical support for this hypothesis using the two alternative measures of systematic default risk exposure. In particular, we find that changes in systematic distress risk exposure predict changes in leverage in the next period. 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

[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.

capital estimates from analysts' forecasts to proxy for ex-ante expected returns, they find a positive relationship between default risk and expected returns. Our paper contributes to the literature by constructing a default risk measure that ranks equities explicitly based on their exposures to systematic default risk rather than ranking firms based on their physical probabilities of default.

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. Section 6 describes the construction and use of an alternative systematic default risk factor and extends the equity return analyses to the full CRSP-COMPUSTAT sample. Finally, Section 7 concludes.

2. Data

Corporate bond data used to compute the credit risk-premium in this study comes from three separate databases: the Lehman Brothers Fixed Income Database (Lehman) for the period 1974 to 1997, the National Association of Insurance Commissioners Database (NAIC) for the period 1994 to 2006, and the Trade Reporting and Compliance Engine (TRACE) system dataset 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.[7] 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 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

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

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[8]; *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.

[8] This is following CHS (2008). Truncation in this setting does not constitute eliminating observations that are priced greater than $15. It means that firm observations with a price greater than $15 is set to $15.

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, 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.[9] 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

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

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:

$$PD_{t-1}^{i}(\mathrm{Y}_{t-1+12}^{i}=1|\mathrm{Y}_{t-2+12}^{i}=0)= \frac{1}{1+\exp\ -\alpha_{12}-\beta_{12}X_{t-1}^{i}} \tag{1}$$

where Y_{t-1+12}^{i} is an indicator that equals one if the firm defaults in 12 months conditional on survival for 11 months. X_{t-1}^{i} is a vector of explanatory variables available at the time of prediction. We use accounting and market-based variables used 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.[10] 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 regressions 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.

[10] 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. 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.

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 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. Corporate Spread as a Measure of Systematic Default Risk Exposure

In this section, we describe our use of corporate bond risk premia to measure systematic distress risk exposure.

There is now a significant body of research that shows that compensation for default risk constitutes a considerable portion of credit spreads. 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.[11]

As mentioned earlier, our focus in this paper is on measuring compensation for systematic default risk exposure. We create this 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 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:

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

[11] In this study we have chosen to use bond spreads instead of CDS spreads because bond data is available for a substantially larger number of companies and is available for a much longer time period.

In Equation (2), PD is the τ-year physical probability of default.[12] 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:

$$\left[\left(1 - PD_{i,t}\right) \times Coupon_{i,t} + PD_{i,t} \times \left(1 - L_{i,t}\right)\right] \times TR. \tag{3}$$

The first part of Equation (3) captures the coupon rate, *Coupon*, 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

[12] 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.

corporate bond returns are explained by their exposure to market risk and liquidity risk factors.[13] We consider two types of liquidity risk, one originating from the equity market and one from the treasury bond 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.[14] 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.[15] We then subtract the computed liquidity premium, *LQ*, from the corporate bond spreads with the corresponding rating and maturity. Table 3 summarizes the computations for different rating-maturity groups.

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. Many papers, however, document difficulties in relating equity factors and bond returns (Fama and French 1993; Elton et al. 2001). To

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[13] 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.

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

[15] 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."

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 firms in the CRSP-COMPUSTAT sample and 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.[16] For the Bond sample we compute default 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

[16] 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.

firms are ranked using physical default probabilities. To save space, we report returns for only the top and bottom deciles, and the difference between the top and bottom deciles.

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:

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{MOM}^i MOM_t + \varepsilon_t^i \qquad (4)$$

In Panel A of Table 4, we report portfolio return results 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 -1.184% 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 4. 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. The negative loading on the momentum factor is consistent with the intuition that distressed stocks tend to have low returns prior to portfolio formation.

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.

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 Premium and Equity Returns

In this section, we examine how *CRP*s (credit risk premia) are related to future realized equity returns[17]. 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

[17] 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*.

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. To save space, we only report returns for the top and bottom decile portfolios, and the return difference between the top and bottom deciles in Table 5.

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 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 raw 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 mainly by the market factor and partly by the size and value factors. The size and value factors have statistically significant positive loadings for the high minus low *CRP* portfolio suggesting that these factors are intimately related to systematic default risk exposure. 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

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 follow Hilscher and Wilson (2010) and identify a measure of systematic default risk exposure that can be calculated for all firms regardless of whether they have bonds outstanding.[18] We form decile portfolios by sorting all equities in the CRSP-COMPUSTAT sample based on their systematic default risk betas and investigate the pricing of systematic default risk in the cross section of equity returns.

We measure a firm's systematic default risk exposure as the sensitivity of its default probability to the median default probability of all firms in the CRSP-COMPUSTAT sample. We refer to this measure as systematic default risk beta. We find that portfolios with high systematic default risk betas, on average, have higher returns than portfolios with low systematic default risk betas, verifying our results in Section 5.2. We also show that systematic default risk beta is significantly priced in the cross-section of credit risk premia validating the use of *CRP* as a measure of systematic default risk exposure.

[18] Hilscher and Wilson (2010) use the systematic default risk exposure measure to examine whether company ratings contain information related to systematic default risk. We analyze the impact of systematic default risk exposure on equity returns.

6.1 Measuring Systematic Default Beta

We assume that historical default probabilities have a single common factor and use the median 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 74.7% of variation in default probabilities.[19] The first principal component and the median default probability have a correlation of 0.96 and are significantly higher during and after recessions. This is consistent with economic theory that suggests that systematic risk (discount rate) is higher during recessions.

To compute each firm's sensitivity to the systematic default factor, we estimate the following regression for each firm over 48-month rolling windows:

$$PD_t^i = \alpha_\tau^i + SYSDEFBETA_\tau^i \times MPD_t + \varepsilon_t^i. \tag{5}$$

PD_t^i is the 12-month annualized physical default probability for firm *i* in month *t*. It is computed each month using coefficients from column 1 in Table 2. As before, 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 default probabilities are measured. MPD_t is the cross-sectional median physical default probability across all firms.[20] $SYSDEFBETA_\tau^i$ is exposure to systematic default risk in month τ, obtained from rolling regressions using the past 48 months of data.

[19] Extracting principal components in the standard way from the full panel of CRSP-COMPUSTAT firms is problematic because the cross-section is much larger than the time series. We therefore first shrink the size of the cross-section by assigning each firm-month to a given rating-month and calculating equal-weighted average 12-month cumulative default probabilities as done by Hilscher and Wilson (2010). We group all firms with ratings of CCC+ and below together. 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.

[20] The results are similar if we instead use the first principal component.

6.2 Default Risk Beta and Credit Spreads

In this 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. This finding provides further evidence that *SYSDEFBETA* is a good measure of systematic default risk exposure, and that investors demand compensation for this exposure. This result also validates our use of *CRPs* to measure firms' exposures to systematic default risk.

Table 6 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 the regression, we control for the CAPM beta (*BETACAPM)*, return volatility (*SIGMA*), profitability (*NIMTAAVG*), leverage (*TLMTA*), amount of liquid assets (*CASHMTA*), market-to-book ratio (*MB*), and relative size of the firm (*RSIZE)*. We also control for two bond characteristics: average issue amount (*OAMT*) and average time to maturity (*TTM)* of a firm's outstanding bonds. As alternative credit risk measures, we include Merton's distance to default (*DD*), physical default probability (*PD*), and the Standard & Poor's (S&P) rating (*RATING*). 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 stock characteristics that have been shown to be important determinants of credit risk by CHS (2008) as well as time to maturity and the offering amount of the firm's outstanding bonds. In column 2 we control for rating and Merton's distance to default, in addition to time to maturity and bond offering amount. In column 3 we control for time to maturity, offering amount of the bond, Merton's distance to default and the physical probability of default. In column 4 we control for all the CHS (2008) variables, firm rating, Merton's distance to default, and the physical probability of default. In all specifications the loading on 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 6 suggest that moving from the 75th percentile systematic default risk beta firm ($SYSDEFBETA = 0.156$) to the 95th percentile firm ($SYSDEFBETA = 0.954$) leads to an increase of 45 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. In the next section we use systematic default risk beta ($SYSDEFBETA$) to examine the pricing of systematic default risk in the cross section of equity returns in the CRSP-COMPUSTAT sample.

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 larger CRSP-COMPUSTAT sample. In

Section 5.2, our analysis was confined to firms that have outstanding bonds because we used the bond credit risk premium as our proxy for systematic default risk compensation.

In this section, 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 obtained at the beginning of the previous month. We then calculate the value-weighted decile portfolio returns for all stocks in the CRSP-COMPUSTAT sample 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 7, we report regression results for only the top and bottom decile portfolios along with the top decile minus bottom decile hedge portfolio to save space.

Results in Table 7, which are obtained from the CRSP-COMPUSTAT sample, are similar to those reported in Table 5, which are obtained using the bond sample. Table 5 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 7 shows that the highest systematic default risk beta decile portfolio in the full CRSP-COMPUSTAT sample earns 46 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, the statistical significance of the hedge portfolio return disappears, suggesting a strong link between systematic default risk and market risk. Controlling for Fama-French size and value factors further reduces the economic and statistical significance of the systematic default risk premium, supporting the Fama and French (1992) conjecture that size and value premiums may be related to systematic distress risk.

Overall, the results in this section verify the robustness of using credit spreads as a proxy for systematic default risk exposure and confirm our results in Section 5.

7. Systematic Default Risk Exposure and Leverage

Systematic default risk exposure measures we have created allow us to verify potential explanations of the distress risk premium anomaly. George and Hwang's (2010) theoretical model suggests that firms with high exposures to systematic distress risk lower their physical default probabilities by choosing low levels of leverage in an attempt to reduce distress costs. We provide empirical evidence for this hypothesis using the two measures of systematic default risk exposure utilized in this paper. In particular, we show that an increase in systematic distress risk exposure predicts a reduction in leverage in the next period.

In Table 8, 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[21]. In Table 9, following Frank and Goyal (2003) and Rajan and Zingales (1995), we run a fixed effects regression to test the relationship more formally. We control for profitability (NIMTA), market-to-book ratio (MB), the log of total sales (LogSALE) and tangibility of assets (TANG). The regression results show that there is a strong negative relationship between systematic default risk exposure and leverage. In addition to

[21] In Table 8 we measure physical probability of default using the CHS-score. CHS-Score is the transformation of the physical default probability computed as $\ln[(1/PD)-1]$: Higher CHS-scores suggest lower physical probabilities of default.

providing empirical support to the George and Hwang (2010) hypothesis, 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.

8. Conclusion

We argue that the distress risk anomaly documented in the cross section of equity returns is due to mismeasuring systematic default risk. Previous papers measure 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, thus failing to appropriately account for the systematic nature of default risk. We use credit risk premium obtained from corporate credit spreads to proxy for a firm's exposure to systematic default risk. Unlike previously used measures that proxy for physical probabilities of default, credit risk premia proxy for risk-adjusted default probabilities, reflecting the risk premium for the non-diversifiable component of distress risk. We find that stocks that have higher credit risk premium 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 factor, suggesting that CAPM beta captures most of the variation in systematic default risk exposure.

The empirical results in the paper 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 potential explanation for the anomalous results previously documented in the literature.

To show that our results are robust to sample biases, we conduct two analyses. First, we show that when firms in our Bond sample are ranked according to traditional measures of default risk used in the literature, the default risk anomaly exists in the bond sample. Second, we construct an alternative proxy to measure systematic default risk exposure ($SYSDEFBETA$) and extend the analyses to the full CRSP sample. We obtain results similar to what we find using the bond sample. These results are consistent with the basic structural models of default in which aggregate risk factors drive the default probability as well as the returns on bonds and equities.

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. *MB* is the market-to-book ratio. Book equity, *BE* is defined as in Davis, Fama, and French (2000). To deal with outliers, we adjust total value of assets, *TA* (COMPUSTAT quarterly data item: ATQ) by the difference between the market equity (*ME*) and book equity (*BE*):

$$MTA_{i,t} = TA_{i,t} + 0.1(ME_{i,t} - BE_{i,t}) \quad \text{(A.1)}$$

NIMTAAVG is a geometrically declining average of past values of the ratio of net income (data item: NIQ) to adjusted total assets:

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^2}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + ... + NIMTA_{t-10,t-12}\right) \quad \text{(A.2)}$$

EXRETAVG is a geometrically declining average of monthly log excess stock returns relative to the S&P 500 index:

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{t-1} + ... + \phi^{11}EXRET_{t-12}\right) \quad \text{(A.3)}$$

The weighting coefficient is set to $\phi = 2^{-1/3}$, such that the weight is halved each quarter.

TLMTA is the ratio of total liabilities (data item: NIQ) 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 (data item: CHEQ) 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 calculate Merton's distance-to-default measure. Market value of equity is modeled as a call option on the company's assets:

$$V_E = V_A e^{-dT} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-dT}) V_A$$
$$d_1 = \frac{\log\left(\frac{V_A}{X}\right) + \left(r - d + \frac{s_A^2}{2}\right) T}{s_A \sqrt{T}}; d_2 = d_1 - s_A \sqrt{T} \tag{A.4}$$

V_E is the market value of a firm. 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:

$$s_E = \frac{V_A e^{-dT} N(d_1) s_A}{V_E} \tag{A.5}$$

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 (data items: DLCQ+1/2*DLTTQ). 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 Annual, (data items: DVP+DVC) 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 $s_A = s_E V_E (V_E + X)$. Once we determine asset values, V_A, we then compute asset returns as in Hillegeist et al. (2004):

$$m_t = max\left[\frac{V_{A,t} + d - V_{A,t-1}}{V_{A,t-1}}\right] \tag{A.6}$$

Because expected returns cannot be negative, if asset returns are below zero, they are set to the risk-free rate.[22] Merton's distance to default is finally computed as:

$$DD = \frac{log\left(\frac{V_A}{X}\right) + \left(m - d - \frac{s_A^2}{2}\right)T}{s_A\sqrt{T}} \tag{A.7}$$

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

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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: Expected Losses, Taxes, and Liquidity Premia in Credit Spreads

In Table 3, we report average credit spreads, spreads in excess of expected losses and taxes and liquidity premium for various rating-maturity groups. Column (1) reports corporate bond yields minus maturity-matched government treasuries; column (2) reports spreads in excess of expected losses and taxes; and column (3) reports the liquidity premium for each corresponding rating/maturity portfolio. The estimation of these components is described in Section 4.1. 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."

Portfolio	Spread	Spread in Excess of Expected Losses and Taxes	Liquidity Premium
AAA short-mat	0.97%	0.62%	0.13%
AAA long-mat	0.95%	0.62%	0.23%
AA short-mat	1.04%	0.56%	0.24%
AA long-mat	1.26%	0.84%	0.35%
A short-mat	1.32%	0.81%	0.33%
A long-mat	1.28%	0.81%	0.41%
BBB short-mat	1.99%	1.20%	0.50%
BBB long-mat	2.06%	1.32%	0.73%
BB	3.78%	2.09%	0.88%
B	5.28%	2.10%	1.30%
CCC	10.36%	4.75%	1.40%

Table 4: Distress Portfolio Returns Sorted on Physical Default Probabilities

Table 4 reports time series averages, CAPM, 3-factor and 4-factor regression results 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 using the CRSP-COMPUSTAT sample (Panel A) and using the bond sample (Panel B). We compute the 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. The factors are obtained from Ken French's website We report regression results for only the top and bottom decile portfolios as well as the high-minus-low distress risk hedge portfolio to save space. 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

	Alpha * 100	MKT	SMB	HML	MOM
10th	0.608**				
	(2.01)				
	0.166	1.041***			
	(0.99)	*(28.01)*			
	0.433***	0.879***	0.109**	-0.462***	
	(2.86)	*(23.63)*	*(2.17)*	*(8.05)*	
	0.096	0.949***	0.083*	-0.37***	0.337***
	(0.72)	*(29.23)*	*(1.94)*	*(7.42)*	*(11.05)*
	Alpha * 100	MKT	SMB	HML	MOM
90th	-0.576				
	(1.19)				
	-1.216***	1.507***			
	(3.87)	*(21.46)*			
	-1.509***	1.511***	0.923***	0.43***	
	(5.29)	*(21.63)*	*(9.82)*	*(3.99)*	
	-0.736***	1.351***	0.981***	0.219***	-0.772***
	(3.24)	*(24.48)*	*(13.45)*	*(2.58)*	*(14.89)*
	Alpha * 100	MKT	SMB	HML	MOM
90th - 10th	-1.184**				
	(2.34)				
	-1.382***	0.466***			
	(2.96)	*(4.28)*			
	-1.942***	0.632***	0.814***	0.892***	
	(4.68)	*(6.04)*	*(6.73)*	*(6.02)*	
	-0.832***	0.402***	0.898***	0.589***	-1.109***
	(2.64)	*(5.69)*	*(10.96)*	*(6.25)*	*(18.14)*

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					
	Alpha * 100	MKT	SMB	HML	MOM
10th	0.825***				
	(3.05)				
	0.382**	0.847***			
	(2.29)	*(22.64)*			
	0.385**	0.891***	-0.274***	0.003	
	(2.36)	*(22.27)*	*(5.18)*	*(0.05)*	
	0.271*	0.913***	-0.283***	0.031	0.114***
	(1.65)	*(22.76)*	*(5.41)*	*(0.51)*	*(3.07)*
	Alpha * 100	MKT	SMB	HML	MOM
90th	0.318				
	(0.82)				
	-0.323	1.224***			
	(1.36)	*(22.92)*			
	-0.694***	1.437***	0.009	0.685***	
	(3.19)	*(26.89)*	*(0.13)*	*(8.39)*	
	-0.217	1.345***	0.047	0.566***	-0.475***
	(1.15)	*(29.42)*	*(0.79)*	*(8.14)*	*(11.24)*
	Alpha * 100	MKT	SMB	HML	MOM
90th - 10th	-0.507*				
	(1.66)				
	-0.705***	0.378***			
	(2.60)	*(5.74)*			
	-1.079***	0.546***	0.284***	0.682***	
	(3.83)	*(7.89)*	*(3.10)*	*(6.45)*	
	-0.487**	0.432***	0.330***	0.535***	-0.589***
	(1.97)	*(7.17)*	*(4.20)*	*(5.84)*	*(10.58)*

Table 5: Monthly Equity Returns for Credit Risk Premium Portfolios

In Table 5, we report time series averages, CAPM, 3-factor, and 4-factor regression results for distress risk portfolios. Each month from January 1981 through December 2010, we sort stocks into 10 portfolios based on their credit risk premia (CRP) at the beginning of the previous month. We compute the value-weighted return 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. The factors are obtained from Ken French's website. We report regression results for only the top and bottom decile portfolios to save space. 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 Credit Risk Premia Portfolios

	Alpha * 100	MKT	SMB	HML	MOM
10^{th}	0.463*				
	(1.65)				
	-0.074	0.826***			
	(0.52)	*(23.63)*			
	-0.021	0.890***	-0.319***	0.020	
	(0.17)	*(27.51)*	*(9.29)*	*(0.47)*	
	0.01	0.878***	-0.314***	0.013	-0.03
	(0.08)	*(26.00)*	*(9.07)*	*(0.29)*	*(1.20)*
	Alpha * 100	MKT	SMB	HML	MOM
90^{th}	0.984***				
	(2.58)				
	0.325	1.014***			
	(1.33)	*(17.12)*			
	-0.193	1.28***	0.157***	0.715***	
	(0.93)	*(22.83)*	*(2.63)*	*(9.62)*	
	0.005	1.205***	0.191***	0.668***	-0.193***
	(0.02)	*(21.65)*	*(3.34)*	*(9.37)*	*(4.64)*
	Alpha * 100	MKT	SMB	HML	MOM
90^{th} - 10^{th}	0.521**				
	(1.98)				
	0.399	0.188***			
	(1.50)	*(2.91)*			
	-0.172	0.391***	0.476***	0.695***	
	(0.75)	*(6.32)*	*(7.25)*	*(8.49)*	
	-0.005	0.327***	0.505***	0.656***	-0.163***
	(0.02)	*(5.21)*	*(7.84)*	*(8.15)*	*(3.48)*

Table 6: Pricing of Systematic Default Risk Beta in the Cross Section of Credit Spreads

In Table 6, we run monthly Fama-MacBeth (1973) regressions of credit risk premium (in %) on default risk prediction variables used in CHS 2008, firm rating, market beta, 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. *BETACAPM* is the firm's CAPM beta at time *t* and is calculated using rolling regressions over the *t-48* to *t-1* time frame. *SYSDEFBETA* is the firm's systematic default risk beta (failure beta) at time t and is calculated as the sensitivity of its default probability to the median default probability. SYSDEFBETA is also 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.

VARIABLES	(1) Credit Risk Premium	(2) Credit Risk Premium	(3) Credit Risk Premium	(4) Credit Risk Premium
BETACAPM	0.072***	0.187**	0.189***	0.082***
	(2.64)	*(4.54)*	*(5.18)*	*(2.90)*
SYSDEFBETA	0.555***	1.424***	1.408***	0.567***
	(3.74)	*(7.08)*	*(6.93)*	*(4.38)*
SIGMA	3.556***			3.320***
	(16.23)			*(13.18)*
NIMTAAVG	-41.575***			-29.324***
	(10.29)			*(8.75)*
TLMTA	0.442***			0.411***
	(5.75)			*(4.50)*
CASHMTA	-1.296***			-0.661***
	(5.16)			*(2.80)*
OAMT	-0.098***	-0.103*	-0.375***	0.023
	(4.39)	*(1.89)*	*(10.28)*	*(1.01)*
TTM	0.009***	0.012***	0.012***	0.009***
	(4.54)	*(7.13)*	*(6.88)*	*(4.30)*
MB	-0.019			-0.009
	(1.10)			*(0.70)*
RSIZE	-0.569***			-0.428***
	(18.00)			*(13.46)*
RATING		0.123***		0.086***
		(16.00)		*(18.19)*
DD		-0.099***	-0.108***	0.023*
		(9.20)	*(9.82)*	*(1.80)*
PD*10^6			29.028***	10.969***
			(6.66)	*(3.73)*
Constant	-3.715***	0.889***	1.828***	-3.843***
	(16.49)	*(5.68)*	*(14.42)*	*(15.85)*
Observations	83,202	83,020	83,124	83,020
R-squared	0.501	0.459	0.370	0.601

Table 7: Equity Returns for Systematic Default Risk Beta Portfolios

In Table 7, we report the time series averages, CAPM, 3-factor, and 4-factor regression results for distress risk portfolios. We sort stocks 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. We calculate the value-weighted decile portfolio returns for all stocks in the CRSP-COMPUSTAT sample on a monthly basis and regress the portfolio return in excess of the risk-free rate on the market-rf (MKTRF), size (SMB), value (HML), and momentum (MOM) factors. The factors are obtained from Ken French's website. We report regression results for only the top and bottom decile portfolios along with the top decile minus bottom decile hedge portfolio to save space. 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 for SYSDEFBETA Portfolios in CRSP

	Alpha*100	MKT	SMB	HML	MOM
10th	1.187***				
	(2.74)				
	0.214	1.199***			
	(0.81)	*(19.82)*			
	0.204	1.069***	0.897***	0.096	
	(0.72)	*(21.3)*	*(13.01)*	*(1.29)*	
	0.501**	0.962***	0.910***	-0.031	-0.320***
	(2.16)	*(20.35)*	*(14.63)*	*(0.45)*	*(7.88)*
	Alpha * 100	MKT	SMB	HML	MOM
90th	1.644***				
	(3.13)				
	0.612*	1.313***			
	(1.66)	*(15.93)*			
	0.502	*1.172****	1.250***	0.322***	
	(1.52)	*(17.18)*	*(13.33)*	*(3.18)*	
	0.909***	1.024***	1.270***	0.144	-0.450***
	(3.08)	*(16.03)*	*(15.09)*	*(1.55)*	*(8.14)*
	Alpha * 100	MKT	SMB	HML	MOM
90th - 10th	0.457*				
	(1.70)				
	0.398	0.114**			
	(1.48)	*(1.97)*			
	0.298	0.104*	0.353***	0.226***	
	(1.13)	*(1.75)*	*(4.32)*	*(2.59)*	
	0.408	0.062	0.360***	0.175**	-0.130***
	(1.54)	*(1.00)*	*(4.43)*	*(1.95)*	*(2.61)*

Table 8: Relationship between Leverage and Systematic Default Risk Exposure

In Table 8, we report average changes in leverage and physical default risk for firms sorted in deciles formed on changes in systematic default risk exposure in the prior year. Leverage is measured as the ratio of total liabilities to the market value of total assets. CHS-Score is the transformation of the physical default probability computed as ln[(1/ PD)-1]: Higher CHS-scores suggest lower physical probabilities of default. For the full CRSP-COMPUSTAT sample, each December from 1980 through 2010, we sort stocks into 10 portfolios based on their year over year change in systematic default risk betas (ΔSYSDEFBETA). For the Bond sample, each December from January 1981 through 2010, we sort stocks into 10 portfolios based on their year over year change in value-weighted credit risk premia (ΔCRP). We then compute cross-sectional average values for changes in leverage (ΔLeverage) and physical default risk (ΔCHS-score) over the next year. If portfolios are formed in December 1990 on changes in systematic default risk from December 1989 to December 1990, then changes in leverage and physical default risk are computed from January 1991 to January 1992

CRSP-COMPUSTAT Sample			Bond Sample		
Portfolio (ΔSYSDEFBETA)	ΔLeverage	ΔCHS-score	Portfolio (ΔCRP)	ΔLeverage	ΔCHS-score
L	0.0078	-0.0064	L	0.0055	-0.0992
2	0.0049	-0.0714	2	0.0056	-0.1000
3	0.0097	-0.1050	3	0.0015	-0.0402
4	0.0094	-0.1022	4	0.0009	-0.0110
5	0.0095	-0.1039	5	0.0041	-0.0397
6	0.0086	-0.0499	6	0.0021	-0.0093
7	0.0069	-0.0324	7	0.0012	-0.0135
8	0.0035	-0.0248	8	0.0053	0.0440
9	-0.0019	0.0185	9	0.0008	0.0131
H	-0.0161	0.1270	H	-0.0070	0.0491

Table 9: Impact of Systematic Default Risk Exposure on Leverage

Table 9 reports regression results where the dependent variable is the year over year change in leverage (ΔLeverage), 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) and is calculated as the sensitivity of its default probability to the median default probability. 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.

VARIABLES	ΔLeverage	ΔLeverage	ΔLeverage
ΔNIMTA	-0.217***	-0.217***	-0.462***
	(0.035)	(0.035)	(0.139)
ΔMB	-0.004***	-0.004***	-0.007***
	(0.001)	(0.001)	(0.002)
ΔLogSALE	0.012***	0.012***	0.022***
	(0.002)	(0.002)	(0.008)
ΔTANG	-0.019***	-0.018***	-0.086***
	(0.005)	(0.005)	(0.016)
LEVERAGE	-0.399***	-0.399***	-0.361***
	(0.006)	(0.006)	(0.018)
ΔSYSDEFBETA		-0.002**	
		(0.001)	
ΔCRP			-0.579***
			(0.140)
Constant	0.160***	0.160***	0.180***
	(0.002)	(0.002)	(0.009)
Firm FE	Yes	Yes	Yes
R-squared	0.279	0.279	0.277

Figure 1: Historical Corporate Default Rates

This figure plots the historical default rates on Moody's rated corporate issuers. The data is from Moody's Investor Services. Grey areas indicate NBER recessions.

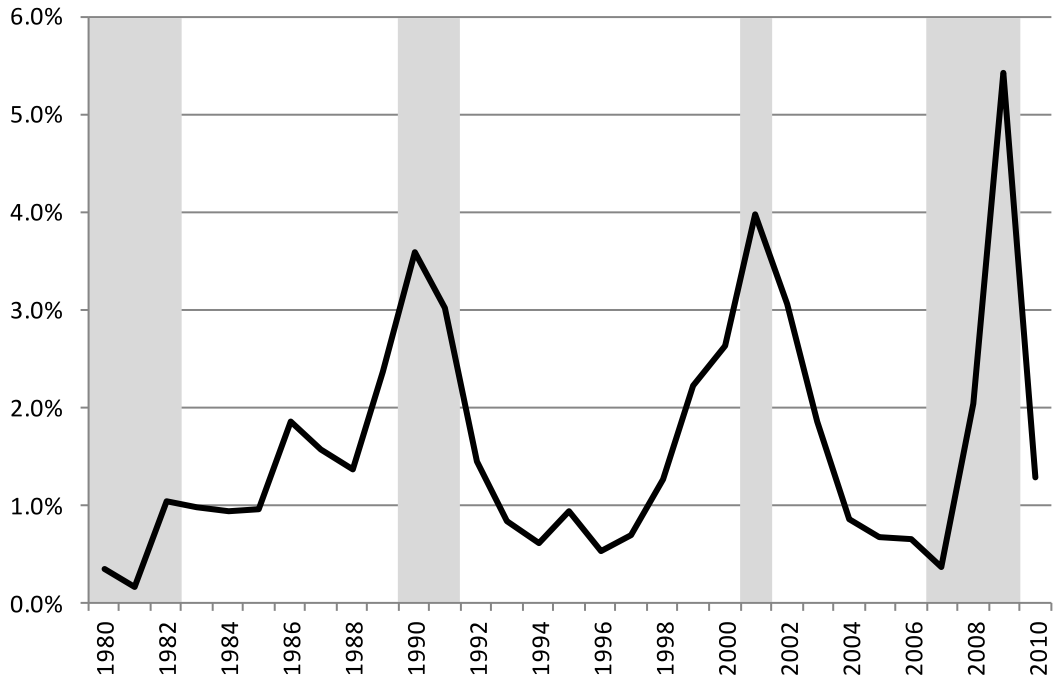

Figure 2: Components of Corporate Spreads

This figure plots the expected losses, taxes, and liquidity premium components of corporate spreads. The estimation of these components is described in Section 4.1. 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."