Essays in Pricing of Credit Risk in Bond and Equity Markets

by

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I dedicate this dissertation to my parents, Muhsine Neyran Yıldızhan and Suat Yıldızhan, my sister, Ceylan Yıldızhan, my grandparents, Dr. Necati Çelim, Kamuran Çelim, Ömer Yıldızhan, Emriye Yıldızhan, all of my teachers and (God willing) my future children.

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Chapter I

Introduction

This work consists of two essays that investigate the pricing of credit risk in the equity and bond markets. The first essay, *"Is there a Distress Risk Anomaly? Bond Spread as a Proxy for Default Risk,"* investigates the pricing of default risk in the cross section of equity returns. The contribution of this paper to the literature is three-fold. First, the paper shows that the distress risk anomaly is an amalgamation of other anomalies and return relationships previously documented in the literature. Second, this is the first paper to use corporate bond spreads to measure the ex-ante probability of default risk. We show that in hazard rate regressions, credit spreads drive out the significance of most of the other measures that are used to predict corporate defaults and significantly improve the pseudo R^2 values in all specifications. Third, contrary to previous findings, we show that default risk is not priced negatively in the cross section of equity returns. We sort firms according to their exposures to the systematic component of default risk as well as their aggregate default risk. To the best of my knowledge we are the first to explicitly rank equity returns according to firms' exposures to the systematic component of default risk. Portfolios sorted both on credit spreads and on credit spreads net of expected losses have positive raw returns but do not deliver significant positive or negative returns after controlling for well known risk factors. These findings challenge the previous studies that have found an anomalous relationship between credit risk and equity returns. The analyses in this paper take the right step towards finding a more appropriate measure of systematic default risk that can explain the cross section of equity returns in line with the rational expectations theory.

The second essay, *"Corporate Reputation and Cost of Debt"*, investigates the role a firm's reputation plays in determining its cost of debt. Although the theoretical literature since Milgrom and Roberts (1982) and Diamond (1989) has recognized that reputation should impact credit relationships, to date that impact has never been fully quantified. We show that firm reputation – that intangible way in which a company is perceived by others – plays an important role in determining the cost of debt. We measure company reputation using the annual ranking of "Most Admired Companies" published by Fortune magazine, which surveys industry experts about firm reputations. We find a robust inverse relationship between a firm's reputation as measured by its score in the Fortune survey and the firm-level value-weighted credit spread on its bonds. A half-point (0.5) improvement in the reputation score, or moving one quintile up in the reputation ranking, leads to a reduction of 10 to 20 basis points in the cost of debt capital, even after controlling for firm-level and macro-level variables that are known to impact bond spreads. Change in the reputation score is also able to explain a substantial amount of the cross-sectional variation in change in credit spreads on corporate bonds. Our findings contribute to the literature that has attempted to explain variation in credit spread changes, as prior studies have been able to explain only a small fraction of that variation. Those studies find that a large component of credit spread changes is not explained by the tangible information their models employ. By explicitly accounting for an intangible element of credit risk, we substantially improve our ability to explain cross-sectional variation in credit spread changes. To our knowledge, we are the first to explicitly account for this intangible component of reputation in explaining changes in the cost of debt capital. Furthermore, we show that the impact of this intangible is most significant for firms that are informationally opaque or that already have high distress risk. The sensitivity of cost of debt capital to changes in the reputation score is highest for smaller firms, for firms with lower analyst coverage, and for firms with higher distress risk. We also show why the Fortune reputation score helps to explain credit spread changes: it captures soft information about whether a firm will fail to honor its commitments. Our reputation measure is a good ex ante predictor of corporate distress and contains information about default risk above and beyond that conveyed by accounting and market variables, corporate ratings and structural parameters. Our results show that credit risk has an important, but largely ignored, intangible aspect.

Chapter II

Is there a Distress Risk Anomaly ?

Corporate Bond Spread as a Proxy for Default Risk[1]

A fundamental tenet of asset pricing is that investors should be compensated with higher returns for bearing systematic risk that can not be diversified. Recently, a number of papers examined whether default risk is such a systematic risk and whether it is priced in the cross section of equity returns. On the theoretical side, default risk can be a priced factor if a firm's *Beta* within the framework of the Capital Asset Pricing Model (CAPM) does not fully capture default-related risk. Default risk may not be fully correlated with the market itself, but could be related to declines in other un-measured components of wealth such as human capital (Fama and French 1996) or risk related to debt securities (Ferguson and Shockley 2003) distinct from risk related to equities. Empirically, research thus far has focused on determining the ex-ante probability of firms failing to meet their financial obligations and testing to see if there is co-movement in security returns of firms in response to changes in an

[1] This chapter has been co-authored with Deniz Anginer. Deniz Anginer can be reached at the World Bank, E-mail: danginer@worldbank.org. Çelim Yıldızhan can be reached at Ross School of Business, University of Michigan, Ann Arbor, MI 48109, E-mail: yildizha@umich.edu. We would like to thank Dennis Capozza, Ilia Dichev, Jens Hilscher, Haitao Li, Paolo Pasquariello, Amiyatosh Purnanandam, Uday Rajan, Nejat Seyhun, Tyler Shumway, Jeff Smith, and Lu Zhang for helpful discussion and guidance.

empirically constructed default risk factor. Previous studies have utilized different proxies and approaches to measure financial distress and have found anomalously low returns for stocks with high probabilities of default.[2] The low returns on stocks with high default risk cannot be explained by Fama and French (1993) risk factors. Stocks with high distress risk tend to have higher market betas and load more heavily on size and value factors leading to significantly negative alphas.

In this paper we argue that the anomalous results documented in the literature are due to the poor quality of the proxies used to measure default risk. First, previous papers measure financial distress by determining firms' physical probabilities of default as opposed to risk-neutral probabilities of default. This calculation ignores the fact that firm defaults are correlated and are more likely to occur in bad times, thus failing to appropriately account for the systematic nature of default risk. In this paper we use risk-neutral probabilities of default calculated from corporate bond spreads in order to account for the systematic variation in default risk.[3] The fixed-income literature has provided substantial evidence for a systematic 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 (see for instance Almeida and Philippon 2007 and Berndt et al. 2005) that there is a substantial difference between the risk-neutral and historical (physical) probabilities of default. Ranking stocks based

[2] See for instance Dichev (1998) and Campbell, Hilscher and Szilagyi (2008).

[3] Almeida and Philippon (2007), Hull, Predescu and White (2006) provide empirical evidence on the difference between real-world and risk-neutral default probabilities implied by credit spreads.

[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), Berndt et. al (2005).

on their physical default probabilities, as done in Dichev (1998), Campbell, Hilscher and Szilagyi (2008) and other papers 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 (2009) show that a firm's physical probability of default does not necessarily reflect the firm's exposure to systematic default risk. In fact, George and Hwang (2009) 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, since such a ranking would not properly reflect firms' exposures to systematic default risk, the only type of default risk that should be rewarded with a premium. Default risk measures previously used in the literature ignore this fundamental fact.

Second, previous papers have shown three stock characteristics – idiosyncratic volatility, leverage and profitability – to be most closely associated with high corporate default rates. High idiosyncratic volatility, high leverage and low profitability predict high default probability. However these are the same characteristics that are known to be associated with 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 stock returns (Korteweg 2004, Dimitrov and Jain 2005, Penman et al. 2007, Ang, Hodrick, Xing and Zhang 2008). It is not clear if the distress anomaly is just the manifestation of one or more of these previously documented return relationships. We show that the difference in returns between high and low distress stock portfolios becomes insignificant once we control for these three stock characteristics.

In this paper, we take a different approach to measuring default risk and use a market based measure, namely corporate credit spreads, to proxy for distress risk. We compute credit spreads as the difference between the bond yield of firm and the corresponding maturity matched treasury rate. This measure offers several advantages over others that have been utilized in the literature thus far. Unlike structural models of corporate bankruptcy that make simplifying assumptions about the capital structure of a firm, our proposed measure is model and assumption free. And 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 quality of the underlying firm. Moreover, credit spreads contain a risk-premium for systematic risk. As such, unlike previously used measures, credit spread, is a proxy for the market-implied risk-adjusted (or risk-neutral) probability of default and is a better measure of exposure to systematic default risk. We show that credit spreads predict corporate defaults better than previously used measures based on structural models, bond ratings and accounting variables. Using credit spreads, we find that there is no evidence of firms with high default risk delivering anomalously low returns, and we do not find default risk to be a priced risk factor in the cross-section of equity returns.

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 during 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 measures, Campbell, Hilscher and Szilagyi (2008) (hereafter CHS) show that stocks with high risk of default deliver anomalously low returns. Garlappi, Shu, and Yan (2005), who obtain default risk measures from Moody's KMV, also find similar results to those of Dichev (1998) and CHS (2008). They attribute their findings to the violation of the absolute priority rule.

George and Hwang (2009) suggest that firms with higher sensitivities to systematic default risk make capital structure choices that reduce their overall physical probabilities of default and argue that the negative relationship between returns and leverage can explain the pricing of distress risk anomaly. Avramov et al. (2007) show that most of the negative return for high default risk stocks is concentrated around rating downgrades. Vassalou and Xing (2004) find some evidence that distressed stocks, mainly in the small value group, earn higher returns.[5] Chava and Purnanandam (2008) 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.

Our paper is different from the rest of the papers in the literature since we specifically aim to construct a default risk measure that ranks firms based on their

[5] Da and Gao (2005) argue that Vassalou and Xing's results are limited to one month returns on stocks in the highest default likelihood group which trade at very low prices. They show that returns are contaminated by microstructure noise and the positive one month return is compensation for increased liquidity risk.

exposures to systematic default risk, rather than ranking firms based on their physical probabilities of default.

Our paper also contributes to a growing literature on bankruptcy prediction.[6] In particular, we show the importance of market based variables in predicting bankruptcy. Corporate bond spreads significantly increase the pseudo R^2's in hazard regressions when we run a horse race of corporate spreads with a comprehensive set of accounting measures, bond ratings and structural model parameters previously used in the literature. Adding corporate spread to the covariates used in CHS (2008), for instance, increases the pseudo R^2 from 27.6% to 37.4%.[7] These results strongly indicate that corporate bond spreads contain default information above and beyond the measures commonly used in the literature.

The rest of the paper is organized as follows. Sections 2.1 and 2.2 describe the data and the different default measures used in this study. Section 2.3 reports the return analyses for high default risk stocks and examines the relationship between various stock characteristics and default risk. Section 2.4 describes the use of credit spreads as a predictor of corporate bankruptcy and as a proxy for default risk, and also contains the asset pricing tests to see if default risk, as measured by credit spreads, is priced in the cross section of equity returns. Section 2.5 concludes.

2.1 Data

In this section, we briefly describe the data sources used in this study. Firm level accounting and price information are obtained from COMPUSTAT and CRSP for the

[6] See for instance Altman (1968), Zmijewski (1984), Ohlson (1986), Shumway (2001), and Chava and Jarrow (2004).

[7] Using corporate spread as the lone predictor variable yields a pseudo R^2 of 26.5% similar to the pseudo R^2 obtained from using all of the CHS (2008) covariates.

1980–2008 time period. We exclude financial firms (SIC codes 6000 through 6999) from the sample. To avoid the influence of microstructure noise we also exclude firms priced less than one dollar in the analyses that follow. The data items used to construct distress measures are explained in detail in the Appendix.

Corporate defaults between 1981 and 2008 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 bankruptcies. We choose 1981 as the earliest year for identifying bankruptcy filings as the Bankruptcy Reform Act of 1978 is likely to have caused the associations between accounting variables and the probability of bankruptcy to change. Furthermore, we have little corporate bond yield information prior to 1980. In all, we obtain a total of 548 firm bankruptcies covering the period 1981–2008, for which we have complete accounting-based measures. 94 of these bankruptcies also have corresponding corporate bond spread information.

Corporate bond data used in this study comes from three separate databases: the Lehman Brothers Fixed Income Database (Lehman) for the period 1974 to 1997, the Fixed Income Securities Database (FISD) for the period 1998 to 2002, and the Trade Reporting and Compliance Engine (TRACE) system dataset from 2003 to 2008. We also use the National Association of Insurance Commissioners Database (NAIC) for bond descriptions. Due to the small number of observations prior to the year 1980, we include only the period 1980 to 2008 in the analyses that follow.

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.[8] 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. For each firm, we calculate a value-weighted average of that firm's outstanding bond spreads, using market values of the bonds as weights. There are 107,692 firm months and 1,011 unique firms with credit spread and firm level data. There is no potential survivorship bias in our sample as we do not exclude bonds that have gone bankrupt or those that have matured.

As not all companies issue bonds, it is important to discuss the limitations of our dataset. 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 2.1. Not surprisingly, companies in the bond

[8] See for instance Duffee (1999), Collin-Dufresne, Goldstein, and Martin (2001) and Avramov et al. (2006).

sample are larger and show a slight value tilt. There is, however, significant dispersion in size, market-to-book, and credit spread values. 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. In section 2.3, we show that the distress anomaly as described by CHS (2008) and others exists in our bond sample.

2.2 Default Risk Measures

There is a vast literature on the statistical modeling of the probability of bankruptcy. In this paper, we create measures of financial distress based on three models of bankruptcy prediction that have been utilized by previous researchers investigating the pricing of distress risk.

2.2.1 Static models

Static models of bankruptcy prediction employ either a multiple discriminant analysis as in Altman (1968) or a conditional logit model as in Ohlson (1980), to assess which firm characteristics are important in determining the probability of financial distress. These models then use the estimates from the single period classification to predict future implied probability of bankruptcy.[9] In this paper, we use parameters used to construct Altman's z-score and Ohlson's o-score, two popular measures that have

[9] Using single period observations introduce a bias in static models that is discussed in Shumway (2001).

been widely used in empirical research and practice. Altman's z-score is defined as the following:

$$\text{z-score} = 1.2\ WCTA + 1.4\ RETA + 3.3\ EBITTA + 0.6\ METL + 1.0\ STA \tag{2.1}$$

where *WCTA* is the ratio of working capital to total assets, *RETA* is the ratio of retained earnings to total assets, *EBITTA* is the ratio of earnings before interest and taxes to total assets, *METL* is the ratio of market equity to total liabilities, and *STA* is the ratio of sales to total assets. Ohlson's o-score is defined as:

$$\begin{aligned} o\text{-score} \ &= -1.32 - 0.407\log(SIZE) + 6.03\ TLTA - 1.43\ WCTA \\ &+0.076\ CLCA - 1.72\ OENEG - 2.37\ NITA - 1.83\ FUTL \\ &+0.285\ INTWO - 0.521\ CHIN \end{aligned} \tag{2.2}$$

where *SIZE* is total assets divided by the consumer price index, *TLTA* is the ratio of total liabilities to total assets, *CLCA* is the ratio of current liabilities to current assets, *OENEG* is a dummy variable set equal to one if total liabilities exceeds total assets and zero otherwise, *NITA* is the ratio of net income to total assets, *FUTL* is the ratio of funds from operations to total liabilities, *INTWO* is a dummy variable equal to one if net income was negative for the past two years and zero otherwise, and *CHIN* is a measure of the change in net income. The accounting variables used to construct the z-score and the o-score are described in detail in the appendix.

2.2.2 Dynamic models

Dynamic models of bankruptcy prediction (Shumway 2001, Chava and Jarrow 2004 and CHS 2008) use a dynamic panel regression approach and incorporate market based variables such as market capitalization and past equity returns. Dynamic models prediction avoid the biases of the static models by adjusting for potential duration dependence issues. In this paper we use the CHS (2008) specification:

$$
\begin{aligned}
CHS\text{-}score_t \;=\;& -9.164 - 20.264\ NIMTAAVG_t + 1.416\ TLMTA_t \\
& -7.129\ EXRETAVG_t + 1.411\ SIGMA_t - 0.045\ RSIZE_t \\
& -2.132\ CASHMTA_t + 0.075\ MB_t - 0.058\ PRICE_t
\end{aligned}
\tag{2.3}
$$

where *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 from above at $15.[10]

2.2.3 Structural Model

The third measure we use in this study is based on the structural default model of Merton (1974). This approach treats the equity value of a company as a call option on the company's assets. The probability of bankruptcy 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.

2.3. Pricing of Default Risk

2.3.1 Returns to Distressed Stocks

In this section we analyze the effect of default risk on stock returns. We sort stocks into deciles each January from 1981 through 2008, according to their default probabilities calculated using the CHS-score.[11] In the analyses that follow, we exclude financial firms (SIC codes 6000 through 6999); we also exclude firms priced less than one dollar as of the portfolio formation date from the sample to avoid the influence of microstructure noise. The stocks in each decile portfolio are held for a year. Following CHS (2008), 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 in our bond dataset. To save space we only report returns for the top and bottom deciles, and the difference between the top and bottom deciles.

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:

$$\mathrm{r}_t^i = \alpha^i + \beta^i_{MKT} MKT_t + \beta^i_{SMB} SMB_t + \beta^i_{HML} HML_t + \beta^i_{MOM} MOM_t + \varepsilon^i_t \tag{2.4}$$

[10] In computing the CHS-score, we use coefficients on the variables calculated from rolling regressions to avoid a look-ahead bias. We thank Jens Hilscher for providing this data.

[11] We obtain similar results using Merton's distance-to-default measure, Ohlson's o-score and Altman's z-score, which are not reported to save space.

The results are reported in Table 2.2. The results under 'Bond Sample' on the right hand side include only the companies in our bond sample.

Our results are consistent with those obtained in the previous studies. Stocks in the highest default risk portfolio have significant negative returns. Using the CHS default probability, the difference in returns between the highest and lowest default risk portfolios is -1.24% per month. The intercepts from the market and the 4-factor models are economically and statistically significant. For the CRSP-COMPUSTAT universe, 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. The results are weaker for the bond sample, but still economically and statistically significant. Using firms that have corresponding 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 -0.32%. We repeat the analyses using Merton's distance-to-default measure, Ohlson's o-score and Altman's z-score. The results are qualitatively similar and we do not report them here to save space.

The loadings on the size and value factors suggest that distressed stocks are mostly small and value stocks. The loading on the momentum factor is consistent with the intuition that distressed stocks tend to have low returns prior to portfolio formation. These results are consistent across different measures of distress, and the results hold in our bond sample suggesting that our study doesn't suffer from sample biases.

2.3.2 Stock Characteristics and Distress Returns

Previous research has identified a number of stock characteristics that predict high default probabilities for companies. However, three characteristics – leverage, idiosyncratic volatility and profitability – have been shown to be most closely associated with corporate default rates. High leverage, high idiosyncratic volatility and low profitability predict higher rates of corporate default. As mentioned earlier, these are the same characteristics that are ex-ante associated with low future returns. Ang, Hodrick, Xing and Zhang (2006, 2008) establish a robust relationship between idiosyncratic volatility and stock returns. This negative relationship has been termed the 'idiosyncratic volatility puzzle', since rational asset pricing theories predict that the relationship be positive or that there be no relationship at all.[12] Korteweg (2004), Dimitrov and Jain (2005), Penman et al. (2007) show a negative relationship between leverage and stock returns – the 'leverage anomaly'. Similarly, low profitability predicts low returns. Q-theory provides a theoretical link between profitability and equity returns (Cochrane 1991, Liu, Whited and Zhang 2009). It is not clear if distress anomaly is just an amalgamation of one or more of these previously documented return relationships. In this section we investigate in detail the relationship between default risk and these three stock characteristics. In particular we want to see if the distress anomaly persists once we explicitly control for idiosyncratic volatility, profitability and leverage.

[12] Merton (1987), Malkiel and Xu (2002) and Jones and Rhodes-Kropf (2003) link higher returns on high- volatility stocks to investors not being able to diversify. There have been some behavioral and agency-based explanations for the negative relationship between idiosyncratic volatility and returns. The behavioral model of Barberis and Huang (2001) predicts that higher idiosyncratic volatility stocks should earn higher expected returns. Falkenstein (1996) reports that mutual fund managers prefer to hold more volatile stocks for the upside option value they provide.

To control for these three stock characteristics, we perform a double sort. We sort stocks into five groups each January from 1981 to 2008 according to the CHS probability of default. Then within each distress group we sort stocks based on the previous year's stock characteristic (idiosyncratic volatility, profitability or leverage) into five groups, creating a total of 25 portfolios. We then calculate 4-factor alphas for the distress portfolios after controlling for the effects of the characteristics. We do this by averaging the returns of the five distress portfolios over each of the characteristic portfolios. We use *NIMTAAVG* as the profitability measure and *TLMTA* as the leverage measure. Both variables are described in Section 2.2. We follow Ang, Hodrick, Xing and Zhang (2006) and calculate idiosyncratic volatility relative to the Fama-French 3-factor model. First, we regress daily stock returns from the previous calendar year on the Fama-French 3 factors:

$$\mathrm{r}_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \qquad (2.5)$$

Idiosyncratic volatility is then calculated as the standard deviation of the residuals: $\sqrt{\mathrm{var}\ \varepsilon_t^i}$.

Panel A of Table 2.3 reports 4-factor alphas for the five distress portfolios, as well as 4-factor alphas for the distress portfolios after controlling for the three stock characteristics. We also report in Panel B of Table 2.3, average idiosyncratic volatility, leverage and profitability values for firms belonging to each of the five distress portfolios. There is a strong relationship between distress risk and the three stock characteristics. Idiosyncratic volatility increases monotonically from 2.5% for the lowest distress group to 4.5% for the highest 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%. The unconditional 4-factor alpha for the zero cost portfolio formed by going long high distress stocks and shorting low distress stocks is -0.88% per month, yet this premium decreases to -0.61% after controlling for leverage. Once we control for idiosyncratic volatility, the return spread between high and low distress stocks reduces to -0.54%. Finally, controlling for profitability reduces the spread to -0.26% per month making it statistically insignificant. These results suggest that the return to high minus low distressed stock portfolios can be attributed to idiosyncratic volatility, leverage and profitability. The results are consistent with the notion that the distress risk anomaly is an amalgamation of other anomalies and return relationships previously documented in the literature.

2.4 Corporate Spreads As a Measure of Default Risk

Given the results in the previous section, instead of using stock characteristics to measure financial distress, we take a different approach and use yields on corporate bonds in excess of the treasury rate to measure ex-ante probability of default. As mentioned earlier, this measure offers several advantages over others that have been used by previous papers. It is available in high frequency, which increases the power of statistical analyses we carry out. Unlike structural models of corporate bankruptcy that make simplifying assumptions about the capital structure of a firm, our proposed measure is model and assumption free. And unlike stock characteristics that are 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 quality of the underlying firm.

There is now a significant body of research that shows that default-risk constitutes a considerable portion of credit spreads. Driessen (2003) finds that default risk accounts for at the minimum18% (AA rated bonds) and as high as 52% (BBB rated bonds) of the corporate bond spread. Huang and Huang (2003) using the Longstaff-Schwartz 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. The similarity in the information content of CDS spreads and bond credit spreads with respect to default is supported by Blanco, Brennan, and Marsh (2005) and Zhu (2005). They confirm, through co-integration tests, that the theoretical parity relationship between these two types of credit spreads holds as a long run equilibrium condition.[13]

2.4.1 Credit Spreads and Bankruptcy Prediction

Consistent with the studies discussed above, in this section we empirically show that bond spreads are a good ex-ante predictor of corporate defaults. In particular, we test to see if credit spreads improve default prediction beyond measures previously used

[13] 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 the literature.[14] To measure the probability that a firm defaults, we estimate a dynamic panel model using a logit specification, following Shumway (2001), Chava and Jarrow (2004), CHS (2008) and others. We use information available at the end of the calendar year to predict defaults twelve months ahead. Specifically, the marginal probability of default (*PD*) for company *i* over the next year *t* is assumed to follow a logistic distribution:

$$PD_t^i = \frac{1}{1+\exp\left(-\alpha-\beta' X_t^i\right)} \qquad (2.6)$$

where *X* is a vector of explanatory variables available at the time of prediction, and includes a comprehensive list of explanatory variables that have been used by previous papers to predict corporate bankruptcy. We utilize accounting variables used in calculating Altman's z-score, Ohlson's o-score, market based variables introduced by Shumway (2001) and CHS (2008), as well as Merton's distance-to-default measure. We also use Standard and Poor's (S&P) corporate ratings obtained from COMPUSTAT. All the variables included in the hazard regressions that follow are described in detail in the Appendix.

Table 2.5 reports results for the first set of hazard regressions. In the first column, we use the same covariates (*NIMTAVG, TLMTA, EXRETAVG, SIGMA, RSIZE, CASHMTA, MB* and *PRICE*) used in CHS (2008). The sample includes only firms that have issued bonds for the 1980 to 2008 time period. As a comparison, we report the estimates using the full sample (including firms that have not issued bonds),

[14] Bharath and Shumway (2004) document that credit spreads contain useful information in predicting defaults. In this paper, we significantly increase the number of defaults used in the hazard regressions,

and also estimates from the CHS (2008) study in columns 7 and 6 respectively. The estimates from these three samples are very similar indicating that the bond dataset is not biased. As we limit the sample to firms with only bonds outstanding, the effects of market capitalization, relative value of the firm, firm profitability and volatility become slightly stronger, while the effects of leverage, liquidity position of the firm, price and recent past returns become slightly weaker. When we use Merton's distance-to-default (*DD*) measure as a predictor, we obtain similar results to those in CHS (2008). Results from this regression are reported in column 4.

Next, we add credit spreads (*SPREAD*) as an additional covariate to the CHS (2008) and the Merton specifications. The estimates from these two regressions are reported in columns 2 and 5 respectively. We also report estimates from a regression using *SPREAD* as the only covariate in column 3. Our proposed measure improves the explanatory power of both the CHS and Merton models. We report McFadden's pseudo R^2 coefficients for each regression.[15] The pseudo R^2 value increases from 27.6% for the CHS model to 37.4% for the CHS model used in conjunction with *SPREAD* in predicting bankruptcies. The specification that uses *SPREAD* alone has a pseudo R^2 value of 26.5% which is similiar to the pseudo R^2 for the CHS specification. Pseudo R^2 improves from 24.1% to 30.4% when Merton's *DD* is used in conjunction with *SPREAD*.

We also investigate whether it is appropriate to use corporate bond ratings as a measure of default risk. Many studies in this literature, including Avramov et al. (2006), use corporate bond ratings as a proxy for distress risk. In this paper we show

and also include a comprehensive list of alternative explanatory variables.

that *SPREAD* and *RATING* are not perfect substitutes. In fact, in Table 2.4 we show that there is much variation in credit spreads within a rating group. The correlation between credit spreads and ratings is only 0.45. AA- bonds, for instance, have an average credit spread of 84.30 basis points with a standard deviation of 43.93 basis points. A one standard deviation move in credit spreads would firmly take an AA- bond's rating to a BBB+ rating which is 4 rating levels down. These results indicate that measuring default risk through company ratings can yield misleading results. This intuition is further supported by hazard regressions in columns 8 and 9 of Table 2.5. Pseudo R^2 improves from 23.6% to 30.5% when *RATING* is used in conjunction with *SPREAD*.

In Table 2.6, we show that adding *SPREAD* to Altman and Ohlson specifications also improves pseudo R^2 values. *SPREAD* has a positive sign and is statistically significant in both models. Finally when we include all of the variables in Table 2.7, *SPREAD* is statistically significant and improves the pseudo R^2 when included. The analyses suggest that credit spread is an important predictor of corporate defaults and contains information related to financial distress not found in other measures commonly used in the literature.

2.4.2 Credit Spreads and Firm Characteristics

To see how corporate bond spreads are related to firm characteristics we form portfolios based on credit spreads. Each month from January 1981 through December 2008, companies in our sample are ranked and put into three portfolios based on the value of their credit spreads in the previous month. As described earlier, credit

[15] McFadden's pseudo R^2 is calculated as 1 − L1/L0, where L1 is the log likelihood of the estimated

spreads are value-weighted averages of firms' outstanding bond spreads in a given month. For each portfolio, we calculate average book-to-market, size, momentum, and beta values for all the companies in that portfolio in a given month. Table 2.8 reports summary statistics for firm characteristics and value-weighted average monthly returns for credit spread portfolios. Credit spreads vary negatively with firm size and positively with book-to-market. The relationship with momentum is not monotonic, but the difference in past returns between the low and the high credit spread portfolios is positive and significant. In contrast to earlier studies, we find that equity returns increase monotonically with credit spreads.

2.4.3 Credit Spreads and Equity Returns

In this section we examine how corporate bond spreads are related to future realized equity returns. In particular we test whether stocks with high default risk as measured by credit spreads have anomalously low returns after controlling for standard risk factors. In the analyses that follow, we create two related but distinct proxies of credit risk. First, we use credit spreads, calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate, to proxy for aggregate default risk. Second, we use credit spreads that are net of expected losses to proxy for each firm's exposure to the systematic component of default risk.

In order to calculate credit spreads that are net of expected losses we adopt a procedure used by Driessen et al. (2007), Elton et al. (2001) and Campello, Chen and Zhang (2004):

model and L0 is the log likelihood of a null model that includes only a constant term.

$$NetSpread_t = \left[PD \times (1 - L) + (1 - PD)\right] \times \left[1 + Spread_t\right] - 1 \qquad (2.7)$$

In Equation (2.7), *NetSpread* is the corporate bond spread net of expected losses, *PD* is the physical probability of default, *L* is the loss rate in the event of default, and *Spread* is the corporate bond credit spread calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate. In Equation (2.7), we assume that default losses are incurred at maturity. We use CHS-score described in Section 2.2 to calculate physical probabilities of default. We follow Elton et al. (2001) and Driessen et al. (2007), and use historical loss rates reported in Altman and Kishmore (1998) by rating category. The loss rates vary from 32% for AAA-rated firms to 62% for CCC-rated firms.

We sort stocks into deciles each January from 1981 through 2008, according to the two distress measures calculated using corporate spreads. The stocks in each decile portfolio are held for a year. 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, and the difference between top and bottom deciles. The return results are reported in Table 2.9. The results under 'Bond Spreads' on the left hand side use credit spreads calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate. The results under 'Bond Spreads In Excess of Expected Losses' on the right hand side use credit spreads that are net of expected losses.

Our results challenge those obtained in the previous studies. Using credit spreads, as a measure of default risk, the difference in raw returns between the highest and lowest default risk portfolios is 0.071% per month and statistically insignificant. The intercepts from the market and the 4-factor models are also economically and statistically insignificant. We find similar results when firms are sorted based on their exposures to the systematic component of default risk. The 4-factor monthly alphas for a portfolio formed by going long stocks in the highest distress portfolio and short stocks in the lowest distress risk portfolio are -0.199% and -0.067% using credit spreads and using credit spreads net of expected losses respectively.

There is a positive relationship between credit spreads and raw equity returns, but the return of the high minus low credit spread portfolio is not statistically significant. CAPM and 4-factor regressions show that alphas are further subsumed in all credit spread portfolios suggesting that default risk is captured mainly by the market factor and partly by the size and the value factors. The size and value factors have statistically significant positive loadings for the high minus low credit risk portfolio, using either measure, suggesting that these factors are related to default risk. In 4-factor regressions the momentum factor has a negative and statistically significant loading in the high minus low credit risk portfolio regressions, consistent with the notion that poor performers of the past are likely to be today's distressed firms.

Ranking stocks on their real-world default probabilities, as done in Dichev (1998) and Campbell, Hilscher and Szilagyi (2008), implicitly assumes that high default probability stocks also have high exposure to the systematic component of default risk. Using corporate spreads we explicitly account for the systematic component in the risk of distress. To the best of our knowledge we are the first to explicitly rank equity returns according to firms' exposures to the systematic component of default risk. Overall, the results suggest that there is no evidence of default risk being negatively priced.

2.4.4 Robustness Checks

As we are using average credit spreads for each firm, to ensure that our results are not biased one way or another, in this section we consider the impact of bond liquidity and maturity on bond spreads and equity returns. In particular we want to make sure that our results are not contaminated by the fact that corporate spreads also reflect information not related to a firm's credit risk. Although credit risk makes up a significant portion of corporate spreads as discussed in Section 2.4, both liquidity and maturity have also been shown to be important components.[16] We repeat the analyses in the previous section but explicitly control for liquidity and maturity by double sorting companies first by liquidity and maturity and then by credit spreads.

We use some of the proxies utilized by Longstaff et al. (2005) in their study to measure corporate bond liquidity.[17] A dummy variable is given each month a value of one or zero depending on the characteristics of the underlying bond. We then add up the dummy variables to come up with an overall liquidity score. The first proxy is used to measure general availability of the bond issue in the market. If the outstanding market value of a bond is larger than the median market value of all bonds, then the dummy variable is assigned a value of one. The second proxy is the age of the bond and parallels the notion of on-the-run and off-the-run bonds in treasury markets, with on-the-run bonds being more liquid. If the age of a bond is

[16] See for instance Elton et al. (2001), Huang and Huang (2003) and Longstaff et. al (2005).
[17] For a small subset of our sample, we have bid-ask, volume and turnover information. We carried out similar analyses described in this section and found qualitatively similar results.

less than the median age of all bonds, then the dummy variable is assigned a value of one. The third proxy is the time to maturity of the bond. It has been shown that there are maturity clienteles for corporate bonds and that shorter-maturity corporate bonds tend to be more liquid than longer-maturity bonds. If the time to maturity of a bond is less than seven years then the dummy variable is assigned a value of one. The fourth proxy that we use is a dummy variable for bonds rated by major rating agencies such as S&P and Moody's. If a bond is rated, then it is more likely to be liquid and the dummy variable is assigned a value of one. The maximum liquidity value assigned to a bond is four and the minimum liquidity value is zero.

We divide our sample into three liquidity groups based on the liquidity score, and calculate average spread and one month ahead equity returns. The average spread for illiquid bonds is 50 basis points higher than for liquid bonds, and the difference is statistically significant. The difference for equity returns, on the other hand, is relatively small and insignificant. Portfolio returns are summarized in Table 2.10. To save space, we only report the differences between the high and low credit spread portfolios within each liquidity group. The difference in raw returns between the highest and lowest credit spread portfolios as well as the alphas from the market and the 4-factor models are economically and statistically insignificant. This is true regardless of whether the underlying bonds are liquid or illiquid. These results indicate that liquidity effects are unlikely to be driving our findings.

To control for the impact of bond maturity, we split our sample into four maturity buckets: 1 to 4, 4 to 7, 7 to 11, and greater than 11 years. For each firm we calculate a weighted (by market value) average of bond spread within each maturity group. We treat each company–maturity spread as a distinct observation. Then, within each maturity bucket, we form three portfolios based on credit spreads. Returns for these portfolios are reported in Table 2.11. In all maturity buckets, the differences in raw returns as well as differences in alphas from the market and the 4-factor models, between the highest and lowest credit spread portfolios are economically and statistically insignificant. Since the uniform ranking of equity portfolio returns with respect to credit spreads yield similar patterns across different time-to-maturity groups, we conclude that our findings are not impacted by using an average credit spread.

2.5 Conclusion

In this paper we examine the pricing of default risk in equity returns. Our contribution to this literature is three-fold. First, we show that the distress risk anomaly is an amalgamation of other anomalies and return relationships previously documented in the literature. Second, ours is the first paper to use corporate bond spreads to measure the ex-ante probability of default risk. We show that in hazard rate regressions, credit spreads drive out the significance of most of the other measures that are used to predict corporate defaults and significantly improve the pseudo R^2 values in all specifications. Third, contrary to previous findings, we show that default risk is not priced negatively in the cross section of equity returns. We sort firms according to their exposures to the systematic component of default risk as well as their aggregate default risk. To the best of our knowledge we are the first to explicitly rank equity returns according to firms' exposures to the systematic component of default risk. Portfolios sorted both on credit spreads and on credit spreads net of expected losses have positive raw returns but do not deliver significant positive or negative returns after controlling for well known risk factors. Our findings challenge the previous studies that have found an anomalous relationship between credit risk and equity returns. The analyses in this paper take the right step towards finding a more appropriate measure of systematic default risk that can explain the cross section of equity returns in line with the rational expectations theory.

APPENDIX

Here we explain the details of the variables used to construct distress measures. Quarterly COMPUSTAT data is used to compute all accounting variables. Our first measure is Altman's z-score, which is defined as the following:

$$\text{z-score} = 1.2\ WCTA + 1.4\ RETA + 3.3\ EBITTA + 0.6\ METL + 1.0\ STA$$

WCTA is the working capital (data40 – data49) divided by total assets. We follow CHS 2008 to adjust total assets calculated as total liabilities (data54) + market equity + 0.1*(market equity – book equity). Book equity is as defined in Davis, Fama, and French (2000). *RETA* is the ratio of retained earnings (data58) to total assets. *EBITTA* is the ratio of earnings before interest and taxes (data21 - data5 + data31) to total assets, *METL* is the ratio of market equity to total liabilities, and *STA* is the ratio of sales (data12) to total assets. Our second measure is Ohlson's o-score, defined as:

$$\begin{aligned} o\text{-score} &= -1.32 - 0.407 \log(SIZE) + 6.03\ TLTA - 1.43\ WCTA \\ &\quad +0.076\ CLCA - 1.72\ OENEG - 2.37\ NITA - 1.83\ FUTL \\ &\quad +0.285\ INTWO - 0.521\ CHIN \end{aligned}$$

where *SIZE* is total assets divided by the consumer price index, *TLTA* is the ratio of total liabilities to total assets, *CLCA* is the ratio of current liabilities (data49) to current assets (data40), *OENEG* is a dummy variable equal to one if total liabilities exceeds total assets and zero otherwise, *NITA* is the ratio of net income (data69) to total assets, *FUTL* is the ratio of funds from operations (data23) to total liabilities, *INTWO* is a dummy variable equal to one if net income was negative for the past two years and zero otherwise, and *CHIN* is change in net income over the last quarter: $(NI_t NI_{t-1})/(|NI_t| + |NI_{t-1}|)$.

The third measure we use is the CHS-score:

$$\begin{aligned} CHS\text{-}score_t \;=\; & -9.164 - 20.264\ NIMTAAVG_t + 1.416\ TLMTA_t \\ & -7.129\ EXRETAVG_t + 1.411\ SIGMA_t - 0.045\ RSIZE_t \\ & -2.132\ CASHMTA_t + 0.075\ MB_t - 0.058\ PRICE_t \end{aligned}$$

where *NIMTAAVG* is a geometrically declining average of past values of the ratio of net income (data69) to total assets:

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^2}{1-\phi^{12}}\ NIMTA_{t-1,t-3} + \ldots + NIMTA_{t-10,t-12}$$

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

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}\ EXRET_{t-1} + \ldots + \phi^{11} EXRET_{t-12}$$

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 (data69) to 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 5 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 (data36) to the value of total assets. *MB* is the market-to-book ratio. Book equity is as defined in Davis, Fama, and French (2000). *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 et al. (2004) to calculate our fourth distress measure, Merton's distance-to-default. The market equity value of a company is modeled as a call option on the company's assets:

$$
\begin{aligned}
V_E &= V_A e^{-\partial T} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-\partial T}) V_A \\
d_1 &= \frac{\log(V_A / X) + (r - \partial - (\sigma_A^2 / 2))T}{\sigma_A \sqrt{T}} \\
d_2 &= d_1 - \sigma_A \sqrt{T}
\end{aligned}
$$

Above V_E is the market value of a firm. V_A is the value of firm's assets. *X* is the face value of debt maturing at time *T*. *r* is the risk-free rate and ∂ is the dividend rate expressed in terms of V_A. σ_A is the volatility of the value of assets, which is related to equity volatility through the following equation:

$$
\sigma_E = V_A e^{-\partial T} N(d_1) \sigma_A / V_E
$$

We simultaneously solve the above two equations to find the values of V_A and σ_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* (data45+1/2*data51). σ_E is the standard deviation of daily equity returns over the past 3 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 (data19 + data21) 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

$\sigma_A = \sigma_E V_E (V_E + X)$. Once we determine asset values, V_A, we then compute asset returns as in Hillegeist et al. (2004):

$$\mu_t = \max\left[\frac{V_{A,t} + Dividends - V_{A,t-1}}{V_{A,t-1}}, r\right]$$

As expected returns cannot be negative, if asset returns are below zero they are set to the risk-free rate.[18] Merton's distance-to-default is finally computed as:

$$MertonDD = -\frac{\log\ \ V_A \,/\, X \ \ + \ \ \mu - \partial - \ \ \sigma_A^2 \,/\, 2 \ \ \ T}{\sigma_A \sqrt{T}}$$

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

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Table 2.1: Summary Statistics

Table 2. 1 reports summary statistics for firm characteristics and distress measures for companies in the CRSP sample (left panel) and the Bond sample (right panel). *tlmta* is the ratio of total liabilities to the market value of total assets, *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, *rsize* is the log ratio of market capitalization to the market value of the S&P 500 index, *totvol* is the standard deviation of daily stock returns over the previous calendar year, *idiovol* is the standard deviation of regression errors obtained from regressing daily excess returns on the Fama and French (1993) factors, *price* is the log price per share truncated from above at $15, *CHS-PD*100* is the CHS probability of default reported as a percentage. *Merton-DD* is the Merton distance-to-default measure. *ta/cpi* is total assets divided by consumer price index, *tl/ta* is the ratio of total assets to total liabilities, *cl/ca* is the ratio of current liabilities to current assets, *wc/ta* is the ratio of working capital to total assets, *ni/ta* is the ratio of net income to total assets, *ffops/tl* is the ratio of funds from operations to total liabilities, *Δni* is the change in net income, *rearn/ta* is the ratio of retained earnings to total assets, *ebit/ta* is the ratio of earnings before interest and taxes to total assets, *me/tl* is the ratio of market equity to total liabilities, and *sales/ta* is the ratio of sales to total assets. How these variables calculated are described in the appendix. P25, P50 and P75 represent 25^{th}, 50^{th} and 75^{th} percentiles respectively.

CRSP SAMPLE					
Variable	**Mean**	**Std Dev**	**P25**	**P50**	**P75**
CHS Variables and Stock Characteristics					
mb	1.95	1.43	0.91	1.52	2.57
me	1156.48	7848.51	24.67	93.11	405.72
cashmta	0.089	0.092	0.021	0.070	0.113
exretavg	-0.009	0.043	-0.032	-0.005	0.018
nimtavg	0.003	0.014	0.000	0.005	0.012
rsize	-10.44	1.76	-11.77	-10.56	-9.22
idiovol	0.034	0.027	0.017	0.027	0.042
totvol	0.036	0.027	0.019	0.029	0.045
price	2.166	0.694	1.749	2.546	2.708
CHS PD * 100	0.081	0.163	0.021	0.038	0.075
Merton Model Variables					
Merton DD	7.267	36.504	3.108	5.358	8.626

BOND SAMPLE					
Variable	**Mean**	**Std Dev**	**P25**	**P50**	**P75**
CHS Variables and Stock Characteristics					
mb	1.76	1.14	0.97	1.45	2.23
me	5104.56	17098.45	322.17	1115.78	3524.17
cashmta	0.051	0.060	0.010	0.028	0.070
exretavg	-0.002	0.032	-0.018	0.000	0.016
nimtavg	0.007	0.009	0.003	0.008	0.012
rsize	-8.19	1.31	-8.95	-7.85	-7.16
idiovol	0.019	0.013	0.012	0.016	0.022
totvol	0.022	0.014	0.014	0.018	0.025
price	2.592	0.350	2.708	2.708	2.708
CHS PD * 100	0.052	0.104	0.020	0.032	0.051
Merton Model Variables					
Merton DD	8.113	5.785	4.776	7.309	10.411

Table 2.1: Summary Statistics

Table 2. 1 reports summary statistics for firm characteristics and distress measures for companies in the CRSP sample (left panel) and the Bond sample (right panel). *tlmta* is the ratio of total liabilities to the market value of total assets, *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, *rsize* is the log ratio of market capitalization to the market value of the S&P 500 index, *totvol* is the standard deviation of daily stock returns over the previous calendar year, *idiovol* is the standard deviation of regression errors obtained from regressing daily excess returns on the Fama and French (1993) factors, *price* is the log price per share truncated from above at \$15, *CHS-PD*100* is the CHS probability of default reported as a percentage. *Merton-DD* is the Merton distance-to-default measure. *ta/cpi* is total assets divided by consumer price index, *tl/ta* is the ratio of total assets to total liabilities, *cl/ca* is the ratio of current liabilities to current assets, *wc/ta* is the ratio of working capital to total assets, *ni/ta* is the ratio of net income to total assets, *ffops/tl* is the ratio of funds from operations to total liabilities, *Δni* is the change in net income, *rearn/ta* is the ratio of retained earnings to total assets, *ebit/ta* is the ratio of earnings before interest and taxes to total assets, *me/tl* is the ratio of market equity to total liabilities, and *sales/ta* is the ratio of sales to total assets. How these variables calculated are described in the appendix. P25, P50 and P75 represent 25^{th}, 50^{th} and 75^{th} percentiles respectively.

Ohlson Model Variables					
ta / cpi	3.947	2.162	2.385	3.801	5.376
tl / ta	0.275	0.147	0.154	0.288	0.400
wcap / ta	0.142	0.414	0.018	0.126	0.260
cl / ca	1.247	61.853	0.305	0.492	0.751
ni / ta	0.001	0.064	0.000	0.004	0.009
ffops / tl	0.070	6.193	-0.002	0.022	0.070
Δ ni	0.025	0.526	-0.190	0.023	0.268
Altman Model Variables					
wcap / ta	0.142	0.414	0.018	0.126	0.260
rearn / ta	0.016	3.887	-0.014	0.058	0.158
ebit / ta	0.007	0.030	0.002	0.010	0.017
me / tl	11.971	273.842	0.526	1.495	4.624
sales / ta	0.075	0.217	0.009	0.031	0.084

Ohlson Model Variables					
ta / cpi	6.588	1.592	5.606	6.605	7.624
tl / ta	0.336	0.107	0.264	0.352	0.419
wcap / ta	0.021	0.166	-0.086	0.020	0.117
cl / ca	3.656	71.806	0.505	0.707	0.991
ni / ta	0.005	0.012	0.002	0.005	0.009
ffops / tl	0.037	0.073	0.006	0.025	0.051
Δ ni	0.026	0.464	-0.120	0.035	0.209
Altman Model Variables					
wcap / ta	0.021	0.166	-0.086	0.020	0.117
rearn / ta	0.094	0.139	0.030	0.085	0.159
ebit / ta	0.013	0.010	0.007	0.012	0.017
me / tl	1.686	7.843	0.389	0.825	1.698
sales / ta	0.013	0.026	0.002	0.005	0.013

Table 2.2: Distress Portfolio Returns

Table 2.2 reports CAPM and 4-factor regression results for distress risk portfolios. We sort stocks into deciles each January from 1981 through December 2008, according to their default probabilities calculated using the CHS hazard rate model. 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. The results under 'Bond Sample' on the right hand side include only the companies in our bond sample. We report regression results for only the top and bottom decile portfolios as well as the high minus low credit risk 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.

"Distress Risk Anomaly" using CHS Probability of Default

	CRSP Sample						**Bond Sample**				
	Alpha * 100	MKT	SMB	HML	MOM		Alpha * 100	MKT	SMB	HML	MOM
10th	0.598					10th	0.455				
	(1.96)**						(2.03)**				
	0.151	1.051					0.111	0.807			
	(0.90)	(28.09)***					(1.04)	(33.69)***			
	0.078	0.962	0.104	-0.347	0.326		0.019	0.900	-0.269	0.172	0.001
	(0.56)	(28.68)***	(2.35)**	(6.73)***	(10.34)***		(1.20)	(39.28)***	(8.89)***	(4.89)***	(0.05)
	Alpha * 100	MKT	SMB	HML	MOM		Alpha * 100	MKT	SMB	HML	MOM
90th	-0.626					90th	0.270				
	(1.31)						(1.72)*				
	-1.255	1.480					-0.514	1.239			
	(3.96)***	(20.92)***					(1.96)**	(25.15)***			
	-0.752	1.335	0.923	0.240	-0.810		-0.302	1.383	0.099	0.668	-0.483
	(3.28)***	(23.92)***	(12.51)***	(2.80)***	(15.42)***		(2.55)***	(35.27)***	(1.90)**	(11.08)***	(13.10)***
	Alpha * 100	MKT	SMB	HML	MOM		Alpha * 100	MKT	SMB	HML	MOM
90th 10th	-1.224					90th -10th	-0.185				
	(2.98)***						(1.66)*				
	-1.406	0.428					-0.625	0.432			
	(3.52)***	(4.80)***					(1.93)**	(6.43)***			
	-0.830	(0.37)	0.819	0.587	-1.136		-0.321	0.483	0.368	0.496	-0.484
	(2.94)***	(5.44)***	(9.02)***	(5.56)***	(17.58)***		(2.15)**	(10.05)***	(6.02)***	(9.51)***	(14.66)***

Table 2.3: Stock Characteristics and Default Risk

Table 2.3 shows the 4-factor alphas for distress portfolios before and after controlling for idiosyncratic volatility, profitability and leverage. Distress portfolios are formed by sorting stocks into five groups each January from 1981 to 2008 according to the CHS probability of default. Then within each default group we first sort stocks based on the previous year's idiosyncratic volatility into five groups creating a total of 25 portfolios. The five distress portfolios are averaged over each of the idiosyncratic volatility portfolios to account for the impact of idiosyncratic volatility. Finally we calculate the 4-factor alphas for the distress portfolios as well as the high distress-low distress hedge portfolio. The same procedure is repeated for profitability and leverage characteristics and we report only the 4-factor alphas for distress portfolios as well as hedge portfolios that have been controlled for the effects of the aforementioned stock characteristics. Idiosyncratic volatility is calculated relative to the Fama-French 3-factor model as in AHXZ (2006). Profitability is measured using *NIMTAVG*, and leverage is measured using *TLMTA*. *NIMTAAVG* is a geometrically declining average of past values of the ratio of net income to the market value of total assets, and *TLMTA* is the ratio of total liabilities to the market value of total assets. 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.

Panel A: 4-Factor Returns

4-Factor Alphas (*100) Before/After Controlling for Stock Characteristics

	L	**2**	**3**	**4**	**H**	**H-L**
Before controls	0.079	0.133	0.014	-0.158	-0.803	-0.882
	-0.71	(1.94)*	-0.13	-1.03	(3.29)***	(2.71)***
Controlling for Idio Volatility	-0.091	-0.219	-0.304	-0.279	-0.627	-0.537
	-0.62	(1.88)*	(2.73)***	(2.01)**	(3.17)***	(2.08)**
Controlling for Profitability	0.012	-0.104	-0.006	0.008	-0.251	-0.263
	(0.14)	(1.89)*	(0.08)	(0.08)	(1.74)*	(1.39)
Controlling for Leverage	0.072	-0.006	0.004	-0.122	-0.545	-0.617
	(0.98)	(0.1)*	(0.05)	(1.1)	(3.01)***	(2.93)***

Panel B: Stock Characteristics

Idiosyncratic Volatility	0.025	0.026	0.027	0.032	0.045	0.019
Profitability	0.012	0.008	0.005	0.001	-0.011	-0.022
Leverage	0.216	0.333	0.456	0.550	0.605	0.389

Table 2.4: Credit spread by rating categories

Table 2.4 reports summary statistics for credit spreads by rating category. The benchmark risk-free yield is the yield of the closest maturity treasury. We include only straight fixed-coupon corporate bonds for the January 1974-December 2008 time period. Bonds for financial firms are excluded. The spreads are given in annualized basis points and ratings in this sample come from Standard and Poor's.

Rating Category (S&P)	Number of Observations	Mean Spread (bps)	Std Dev Spread (bps)
AAA	1157	64.30	27.47
AA+	316	87.58	32.07
AA	2973	77.51	35.70
AA-	2966	84.30	43.93
A+	5155	96.99	45.77
A	7778	102.28	51.99
A-	5397	112.24	61.65
BBB+	4801	124.45	67.24
BBB	4882	146.47	88.86
BBB-	3559	185.86	113.99
BB+	1224	272.54	142.87
BB	949	321.31	134.27
BB-	709	384.52	142.45
B+	342	405.91	129.51
B	266	448.77	156.50
B-	57	508.09	148.10
CCC+	34	455.60	117.19
CCC	29	583.79	116.17
All Ratings	42605	133.67	104.39

Table 2.5: Bankruptcy Prediction – CHS Covariates, Ratings and Distance-to-Default

Table 2.5 reports results from logit regressions of the bankruptcy indicator on predictor variables. 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 from above at $15, DD is Merton's distance-to-default. These variables are described in detail in the appendix. SPREAD is the corporate bond credit spread calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate. RATING is the Standard and Poor's (S&P) corporate rating obtained from COMPUSTAT. Results under 'All Firms' are estimates computed using the full sample of defaults with available accounting information. Results under 'Firms with bonds' are estimates computed using the sample of defaults from companies that have issued bonds with available accounting information. Results under 'CHS sample' shows the estimates CHS report in their paper. Absolute values of z-statistics are reported in parentheses below coefficient estimates. McFadden pseudo R2 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)	(7)
Sample Period:	1981-2008	1981-2008	1981-2008	1981-2008	1981-2008	1963-1998	1981-2008
NIMTAAVG	-25.922	-21.423				-32.518	-26.587
	(3.08)***	(2.17)**				(17.65)***	(10.17)***
TLMTA	1.848	0.864				4.322	3.654
	(2.34)**	(1.01)				(22.82)***	(16.64)***
EXRETAVG	-8.730	-11.176				-9.51	-11.113
	(2.92)***	(3.27)***				(12.05)***	(10.38)***
SIGMA	1.735	1.038				0.92	1.163
	(5.13)***	(2.53)**				(6.66)***	(7.44)***
RSIZE	-0.394	-0.462				0.246	0.167
	(4.02)***	(4.04)***				(6.18)***	(5.08)***
CASHMTA	-1.283	-1.050				-4.888	-3.685
	(0.85)	(0.62)				(7.96)***	(6.88)***
MB	0.086	0.136				0.099	0.129
	(0.80)	(1.28)				(6.72)***	(3.46)***
PRICE	-0.294	0.040				-0.882	-0.657
	(1.10)	(0.13)				(10.39)***	(7.50)***
SPREAD		15.307	26.761		16.14		
		(5.90)***	(10.26)***		(5.73)***		
DD				-0.723	-0.525		
				(7.26)***	(5.88)***		
RATING							
CONSTANT	-9.430	-10.686	-5.481	-1.548	-2.991	-7.648	-5.882
	(7.38)***	(6.24)***	(37.12)***	(5.11)***	(8.97)***	(13.66)***	(11.86)***
Observations	8096	8096	9117	7248	7248	1282853	136468
Bankruptcies	94	94	114	55	55	797	548
Pseudo R^2	0.276	0.374	0.265	0.241	0.304	0.299	0.255
Sample Type	Firms with Bonds	Firms with Bonds	Firms with Bonds	Firms with Bonds	Firms with Bonds	CHS Sample	All Firms

Table 2.5 continued: Bankruptcy Prediction – CHS Covariates, Ratings and Distance-to-Default

Table 2.5 reports results from logit regressions of the bankruptcy indicator on predictor variables. 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 from above at $15, DD is Merton's distance-to-default. These variables are described in detail in the appendix. SPREAD is the corporate bond credit spread calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate. RATING is the Standard and Poor's (S&P) corporate rating obtained from COMPUSTAT. Results under 'All Firms' are estimates computed using the full sample of defaults with available accounting information. Results under 'Firms with bonds' are estimates computed using the sample of defaults from companies that have issued bonds with available accounting information. Results under 'CHS sample' shows the estimates CHS report in their paper. Absolute values of z-statistics are reported in parentheses below coefficient estimates. McFadden pseudo R2 values are reported for each regression. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

	(8)	(9)	(10)	(10)	(11)	(12)
Sample period:	1981-2008	1981-2008	1981-2008	1981-2008	1981-2008	1981-2008
NIMTAAVG					-15.667	-12.039
					(1.28)	(1.40)
TLMTA					1.890	1.205
					(1.60)	(2.34)**
EXRETAVG					-15.753	-16.015
					(4.31)***	(5.34)***
SIGMA					0.692	0.037
					(0.84)	(0.43)
RSIZE					-0.233	-0.330
					(1.09)	(1.09)
CASHMTA					-2.064	-2.657
					(1.11)	(1.11)
MB					-0.009	0.055
					(0.27)	(0.27)
PRICE					0.022	0.188
					(0.31)	(0.31)
SPREAD		17.870		15.229		14.600
		(6.43)***		(4.34)***		(3.19)***
DD			-0.666	-0.556	-0.260	-0.302
			(5.70)***	(6.14)***	(1.74)*	(1.78)*
RATING	0.410	0.257	0.122	0.015	0.086	-0.014
	(13.26)***	(6.98)***	(2.47)**	(0.30)	(1.12)	(0.15)
CONSTANT	-9.149	-8.116	-3.154	-3.017	-8.464	-8.286
	(21.69)***	(18.90)***	(3.78)***	(4.21)***	(3.07)***	(2.74)***
Observations	8068	8068	6814	6814	6736	6736
Bankruptcies	77	77	51	51	51	51
Pseudo R^2	0.236	0.305	0.279	0.315	0.351	0.377
Sample Type	Firms with Bonds	Firms with Bonds	Firms with Bonds	Firms with Bonds	Firms with Bonds	Firms with Bonds

Table 2.6: Bankruptcy Prediction – Altman and Ohlson Covariates

Table 2.6 reports results from logit regressions of the bankruptcy indicator on predictor variables. SIZE is total assets divided by the consumer price index, TLTA is the ratio of total liabilities to total assets, WCTA is the ratio of working capital to total assets, CLCA is the ratio of current liabilities to current assets, NITA is the ratio of net income to total assets, FUTL is the ratio of funds from operations to total liabilities, CHIN is a measure of the change in net income, INTWO is a dummy variable equal to one if net income was negative for the past two years and zero otherwise, OENEG is a dummy variable equal to one if total liabilities exceeds total assets and zero otherwise, RETA is the ratio of retained earnings to total assets, EBITTA is the ratio of earnings before interest and taxes to total assets, METL is the ratio of market equity to total liabilities, STA is the ratio of sales to total assets, and SPREAD is the corporate bond credit spread calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate. These variables are described in detail in the appendix. Absolute values of z-statistics are reported in parentheses below coefficient estimates. McFadden pseudo R2 values are reported for each regression. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample period:	1981-2008	1981-2008	1981-2008	1981-2008
SIZE	-0.254	-0.208		
	(2.38)**	(1.67)*		
TLTA	20.372	14.304		
	(4.80)***	(3.54)***		
WCTA	0.068	-0.348		
	(0.09)	(0.63)		
CLCA	-0.002	-0.112		
	(1.88)*	(0.51)		
NITA	6.441	7.126		
	(0.35)	(0.35)		
FUTL	-8.076	-8.044		
	(1.15)	(1.07)		
CHIN	-0.300	-0.355		
	(1.31)	(1.37)		
INTWO	0.905	0.600		
	(2.76)***	(1.65)*		
OENEG	1.095	0.904		
	(2.69)**	(1.83)*		
WCTA			0.815	0.203
			(0.77)	(0.24)
RETA			-2.453	-0.530
			(2.28)**	(0.44)
EBITTA			-24.779	-22.096
			(1.78)*	(1.61)
METL			-2.947	-1.737
			(3.31)***	(2.52)**
STA			28.703	30.320
			(1.32)	(1.46)
SPREAD		15.011		20.168
		(4.02)***		(5.20)***
CONSTANT	-11.409	-9.640	-2.977	-4.291
	(6.70)***	(6.29)***	(9.65)***	(8.87)***
Observations	6349	6349	5896	5896
Bankruptcies	51	51	48	48
Pseudo R^2	0.245	0.324	0.179	0.277
Sample Type	Firms with Bonds	Firms with Bonds	Firms with Bonds	Firms with Bonds

Table 2.7: Bankruptcy Prediction – All Covariates

Table 2.7 reports results from logit regressions of the bankruptcy indicator on predictor variables. The explanatory variables are all the covariates described in Tables 2.6 and 2.7. Absolute values of z-statistics are reported in parentheses next to coefficient estimates. McFadden pseudo R2 values are reported for each regression. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

	(1)		(2)	
Sample period:	1981-2008		1981-2008	
NIMTAAVG	31.04	(1.48)	44.82	(1.89)*
TLMTA	1.39	(0.12)	4.89	(0.38)
EXRETAVG	-12.93	(2.81)***	-13.98	(2.90)***
SIGMA	-0.05	(0.04)	-1.08	(0.79)
RSIZE	-0.89	(2.47)**	-1.15	(3.09)***
CASHMTA	-6.09	(1.40)	-8.31	(1.43)
MB	-0.44	(2.28)**	-0.47	(2.31)**
PRICE	-0.06	(0.12)	0.07	(0.12)
DD	-0.31	(1.49)	-0.37	(1.52)
RATING	0.09	(0.86)	-0.04	(0.33)
SIZE	0.82	(2.44)**	1.00	(3.03)***
TLTA	-10.48	(0.29)	-30.15	(0.71)
WCTA	0.29	(0.30)	-0.17	(0.17)
CLCA	0.14	(0.65)	-0.09	(0.29)
NITA	-14.29	(1.19)	-19.27	(1.35)
FUTL	-2.35	(0.50)	-1.84	(0.32)
CHIN	-0.42	(1.66)*	-0.37	(1.38)
INTWO	0.82	(1.77)*	0.77	(1.52)
OENEG	2.55	(3.28)***	3.05	(3.45)***
RETA	1.75	(1.06)	1.53	(0.42)
EBITTA	-1.99	(0.11)	-10.74	(0.57)
STA	-0.37	(0.35)	-1.38	(0.89)
METL	40.10	(1.55)	48.21	(1.68)*
SPREAD			17.97	(3.59)***
CONSTANT	-14.53	(0.66)	-10.57	(1.11)
Observations	5175		5175	
Bankruptcies	43		43	
Pseudo R^2	0.415		0.455	
Sample Type	Firms with Bonds		Firms with Bonds	

Table 2.8: Stock characteristics and credit-spreads

In table 2.8 we report summary statistics of stock characteristics for firms belonging to three credit-spread portfolios. Each month from January 1981 through December 2008, we rank and put stocks in to three portfolios based on their value-weighted credit spreads. We then compute cross-sectional average values and standard deviations for various stock characteristics in each group. *Size* is the market value of equity in millions of dollars. Book-to-market (*BM*) is calculated as the ratio of book equity in the previous calendar month to market equity in the previous month. *Prev Return* is the compounded raw returns of the past 12 months. We calculate each firm's *Beta* for month *t* by regressing each stock's monthly returns on the value-weighted NYSE/AMEX index during the past 36 months.

Spread Rank	Variable	Mean	Std Dev
	Return	0.00986	0.0655
	Size	26,237	64,575
Low	BM	0.48695	0.30274
	Prev Return	0.17002	0.24911
	Beta	0.93860	0.48353
	Return	0.01307	0.07279
	Size	14,130	46449
Intermediate	BM	0.61622	0.42316
	Prev Return	0.17671	0.27025
	Beta	0.98480	0.49288
	Return	0.01359	0.10542
	Size	5,927	21647
High	BM	0.83271	0.64552
	Prev Return	0.15031	0.40985
	Beta	1.09971	0.64248

Table 2.9: Monthly equity returns for credit spread portfolios

In table 2.9 we report CAPM and 4-factor regression results for distress portfolios. We sort stocks into deciles each January from 1981 through December 2008, according to their credit spreads obtained at the beginning of December of the most recent year ended. We compute the value-weighted return for these decile portfolios on a monthly basis and regress the portfolio return in excess of risk-free rate on the market (*MKT*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors. The factors are obtained from Ken French's website. The results under 'Bond Spreads' on the left hand side use credit spreads calculated as the difference between the corporate bond yield and the corresponding maturity matched treasury rate. The results under 'Bond Spreads In Excess of Expected Losses' on the right hand side use credit spreads that are net of expected losses. The 'Bond Spread' variable is a measure of the total default risk while the 'Bond Spreads In Excess of Expected Losses' proxy for only the systematic portion of default risk. 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.

Monthly Equity Returns For Default Risk Portfolios

	Bond Spreads						**Bond Spreads In Excess of Expected Losses**				
	Alpha * 100	MKT	SMB	HML	MOM		Alpha * 100	MKT	SMB	HML	MOM
10th	0.497					10th	0.474				
	(2.01)***						(1.88)**				
	0.161	0.766					0.129	0.783			
	(1.19)	(25.79)***					(0.95)	(26.074)***			
	0.140	0.851	-0.246	0.191	-0.074		0.103	0.871	-0.234	0.212	-0.078
	(1.19)	(30.27)***	(6.77)***	(4.39)***	(2.83)***		(0.87)	(30.71)***	(6.35)***	(4.83)***	(2.98)***
	Alpha * 100	MKT	SMB	HML	MOM		Alpha * 100	MKT	SMB	HML	MOM
90th	0.568					90th	0.643				
	(1.17)						(1.34)				
	-0.013	1.323					0.075	1.291			
	(0.41)	(18.197)***					(0.23)	(17.84)***			
	-0.059	1.441	0.695	0.919	-0.397		0.036	1.407	0.684	0.910	-0.400
	(0.22)*	(22.40)***	(8.34)***	(9.22)***	(6.66)***		(0.14)	(21.99)***	(8.25)***	(9.18)***	(6.75)***
	Alpha * 100	MKT	SMB	HML	MOM		Alpha * 100	MKT	SMB	HML	MOM
90th - 10th	0.071					90th - 10th	0.169				
	(0.19)						(0.46)				
	-0.174	0.557					-0.054	0.507			
	(0.50)	(7.31)***					(0.16)	(6.76)***			
	-0.199	0.591	0.941	0.728	-0.323		-0.067	0.536	0.918	0.698	-0.322
	(0.68)	(8.51)***	(10.46)***	(6.77)***	(5.03)***		(0.23)	(7.79)***	(10.29)***	(6.55)***	(5.05)***

Table 2.10: Monthly equity returns bond liquidity / credit spread portfolios

In table 2.10, we report monthly equity returns of credit-spread sorted portfolios for companies associated with different levels of bond market liquidity. For each bond we compute a liquidity measure using 4 proxies as described in the text. We value weight the liquidity scores of the bonds that belong to the same firm and assign each firm a single bond market liquidity measure in a given month. Weights are the outstanding market values of the bonds. In a similar fashion we calculate firm level credit spreads for each firm on a monthly basis. Every month, we group firms into three buckets based on their bond market liquidity level. Then within each bond market liquidity bucket, firms are grouped in to three portfolios based on their value weighted credit spreads. For each credit risk portfolio we calculate value weighted equity returns and report raw return differences, CAPM and 4-factor model based monthly alphas between high credit spread and low credit spread portfolios. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Bond Liquidity Rank	Spread Rank	Mean	t-stat
High	Raw Alpha H-L	0.0500	0.22
	CAPM Alpha H-L	-0.0810	-0.34
	4-factor Alpha H-L	-0.0290	0.14
2	Raw Alpha H-L	0.1388	0.54
	CAPM Alpha H-L	0.0200	0.08
	4-factor Alpha H-L	0.0165	0.07
Low	Raw Alpha H-L	-0.1184	-0.49
	CAPM Alpha H-L	-0.2260	-0.96
	4-factor Alpha H-L	-0.3190	-1.49

Table 2.11: Monthly equity returns for credit spread/maturity portfolios

In table 2.11, we report returns of credit-spread sorted portfolios in different time-to-maturity groups. Maturity is the remaining time to maturity in years of the bonds. We allocate each bond to one of four maturity groups: Bucket 1 includes bonds with maturities less than 4 years but more than 1 year, Bucket 2 includes bonds with maturities greater than 4 years but less than 7 years, Bucket 3 includes bonds with maturities greater than 7 years but less than 11 years, and Bucket 4 includes bonds with maturities greater than 11 years. Each month from January 1981 through December 2008 bonds are assigned to four groups based on their time to maturity. For each firm we calculate four different credit-spread values: one for each maturity bucket. All credit spreads are value-weighted with respect to the market values of a firm's outstanding bonds. Then within each maturity bucket firms are assigned to three portfolios based on their credit spreads. In all time-to-maturity buckets we calculate value-weighted subsequent realized monthly equity returns for each credit-spread portfolio. In each maturity bucket we report raw return differences, CAPM and 4-factor model based monthly alphas between high credit spread and low credit spread portfolios. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Maturity Groups	Spread rank	Mean	t-stat
1<=TTM<=4	Raw Alpha H-L	0.0599	0.21
	CAPM Alpha H-L	-0.033	-0.12
	4-factor Alpha H-L	-0.096	-0.41
4<TTM<=7	Raw Alpha H-L	-0.0229	0
	CAPM Alpha H-L	-0.159	-0.69
	4-factor Alpha H-L	-0.073	-0.36
7<TTM<=11	Raw Alpha H-L	0.0799	0.02
	CAPM Alpha H-L	-0.151	-0.62
	4-factor Alpha H-L	-0.137	-0.6
11<TTM	Raw Alpha H-L	0.0978	0.39
	CAPM Alpha H-L	-0.037	-0.15
	4-factor Alpha H-L	0.099	0.47

Chapter III

Corporate Reputation and Cost of Debt[19]

Reputation is an intangible, and intangibles are hard to quantify. Theoretical papers on the subject have shown that reputations emerge from information asymmetries. The seminal work in this area was written by Milgrom and Roberts (1982). Asymmetric information about a player's true type gives rise to reputation, a formalized belief about the player's type. Milgrom and Roberts state that "where individuals are unsure about one another's options or motivation…, we would expect to see reputations develop…. examples in economics arise in credit relationships." But this impact of reputation on credit relationships has never been fully quantified. Reputation is an elusive concept that encompasses perceptions of many aspects of the firm – the quality, integrity and character of a firm's managers, the innovativeness of the firm, the quality of its products, the firm's ability to attract, retain and train talented workers, to name a few. There is, however, a measure of these perceptions that comes from Fortune magazine. Each year, Fortune magazine surveys industry experts, along these dimensions and more, in order to gauge a firm's reputation – that intangible way in which the company is perceived by others.

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In this paper, we show that a firm's reputation plays an important role in determining its cost of debt. After controlling for tangible measures of credit risk and other known determinants of credit spreads, we find a robust inverse relationship between a firm's reputation, as measured by the Fortune survey, and the credit spread on its bonds. By explicitly accounting for an intangible element of credit risk, we substantially improve upon the existing literature which, relying on more tangible factors, concludes that a large component of credit spread variation remains unexplained (see, for instance, Collin-Dufresne, Goldstein and Martin 2001). We also show that the Fortune reputation measure is a good ex ante predictor of corporate failure, improving upon standard measures used in the literature.

The finance literature has, to a large extent, equated a firm's reputation with its repayment history (e.g., Diamond 1989, 1991). In this view, a firm starts its life without any reputation, and accumulates one over time with consistent and timely repayment of its debt obligations. Diamond suggests that a reputation acquired in this manner determines firm borrowing costs, with more reputable firms enjoying more access to capital and at a lower cost. From this perspective, reputation should be fully captured by the firm's repayment track record or its credit rating. This notion is consistent with Milgrom and Roberts (1982) who believe that, through its actions, a firm can shape its reputation. But non-payment of debt is a rather extreme outcome. Looking at consistency of repayment alone makes it difficult to distinguish healthy firms with similar repayment records. Firms may adopt a wide range of other actions that influence how its credit worthiness is perceived. A firm may hire quality managers or take a conservative approach to risk

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management, for example, leading it to be perceived as a high quality firm in terms of its credit risk.

Intuition also suggests that a firm's credit worthiness is determined by more than its repayment track record. Take a lender reviewing an application for a loan. It may collect both "hard" and "soft" information about the applicant. Hard information is information that is documentable and verifiable, such as a firm's repayment history, as contemplated by Diamond (1989, 1991). Hard information can be quantified and saved in the lender's files. Soft information refers to any information that is not easily documentable or verifiable. It tends to involve qualitative information requiring subjective assessment. Examples of soft information include a lender's judgment about the quality of the firm's managers and products, the innovativeness of the firm, and the talent of its workforce. Both hard and soft information can play a valuable role in screening loan applicants and determining borrowing costs (Stein 2002).

The finance literature focuses on the "hard" aspect of credit risk (such as repayment history, credit rating, etc.), overlooking its "soft" aspect (such as reputation). This neglect of the intangible element may explain why the literature has not been very successful with the pricing of credit risk. Prior studies have been able to explain only a small fraction of the variation in credit spreads (see, for example, Collin-Dufresne, Goldstein and Martin 2001; Duffee 1999; Amato and Remolona 2003; Elton et al. 2001). These studies have mostly relied upon hard information such as balance sheet and market data, assigning no explicit role to such intangible factors as firm reputation. These studies conclude that there is a large component of credit spread variation that remains unexplained.

In this paper, we show that by incorporating an important intangible, firm reputation, into these models, we improve our understanding of credit risk. Our measure of reputation comes from Fortune magazine's annual ranking of "Most Admired Companies." To produce its list, Fortune magazine conducts an annual survey in which industry experts are asked to rank companies along eight attributes. The executives, directors, and analysts who participate in the survey are from the same industry as the companies being measured and have *expert knowledge* of the product markets and abilities of the management teams of the companies they assess. The survey is widely used by academics in a number of disciplines to measure corporate reputation (see, e.g., Davies 2003; and Fombrun, Gardberg and Sever 1999). The reputation scores arising out of the Fortune survey contain information that is not captured by balance sheet or market data or by the other tangible factors commonly employed in the finance literature.

We find that the Fortune reputation score substantially improves our ability to explain the cross-section of corporate bond credit spreads. A higher reputation score leads to lower monthly credit spreads, after controlling for standard credit-risk predictors. We find the same relationship when using year-over-year changes in variables. A half-point (0.5) improvement in the reputation score, or moving up one quintile in the reputation rankings, reduces the cost of debt capital by 10 to 20 basis points, even after taking into account the impact of all other firm-level and macro-level variables that are known to affect credit risk. Moreover, the impact of the reputation score on credit spreads varies with the information environment. The effect of reputation is more pronounced for firms that are more opaque. These findings suggest that the Fortune reputation score captures an intangible element of credit risk that is an important factor in bond pricing.

The Fortune reputation score helps to explain credit spreads because it captures an aspect of default not captured by the standard tangible measures: the reputation score conveys "soft" information about whether a company will fail to honor its commitments. We find a highly significant inverse relationship between our measure of reputation and corporate failures, even after controlling for credit rating, Merton's distance-to-default parameter, and a comprehensive list of accounting and market variables used by Campbell, Hilscher and Szilagyi (2008, hereafter CHS). While these other factors have been found to predict failures, they reflect only tangible aspects of a firm. We have identified a failure predictor that is derived from industry experts' perception of the firm and thus contributes soft information about default risk.

Our finding shows that intangibles are important in bond pricing, and indicates that the Diamond approach to measuring reputation is incomplete. This finding that an intangible affects the cost of debt is consistent with studies in other lines of the finance literature. Compared to the fixed-income literature, the equities literature has given more attention to the role of intangibles in the cost of capital. Previous studies have shown that stock returns are impacted by investors' perceptions of the company, such as whether the firm is an "admired" or "glamor" company (Anginer and Statman 2010; Statman, Fisher and Anginer 2008; Sherfrin and Statman 1995; Lakonishok, Shleifer and Vishney 1994; Del Guercio 1996; Hankins, Flannery and Nimalendran 2008). Studies have also found that stock prices are impacted by employee satisfaction (Edmans 2010), advertising (Chan, Lakonishok and Sougiannis 2001; Chemmanur and Yan 2009), R&D (Lev and Sougiannis 1996; Chan, Lakonishok and Sougiannis 2001), patents (Deng, Lev and Narin 1999), software development (Aboody and Lev 1998) and firm governance (Gompers, Ishii and Metrick

2003). But despite a growing recognition that intangibles affect equity prices, little is known about how intangibles impact the debt market. That appears to be changing. Bauer, Derwall and Hann (2009), for example, examine how a company's relationship with its employees impacts its cost of debt.[20] In the consumer context, Keys et al. (2010a, 2010b, 2009) and Rajan, Seru and Vig (2010) show empirically that soft information can play a significant role in mortgage lenders' credit decisions.

Economic models show that it can make sense for firms to take actions counter to their short-term interests, such as by spending on advertising, offering money back guarantees, or engaging in socially responsible activities, in order to establish a reputation from which they can profit in the future (e.g., Milgrom and Roberts 1986; Mailath and Samuelson 2001). This view has even given rise to the notion that there is a market for reputations among firms (Kreps 1990; Tadelis 1999, 2002a, 2002b; and Mailath and Samuelson 2001). A related strand of this literature examines the role of reputation as an enforcement mechanism in commercial trade between firms. Reputational concerns facilitate commercial transactions by encouraging firms to perform even in the absence of formal contract enforcement (see MacLeod 2007; Klein and Leffler 1981). Recent empirical work shows that reputation is a qualitatively important determinant of default rates under commercial contracts, deterring short-term opportunism (Macchiavello and Morjaria 2010; Banerjee and Duflo 2000; McMillan and Woodruff 1999).

Notwithstanding these attempts to incorporate intangibles, however, the fixed-income literature has, for the most part, persisted with the Diamond (1989, 1991) approach of

[20] While employee relations may constitute an intangible element of firm reputation, the reputation of a company, clearly, encompasses more than just its relationship with its employees. Our measure of reputation is based on a wider set of components.

equating a firm's reputation with its repayment history. If the narrow Diamond approach to reputation is correct, credit ratings should provide a perfect measure of default risk. The empirical literature, however, has shown that they do not. In this paper, we show that the Fortune score conveys information about credit risk not captured by credit ratings or other measures traditionally used in the finance literature, and improves assessment of default risk.

The rest of the paper is organized as follows. Section 3.1 describes the Fortune reputation score and the other data used in this study, and gives an overview of the methodology used. Section 3.2 provides descriptive statistics. Section 3.3 establishes that the Fortune reputation score is not merely another proxy for default risk. Our main results appear in Section 3.4. Section 3.5 concludes.

3.1 Data and Methodology

We measure firm reputation by using Fortune magazine's annual ranking of "Most Admired Companies." Fortune magazine has published an annual survey of company reputations since 1983. Each year, Fortune asks senior executives, directors and securities analysts to rate the ten largest companies in their industry on eight attributes of reputation, using a scale from zero (poor) to ten (excellent). The attributes are quality of management; quality of products or services; innovativeness; long-term investment value; financial soundness; ability to attract, develop, and keep talented people; responsibility to the community and the environment; and wise use of corporate assets. The overall score of a company is the mean of the ratings on the eight attributes. This overall mean score is used to rank companies by reputation. Our approach follows that taken by Anginer and Statman (2010) and Statman, Fisher and Anginer (2008) in the equities literature. Those studies compare the stock performance of high-scoring companies to the stock performance of low-scoring companies. In this paper, we compare the cost of debt capital incurred by high-scoring companies to the cost of debt capital incurred by low-scoring companies.

The Fortune surveys are completed by respondents around September 30th of each year, and the results are published during the first quarter of the subsequent year. Since we are interested in the opinions of respondents at the time they are surveyed (as opposed to the time the information becomes public), we match a company's Fortune reputation score with its firm-level data as of September 30 of the preceding year. We also construct portfolios on that date. The Fortune survey published in early 2007 includes 590 companies. In conducting the survey, Fortune asked 10,000 senior executives, directors and securities analysts to rate the ten largest companies in their industries on eight attributes of reputation (from zero (poor) to ten (excellent)). In 2007, FedEx Corporation ranked highest with an overall score of 8.70, followed by CHS with an overall score of 8.67 and Procter & Gamble with an overall score of 8.58. Dana Corporation ranked at the very bottom with an overall score of 3.09. Repeating our analyses using each of the attributes individually yields results that are qualitatively and quantitatively similar to the results utilizing the overall Fortune score. The different attributes are highly correlated, suggesting that there is common component driving all attributes.[21]

Firm-level accounting and price information are obtained from COMPUSTAT and CRSP for the 1983–2007 time period. We exclude financial firms (SIC codes 6000 through 6999) from the sample. To avoid the influence of microstructure noise, we also exclude firms priced less than one dollar. It is important for us to control for tangible determinants of credit spreads, especially those that relate to credit risk. We use a number of distress measures that have been previously used in the literature (see, for instance, Anginer and Yildizhan 2010; Campbell et al. 2008). The data items used to construct distress measures are explained in detail in the appendix.

Corporate bond data used in this study come from three separate databases: the Lehman Brothers Fixed Income Database (Lehman) for the period 1983 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 from 2003 to 2007. We also use the Fixed Income Securities Database (FISD) for bond descriptions. 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 (see, e.g., Anginer and Yildizhan 2010; and Anginer and Warburton 2011). 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 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

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[21] We also repeated our analysis using the first principal component of the attributes and obtained results that

winsorized in the same manner. For each firm, we calculate a value-weighted average of that firm's outstanding bond spreads, using market values of the bonds as weights. Since Fortune magazine calculates reputation scores once a year, at the end of each September, we use the average of monthly firm-level spreads between consecutive Octobers to assign each firm one annual cost of debt capital value.[22] There are 15,434 firm years and 315 unique firms with credit spread and firm-level data for which we also have a corresponding Fortune reputation score. There is no potential survivorship bias in our sample, as we do not exclude bonds that have gone bankrupt or those that have matured.

In this paper, we show that a higher Fortune reputation score leads to a lower cost of debt capital, by regressing credit spreads on the reputation score and control variables. In addition, we repeat our analysis by regressing year-over-year changes in spreads on year-over-year changes in reputation scores as well as year-over-year changes in other independent variables. Essentially the same individuals participate in the Fortune survey from year to year, so the change in the Fortune score reveals whether respondents perceive improvement or deterioration in the quality of the firm, independent of their base-level assessment. Moreover, in addition to removing firm fixed effects, regressions involving changes also make it less likely to capture spurious relationships. Our analysis using changes in variables produces results that are qualitatively and quantitatively similar to the analysis that utilizes levels of variables. These results confirm our finding that better reputation, above and beyond tangible factors, leads to lower cost of debt capital. To the best of our knowledge, our paper is the first to show that an improvement in reputation

are qualitatively and quantitatively similar to the results using the overall Fortune score.

[22] Results of our analysis are qualitatively the same and quantitatively very similar if we use the end of September credit spreads instead of annual averages.

predicts a reduction in the cost of debt capital, controlling for changes in other independent variables.

3.2 Descriptive Statistics

Since not all companies are surveyed by Fortune and since not all companies issue bonds, it is important to discuss the limitations of our dataset. We compute summary statistics on default measures and financial characteristics for (i) all companies in CRSP, (ii) the companies in our bond sample, and (iii) the companies in our Fortune sample. These results are summarized in Table 3.1. While companies in the Fortune sample on average are larger than those in the bond sample, and show a slight growth tilt, the two samples are otherwise similar. Not surprisingly, companies in the Fortune sample and the bond sample are larger on average than those in the CRSP sample. There is, however, significant dispersion in size, market-to-book, and credit spread values. There is an average of 437 companies in the Fortune sample that have been matched with companies in the CRSP sample. Of these, there is an average of 134 companies that have been matched with companies in the bond sample. While the Fortune and bond samples cover a small portion of the total number of companies, they cover a substantial portion in terms of total market capitalization. For instance, in the year 1997, the number of firms with Fortune scores in our sample constitutes about 4% of all the firms in the market, and the number of firms with active bonds in our sample also constitutes about 4% of all the firms in the market. But in terms of market capitalization, the respective samples capture about 52% and 40% of aggregate equity market value in 1997.

To see how firm reputation is related to default risk measures and firm characteristics, we form portfolios based on reputation. Table 3.2 reports summary statistics for portfolios of companies sorted by the reputation score. According to Table 3.2, more reputable firms have higher market-to-book ratios, in both an economic and statistical sense. That is, more reputable firms are more like growth companies; they receive higher Q values.

Previous research has shown that three characteristics – leverage, idiosyncratic volatility, and profitability – are closely associated with corporate default rates. Low leverage, low idiosyncratic volatility, and high profitability predict lower rates of corporate defaults. Table 3.2 indicates a monotonic relationship between reputation and the three characteristics. The more reputable firms exhibit lower leverage (TLMTA), lower idiosyncratic volatility (IDIOVOL), and higher profitability (NIMTAVG). Highly reputable firms were also found to possess these characteristics in Anginer and Statman (2010). Table 3.2 also indicates that the more reputable firms have experienced better recent stock performance.

There is a monotonic relationship between reputation score and Merton's distance-to-default measure. As the reputation score increases so does the distance-to-default measure. There is a similar monotonic relationship between reputation score and corporate ratings obtained from Standard and Poor's.[23] The value of the S&P rating decreases as we move from the lowest reputation group (L) to the highest reputation group (H) indicating, once again, that higher reputed firms have lower default risk. We observe a similar monotonic pattern in portfolios that are sorted with respect to the log-inverted Campbell-Hilscher-Szilagyi probability of default (hereafter CHS z-score). The value of the CHS z-score increases as we move from the lowest reputation group (L) to the highest reputation group

[23] We follow convention and use a numerical rating scale to covert ratings. The numerical values corresponding to rating notches are 1 for AAA, …, 13 for C.

(H). These monotonic relationships suggest that there may be some overlap between the reputation score and standard distress measures. To better understand the extent of any potential overlap, we conduct a more detailed analysis in Section 3.3.

3.3 Disentangling Reputation from Default Risk

Previous research has identified that low default risk firms have substantially lower credit spreads, i.e. lower costs of debt capital. Could it be that high reputation firms have lower costs of capital simply because reputation is a direct proxy for default risk? In this section, we investigate in detail the relationship between reputation and default risk.

In particular, we want to see if the inverse and monotonic relationship between firm reputation and cost of debt capital persists once we explicitly control for the impact of distress risk. To control for the impact of distress risk, we perform a double sort. We sort stocks into five groups each January from 1983 to 2007 according to reputation scores. Then, within each reputation group, we sort stocks based on the previous year's distress risk measure (using, alternatively, Merton's distance to default, S&P rating and CHS z-score) into five groups, creating a total of 25 portfolios. We then calculate average spreads for the reputation portfolios after controlling for the effects of distress risk. We do this by averaging the spreads of the five distress portfolios over each of the characteristic portfolios. We use, separately, Merton's distance to default, S&P rating and CHS z-score as the distress measure. All three of these variables are described in detail in the appendix.

Panel A of Table 3.3 reports average spreads for the five reputation portfolios without controlling for distress risk, as well as average spreads after controlling for each of the three distress risk measures. We report, in Panel B of Table 3.3, average values of Merton's distance to default, S&P rating and CHS z-score for each of the five reputation portfolios. There is a strong relationship between reputation and the three distress risk measures. Merton's distance to default increases monotonically from 4.36 for the lowest reputation group to 13.77 for the highest reputation group. S&P rating decreases from 11.7 for the lowest distress group to 4.18 for the highest distress group. Similarly, CHS z-score increases monotonically from 7.37 for the lowest distress group to 8.83 for the highest distress group.

According to Panel A, a zero cost portfolio formed by going long high-reputation firms and shorting low-reputation firms has an average spread difference of -109.5 basis points. This premium decreases to only -93.6 basis points when we control for the impact of distress risk using the CHS z-score. When we control for distress risk using Merton's distance to default or S&P rating, the spread difference for the hedge portfolio is not reduced. To the contrary, it is somewhat higher than in the uncontrolled case. These results suggest that the cost of debt capital difference to high-reputation minus low-reputation bond portfolios cannot be explained away by the impact of distress risk, when distress risk is proxied via the traditional measures. Although there is a significant relationship between our reputation score and different (tangible) measures of distress risk, as suggested by Table 3.2, the reputation score measures a distinct risk factor affecting the cost of debt capital that is not captured by the traditional (tangible) measures of distress risk.

Panel C of Table 3.3 shows that the impact of reputation is greatest for firms in the highest distress risk portfolios. A zero cost portfolio formed by going long high-reputation firms and shorting low-reputation firms has an average spread difference of

-284.54 basis points, when these firms are in the highest distress risk group. However, the zero cost portfolio has an average spread difference of only -57.70 basis points, when these firms are in the lowest distress risk group. These results suggest that borrowing costs of high distress risk firms are a lot more sensitive to the impact of reputation.

3.4. Results

In this section, we first examine in greater detail the relationship between the cost of debt capital and a firm's reputation, as measured by its Fortune score. We then show empirically that the reputation measure is a good ex ante predictor of corporate default. We find that our measure of reputation contains information on default risk above and beyond that conveyed by the standard measures.

3.4.1 Reputation and Credit Spreads

To examine the relationship between the cost of debt capital and firm reputation, we run Fama MacBeth regressions and OLS regressions with year fixed effects and firm-level clustered standard errors, where we proxy for the cost of debt capital via firm-level corporate bond spreads described in Section 3.1.

Table 3.4 reports Fama-Macbeth regressions of credit spreads on the reputation score, with standard credit-risk controls. In Panel A, both the dependent and the independent variables are in levels, while in Panel B, they are in changes. In each specification, the coefficient on the reputation variable is highly significant and takes a negative value. That is, Panel A shows a robust inverse relationship between a firm's reputation and the credit spread on its bonds. Firms with better reputations enjoy lower credit spreads. Panel B shows the same robust inverse relationship using changes in reputation. Firms with improving reputations see their credit spreads decline, and firms with deteriorating reputations see their credit spreads increase.

The reputation score is able to explain a substantial amount of the cross-sectional variation in credit spreads. To see this, consider the first column of Panel A, where credit spreads are regressed on the reputation variable alone. That regression produces an R^2 value of 25%. In the second column, credit spreads are regressed on the covariates used by CHS (2008). That regression produces an R^2 value of 60%. A comparison of these two R^2 values shows that reputation, by itself, is able to explain a surprisingly large amount of cross-sectional variation.

More importantly, we find the same result when we use changes in variables, as observed in Panel B of Table 3.4. In the first column of Panel B, year-over-year changes in credit spreads are regressed on the year-over-year change in the reputation variable alone, which produces an R^2 value of 9%. In the second column, year-over-year changes in credit spreads are regressed on changes in the year-over-year CHS covariates, and this regression produces an R^2 value of 35%. Our *change-in-reputation* measure is able to explain a substantial amount of cross-sectional variation. When change in reputation is added as a covariate to the CHS model (in the third column), the R^2 value increases from 35% to 39%. Whether we use levels of variables or changes in variables, our reputation measure substantially increases the credit spread variation we are able to explain.

Next, we regress credit spreads on the reputation variable in conjunction with another default measure – either Merton's distance to default, the CHS z-score, or the S&P rating – in columns (4), (5), and (6), respectively. In each case, the coefficient on reputation remains significant and negative despite the inclusion of the other default measure. This is true regardless of whether we examine levels (Panel A) or changes (Panel B). Moreover, these pairs of variables are able to explain a large portion of the cross-sectional variation in credit spreads, with R^2 values of 32%, 37%, and 51% respectively when using levels, and with R^2 values of 16%, 17% and 16% respectively when using changes.

The impact of reputation on the cost of debt capital, in addition to being highly statistically significant, is also highly economically significant. In the first column of Panel B in Table 3.4, we see that a half-point (0.5) increase in the reputation score, or moving one quintile up in the reputation ranking, reduces the cost of debt capital by an economically significant 0.25%, or 25 basis points. In the third column of the same panel, we see that the impact of reputation is somewhat reduced after introducing the firm-level variables known to affect credit risk. Nevertheless, even in the presence of these default-risk related variables, we observe that a half-point (0.5) increase in the reputation score, or moving one quintile up in the reputation ranking, reduces the cost of debt capital by an economically significant 0.1%, or 10 basis points.[24]

Our findings contribute to the literature that has attempted to explain the variation in credit spread changes. Prior studies have been able to explain only a small fraction of changes in credit spreads using tangible factors (see, for example, Collin-Dufresne,

[24] We also controlled for firm age, which some in the finance literature have previously suggested as a proxy for reputation. But most firms with Fortune scores are mature firms, and adding firm age to our analysis

Goldstein and Martin 2001). Those studies find that there is a large component of credit spread changes that is not explained by the tangible information employed by their models. Our measure of reputation captures intangible information - the knowledge and perceptions of industry experts - and the incorporation of that intangible substantially improves our ability to explain cross-sectional variation in credit spread changes.

As a robustness check, we confirm our results by conducting ordinary-least-squares regressions with year fixed effects and standard errors clustered at the firm level. The results appear in Table 3.5, with Panel A employing levels and Panel B employing changes. The results are similar to those in Table 3.4 using Fama-Macbeth style regressions. The reputation score consistently improves our ability to explain credit spread changes. In addition, in column (7), we introduce three macro variables to control for the market risk premium (MKT), the yield spread between long-term (10-year) treasury bonds and the short-term (three-month) treasuries (TERM) as a proxy for unexpected changes in the term structure, and the BAA-AAA corporate bond spread (DEF) as a proxy for default risk. Notwithstanding these controls, the reputation variable retains its statistical and economic significance, both in terms of levels of variables and changes in variables.

Since Diamond and Milgrom and Roberts view reputations as emerging out of asymmetric information, it is important to examine how the information environment affects the relationship between reputation and the cost of debt. Reputation can substitute for tangible information about a borrower. When there is less tangible information about a firm readily available to investors, reputation should play a greater role in determining the

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neither improves the explanatory power of our regressions nor reduces the impact of the Fortune reputation score on the cost of debt capital.

cost of debt. Thus, the ability of market participants to observe and gather tangible information about the firm should affect the value they attach to a company's reputation.

Prior research suggests that financial analysts play a key role in mitigating information asymmetry between firms and market participants (see Brennan and Hughes 1991; Hong, Lim and Stein 2000; and Agarwal and O'Hara 2006). Hence, reputation should be more important for firms with lower analyst coverage. We include the number of analysts following a firm, ANALYSTS, in specification (7) of Table 3.4 and specification (8) of Table 3.5. To construct that variable, we take the average number of analysts making annual estimates for a firm in a given year.

The coefficient on ANALYSTS is significant and negative. Firms with lower analyst coverage have greater credit spreads. More importantly, the reputation variable remains highly significant despite the inclusion of the ANALYSTS variable. The impact of reputation is not subsumed by the firm's analyst coverage.

If firm reputation helps to determine a company's cost of debt, its impact should be most pronounced when this type of intangible information is most valuable to investors – when other information about the firm is less readily available from analysts. To test this, we interact the analyst coverage measure with the reputation measure. The coefficient on this interaction term is positive and significant, both in the Fama-Macbeth regression using levels (Panel A of Table 3.4) and in the OLS regression using levels (Panel A of Table 3.5). Firms with lower analyst coverage, but higher reputation scores, have lower credit spreads. The result indicates that firm reputation has an even larger impact on credit spreads when a company is covered by fewer analysts - that is, when it is more informationally opaque. Once again, we find similar results using changes in variables (in Panel B of each Table).

The coefficient on the change in ANALYSTS is significant and negative. Firms with decreasing analyst coverage have greater credit spreads. And the coefficient on the interaction term, ΔREPUTATION * ΔANALYSTS, is significant and positive for the ordinary-least-squares regressions with year fixed effects and firm-level clusters (Panel B of Table 3.5). This result suggests that when declining analyst coverage is accompanied by improving firm reputation, firms see statistically and economically significant reductions in their credit spreads.

In addition to analyst coverage, we also use firm size to measure the availability of tangible information.[25] Fama (1985) argues that the information supplied by a firm increases with its size. Similarly, Easley and O'Hara (2004) show that size acts as a measure of the information structure of the firm. Hence, reputation should play a greater role for smaller companies. Results appear in Panel A of Tables 3.4 and 3.5 (in specifications (8) and (9), respectively). Indeed, the significant negative coefficient on log ME indicates that small firms have higher credit spreads. More importantly, the coefficient on the interaction term, REPUTATION * log ME, is significant and positive. Small firms that have high reputation scores see a further reduction in credit spreads.

Whether we measure the availability of information using analyst coverage or firm size, we reach a similar conclusion: as less information is available to outsiders, a firm's reputation carries more weight in the pricing of its debt. The value that market participants attach to a firm's reputation varies with their ability to observe and gather tangible information about the firm. Stating it in broader terms, the impact of firm reputation on the

[25] We also used PIN (Probability of Informed Trading), an alternative measure of information asymmetry, and got qualitatively similar results. However, we do not include in this paper the results with the PIN measure, as there can be alternative interpretations of what PIN measures in this context.

cost of debt varies with the information environment of the firm. In that sense, our study extends recent papers that examine how firms can lower borrowing costs by engaging reputable third-party certifiers, such as auditors, underwriters, banks and securities exchanges. Studies suggest that third-party certification can lower borrowing costs by overcoming information problems between insiders and outsiders (Fang 2005; Pittman and Fortin 2004; Mansi et al. 2004; Andres, Betzer and Limbach 2011; Livingston and Miller 2000; Datta et al. 1997). In addition to exploiting the reputations of third-party certifiers, firms exploit their own reputations as well.

The results in Tables 3.4 and 3.5 suggest that a half-point (0.5) improvement in the reputation score, or moving up a quintile in reputation rankings, reduces the cost of debt capital by at least 10 basis points, even after taking into account the impact of all other firm-level and macro-level variables that are known to affect credit risk. This impact is more significant for firms that are informationally opaque and for firms that have high distress risk.

3.4.2 Reputation and Failure Prediction

While the previous section shows that the Fortune reputation score helps to explain changes in credit spreads, this section reveals the reason why it does so: the reputation score captures soft information about whether a firm will fail to honor its commitments. In this section, we show that the reputation score improves failure prediction above and beyond measures previously used in the literature.

To measure the probability of a corporate failure, we estimate a dynamic panel model using a logit specification, following Anginer and Yildizhan (2010), Shumway

(2001), Chava and Jarrow (2004), CHS (2008), and others. We use information available at the end of the calendar year to predict failures twelve months ahead. Specifically, the marginal probability of failure (*PF*) for company *i* over the next year *t* is assumed to follow a logistic distribution:

$$PF_t^i = \frac{1}{1 + \exp\ -\alpha - \beta' X_t^i} \qquad (3.1)$$

where *X* is a vector of explanatory variables available at the time of prediction, and includes a comprehensive list of explanatory variables that have been used by previous papers to predict corporate failures. Our failure measure is defined as a rating downgrade to CCC+ or below by Standard and Poor's, a severely negative assessment of a company's capability of meeting its obligations. We employ accounting variables used in CHS (2008) as well as Merton's distance-to-default measure. All variables included in the hazard regressions that follow are described in detail in the appendix.

Results are reported in Table 3.6. In the first two columns, we include only covariates used by CHS (2008). The first column includes all observations, and the second column includes only observations with an associated reputation score. The coefficient estimates, and the McFadden's pseudo R^2 values[26], are very similar, indicating that the sub-sample of firms with a reputation score does not differ significantly from the overall sample. Coefficient estimates in both specifications are as expected. The coefficients on NIMTAAVG and EXRETAVG are significant and negative, indicating that greater profitability and greater stock performance lower default probability, in line with the

[26] McFadden's pseudo R^2 is calculated as 1 − L1/L0, where L1 is the log likelihood of the estimated model and L0 is the log likelihood of a null model that includes only a constant term.

literature's findings. The coefficients on TLMTA and SIGMA are significant and positive, indicating that greater leverage and greater stock volatility increase default probability, again in line with established results. The coefficients on CASHMTA and MB are statistically insignificant, which is not surprising given that these are large firms.

In the third column, we add the reputation score, REPUTATION, as an additional covariate to the CHS specification. The reputation variable improves the explanatory power of the CHS model. The pseudo R^2 value increases from 22.6% for the CHS model to 24.1% for the CHS model used in conjunction with the reputation variable. The reputation variable supplies substantial additional information for failure prediction. Moreover, the coefficient on reputation is highly significant, with the anticipated negative sign. A higher reputation score significantly lowers failure probability.

We confirm that the reputation variable adds explanatory power by running additional regressions in columns (4) and (5). The specification in column (4) uses Merton's distance to default alone, and has a pseudo R^2 of 21.6%. When the reputation score is added as a covariate to Merton's distance to default, in column (5), pseudo R^2 increases to 23.4%. Thus, the reputation score contributes failure-related information that is not already captured by Merton's distance to default. Moreover, the coefficient on reputation remains highly significant, with the anticipated negative sign.

The common conclusion is that our reputation measure helps to predict failures better than using only the CHS variables, Merton's distance to default or S&P rating. The perception of a firm among industry experts improves failure prediction, even when we control for the tangible determinants of credit risk. The success of the reputation variable in failure prediction suggests that the reputation measure is capturing intangible information not contained by the standard variables.

3.4.3 Robustness Tests

We repeated all of the analysis conducted in Tables 3.1 through 3.6 using the individual reputation components separately. Our results, qualitatively and statistically, remained the same.

We also conducted a Principal Component Analysis on the eight sub components of our Reputation score: long term investment value; quality of management; quality of products or services; financial soundness; wise use of assets; innovativeness; responsibility to the community and the environment; and the ability to attract, develop, and keep talented people. Our analysis suggests that the first principal component of these eight reputation attributes explains 85% of the variation for Reputation. The first principal component is the only component that has an Eigenvalue greater than 1 and as such it is the only significant principal component as would be suggested by the Kaiser criteria. There are no outliers in any of our reputation observations so this traditional principal component analysis is robust. Most importantly the correlation between the first principal component and the mean reputation score utilized in Tables 3.1 through 3.6 (overall score) is 99.97%. Repeating the analysis, conducted in Tables 3.1 through 3.6, using the first principal component yields results that are qualitatively and statistically similar. Results of the principal component analysis are reported in Table 3.7

3.5 Conclusion

Although the theoretical literature since Milgrom and Roberts (1982) and Diamond (1989) has recognized that reputation should impact credit relationships, to date that impact has never been fully quantified. We show that firm reputation – that intangible way in which a company is perceived by others – plays an important role in determining the cost of debt. We measure company reputation using the annual ranking of "Most Admired Companies" published by Fortune magazine, which surveys industry experts about firm reputations. We find a robust inverse relationship between a firm's reputation as measured by its score in the Fortune survey and the firm-level value-weighted credit spread on its bonds. A half-point (0.5) improvement in the reputation score, or moving one quintile up in the reputation ranking, leads to a reduction of 10 to 20 basis points in the cost of debt capital, even after controlling for firm-level and macro-level variables that are known to impact bond spreads. Change in the reputation score is also able to explain a substantial amount of the cross-sectional variation in change in credit spreads on corporate bonds. Our findings contribute to the literature that has attempted to explain variation in credit spread changes, as prior studies have been able to explain only a small fraction of that variation. Those studies find that a large component of credit spread changes is not explained by the tangible information their models employ. By explicitly accounting for an intangible element of credit risk, we substantially improve our ability to explain cross-sectional variation in credit spread changes. To our knowledge, we are the first to explicitly account for this intangible component of reputation in explaining changes in the cost of debt capital. Furthermore, we show that the impact of this intangible is most significant for firms that are informationally opaque or that already have high distress risk. The sensitivity of cost of debt capital to changes in the reputation score is highest for smaller firms, for firms with lower analyst coverage, and for firms with higher distress risk.

We also show why the Fortune reputation score helps to explain credit spread changes: it captures soft information about whether a firm will fail to honor its commitments. Our reputation measure is a good ex ante predictor of corporate distress, improving upon standard measures used in the literature. Our reputation variable contains information about default risk above and beyond that conveyed by accounting and market variables, corporate ratings and structural parameters. Our results show that credit risk has an important, but largely ignored, intangible aspect.

APPENDIX

Here we explain the details of the variables used to construct distress measures. Quarterly COMPUSTAT data is used to compute all accounting variables.

Our first measure is the CHS probability of default:

$$\begin{aligned} CHS\text{-}score_t \;=\; & -9.164 - 20.264\ NIMTAAVG_t + 1.416\ TLMTA_t \\ & -7.129\ EXRETAVG_t + 1.411\ SIGMA_t - 0.045\ RSIZE_t \\ & -2.132\ CASHMTA_t + 0.075\ MB_t - 0.058\ PRICE_t \end{aligned}$$

where *NIMTAAVG* is a geometrically declining average of past values of the ratio of net income (data69) to total assets:

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^2}{1-\phi^{12}}\ NIMTA_{t-1,t-3} + \ldots + NIMTA_{t-10,t-12}$$

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

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}\ EXRET_{t-1} + \ldots + \phi^{11} EXRET_{t-12}$$

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 (data69) to 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 5 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 (data36) to the value of total assets. *MB* is the market-to-book ratio. Book equity is as defined in Davis, Fama and French (2000). All variables are winsorized using a 1/99 percentile interval in order to eliminate outliers. CHS probabilities are calculated using coefficients obtained from hazard regressions that are used to predict bankruptcies in the full CRSP-COMPUSTAT tape. We transform CHS probability of bankruptcy into a "CHS Z-score" form using the inverse logistic function, so that

$$CHS - Z - score = \ln \left(\frac{CHS \Pr obability}{1 - CHS \Pr obability} \right)$$

As CHS probability approaches zero (one), CHS Z-score approaches negative (positive) infinity. Including such extremely large (absolute) values in the regression will cause very large standard errors and result in low likelihood values. To avoid these statistical problems, we winsorize the sample so that the minimum (maximum) value of CHS probability equals 0.00001 (0.99999).

We follow CHS (2008) and Hillegeist et al. (2004) to calculate our second distress measure, Merton's distance to default. The market equity value of a company is modeled as a call option on the company's assets:

$$\begin{aligned}
V_E &= V_A e^{-\partial T} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-\partial T}) V_A \\
d_1 &= \frac{\log(V_A / X) + (r - \partial - (\sigma_A^2 / 2))T}{\sigma_A \sqrt{T}} \\
d_2 &= d_1 - \sigma_A \sqrt{T}
\end{aligned}$$

Above V_E is the market value of a firm. V_A is the value of firm's assets. *X* is the face value of debt maturing at time *T*. *r* is the risk-free rate and ∂ is the dividend rate expressed in terms of V_A. σ_A is the volatility of the value of assets, which is related to equity volatility through the following equation:

$$\sigma_E = V_A e^{-\partial T} N(d_1)\sigma_A \ / V_E$$

We simultaneously solve the above two equations to find the values of V_A and σ_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* (data45+1/2*data51). σ_E is the standard deviation of daily equity returns over the past 3 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 (data19 + data21) 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 $\sigma_A = \sigma_E V_E (V_E + X)$. Once we determine asset values, V_A, we then compute asset returns as in Hillegeist et al. (2004):

$$\mu_t = \max\left[\frac{V_{A,t} + Dividends - V_{A,t-1}}{V_{A,t-1}}, r\right]$$

Since expected returns cannot be negative, asset returns below zero are set to the risk-free rate.[27] Finally, Merton's distance to default is computed as:

$$MertonDD = -\frac{\log\left(V_A / X\right) + \left(\mu - \partial - \sigma_A^2 / 2\right)T}{\sigma_A \sqrt{T}}$$

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

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Table 3.1: Summary Statistics

Table 3.1 reports summary statistics for firm characteristics and distress measures for companies in the CRSP sample (left panel), the Bond sample (middle panel), and the Fortune sample (right panel). *SPREAD* is the firm-level credit spread calculated as described in Section 3.1, *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, *CASHMTA* is the ratio of cash to the market value of total assets, *TOTVOL* is the standard deviation of daily stock returns over the previous calendar year, *IDIOVOL* is the standard deviation of regression errors obtained from regressing daily excess returns on the Fama and French (1993) factors, *MB* is the market-to-book ratio, *ME* is market capitalization (measured in thousands), *MERTONDD* is the Merton distance-to-default measure, *CHS-Z* is the CHS z-score, *RATING* is the Standard & Poor's corporate rating obtained from COMPUSTAT where the rating has been converted to numeric value (AAA=1, ..., C=13), *MOMENTUM* is the cumulative return over the prior twelve months. The computation of these variables is described in the appendix. P25, P50 and P75 represent 25th, 50th and 75th percentiles, respectively.

	CRSP SAMPLE				
Variable	Mean	Std Dev	P25	P50	P75
SPREAD					
NIMTAVG	0.002	0.015	-0.001	0.004	0.011
TLMTA	0.418	0.280	0.168	0.386	0.643
EXRETAVG	-0.010	0.044	-0.034	-0.006	0.016
CASHMTA	0.090	0.094	0.019	0.067	0.114
TOTVOL	0.037	0.029	0.019	0.030	0.046
IDIOVOL	0.035	0.028	0.017	0.028	0.045
MB	2.043	1.460	0.978	1.610	2.694
ME	1,203	7,993	29	103	434
MERTONDD	7.331	38.428	3.046	5.322	8.661
CHS-Z	7.795	1.071	7.212	7.865	8.426
RATING	10.584	3.861	8.000	10.000	14.000
MOMENTUM	0.167	0.818	-0.245	0.050	0.375

	BOND SAMPLE				
Variable	Mean	Std Dev	P25	P50	P75
SPREAD	0.016	0.015	0.008	0.012	0.018
NIMTAVG	0.006	0.008	0.002	0.007	0.010
TLMTA	0.542	0.224	0.371	0.538	0.708
EXRETAVG	-0.003	0.032	-0.019	-0.001	0.015
CASHMTA	0.042	0.056	0.008	0.021	0.054
TOTVOL	0.020	0.010	0.014	0.018	0.023
IDIOVOL	0.017	0.009	0.012	0.016	0.020
MB	1.982	1.183	1.152	1.682	2.473
ME	9,449	22,737	1,242	2,995	7,978
MERTONDD	8.223	4.625	5.034	7.444	10.594
CHS-Z	7.842	0.600	7.517	7.892	8.232
RATING	8.350	2.776	7.000	8.000	10.000
MOMENTUM	0.159	0.401	-0.069	0.131	0.329

	FORTUNE SAMPLE				
Variable	Mean	Std Dev	P25	P50	P75
SPREAD	0.015	0.014	0.008	0.010	0.016
NIMTAVG	0.006	0.010	0.003	0.008	0.011
TLMTA	0.461	0.234	0.278	0.443	0.627
EXRETAVG	-0.002	0.032	-0.018	0.000	0.017
CASHMTA	0.051	0.063	0.011	0.026	0.067
TOTVOL	0.022	0.011	0.015	0.019	0.026
IDIOVOL	0.019	0.011	0.013	0.017	0.022
MB	2.228	1.353	1.228	1.905	2.880
ME	12,934	31,127	1,360	3,658	10,833
MERTONDD	8.759	5.677	4.928	7.664	11.228
CHS-Z	8.047	0.775	7.659	8.085	8.433
RATING	8.590	3.403	6.000	8.000	11.000
MOMENTUM	0.174	0.513	-0.082	0.138	0.351

Table 3.2: Fortune Companies

Table 3.2 reports summary statistics for firm characteristics and distress measures for portfolios of companies sorted by the level of the REPUTATION score from low (L) to high (H). SPREAD is the firm-level credit spread calculated as described in Section 3.1, 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, CASHMTA is the ratio of cash to the market value of total assets, TOTVOL is the standard deviation of daily stock returns over the previous calendar year, IDIOVOL is the standard deviation of regression errors obtained from regressing daily excess returns on the Fama and French (1993) factors, MB is the market-to-book ratio, Log ME is log value of the market capitalization (measured in thousands), MERTONDD is the Merton distance-to-default measure, CHS-Z is the CHS z-score, RATING is the Standard & Poor's corporate rating obtained from COMPUSTAT where the rating has been converted to numeric value (AAA=1, …, C=13), MOMENTUM is the cumulative return over the prior twelve months. The computation of these variables is described in the appendix. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

	Companies sorted based on REPUTATION					
	L	2	3	4	H	H-L
REPUTATION	5.115	5.956	6.418	6.897	7.645	2.551***
SPREAD	0.017	0.012	0.010	0.009	0.007	-0.009***
NIMTAVG	0.003	0.006	0.006	0.007	0.007	0.005***
TLMTA	0.603	0.544	0.528	0.504	0.398	-0.204***
EXRETAVG	-0.005	-0.002	-0.002	-0.001	0.001	0.006***
CASHMTA	0.060	0.050	0.066	0.052	0.051	-0.009***
TOTVOL	0.023	0.019	0.018	0.018	0.017	-0.005***
IDIOVOL	0.021	0.017	0.016	0.015	0.014	-0.006***
MB	1.718	2.084	2.122	2.317	2.971	1.252***
Log ME	8.128	8.861	8.947	9.271	10.070	1.943***
MERTONDD	6.881	8.087	8.571	8.934	11.167	4.286***
CHS-Z	7.699	7.882	7.978	7.980	8.166	0.467***
RATING	9.865	8.627	7.827	7.422	5.934	-3.931***
MOMENTUM	0.217	0.175	0.177	0.179	0.147	-0.071***

Table 3.3: Cost of Capital in Reputation-Sorted Portfolios, Controlling for Default Risk

Panel A of Table 3.3 reports the mean annual spreads for reputation portfolios before and after controlling for different measures of default risk, i.e. Merton's distance to default, S&P ratings and Campbell, Hilscher, Szilagyi z-score (CHS z-score). Default risk portfolios are formed by sorting stocks into five groups each January from 1983 to 2007 according to Merton's distance to default. Then within each default risk group we sort stocks into five groups based on their Fortune reputation score, creating a total of 25 portfolios. The five reputation portfolios are averaged over each of the distance to default portfolios to account for the impact of distress risk. Finally we calculate the average spreads for the reputation portfolios as well as the high-reputation minus low-reputation hedge portfolio. The same procedure is repeated for S&P rating and CHS z-score. In Panel B of Table 3.3 we report the average values of different distress risk measures in the five reputation portfolios as well as the mean difference for these measures for the high-reputation minus low-reputation hedge portfolio. In Panel C of Table 3.3 we first sort firms each year into five quintiles on the basis of their most recent CHS z-score. Then, within each default risk quintile, we sort stocks into five portfolios based on their Fortune reputation scores, creating a total of 25 portfolios. We report average spreads for each of the twenty-five portfolios as well as the high-reputation minus low-reputation hedge portfolios in each default risk (CHS z-score) category. Merton's distance to default, S&P rating and CHS z-score are calculated as described in the appendix. 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.

Panel A: Average Spreads for Reputation-Sorted Portfolios (in basis points) Before/After Controlling for Default Risk						
	L	**2**	**3**	**4**	**H**	**H-L**
Before controls	203.6***	142.5***	118.1***	113.2***	94.1***	-109.5***
	(9.31)	(11.21)	(18.66)	(13.67)	(11.66)	(5.05)
Controlling for Distance to Default	226.6***	148.9***	129.8***	112.6***	96.6***	-129.9***
	(7.23)	(10.26)	(9.27)	(12.74)	(12.70)	(4.78)
Controlling for S&P Rating	212.1***	163.4***	136.6***	110.4***	88.8***	-123.3***
	(8.65)	(7.48)	(5.44)	(7.77)	(13.87)	(5.61)
Controlling for CHS Z-Score	198.8***	141.8***	131.4***	112.1***	105.2***	-93.6***
	(6.71)	(10.02)	(7.98)	(13.03)	(10.07)	(4.25)

Panel B: Mean Values of Default Risk Measures in Reputation-Sorted Portfolios						
Merton's Distance to Default	4.36***	6.22***	7.79***	9.53***	13.77***	9.41***
S&P Rating	11.7***	8.96***	7.21***	5.78***	4.18***	-7.49***
CHS Z-Score	7.37***	7.87***	8.15***	8.41***	8.83***	1.48***

Table 3.3: Cost of Capital in Reputation Sorted Portfolios, Controlling for Default Risk

Table 3.3, Panel C

Panel C: Average Spreads (in basis points) for Portfolios Double-Sorted Based on Reputation and CHS Z-Score

	Reputation					
CHS Z-Score	L	1	2	3	H	H-L
L	383.57***	225.21***	158.88***	127.46***	99.02***	-284.54***
Highest Default Risk Group	*(5.25)*	*(3.90)*	*(10.08)*	*(7.76)*	*(10.02)*	*(4.16)*
1	240.55***	152.04***	109.92***	114.76***	91.71***	-148.84***
	(6.48)	*(9.84)*	*(11.86)*	*(8.76)*	*(9.03)*	*(4.66)*
2	214.48***	130.84***	120.49***	114.37***	76.73***	-137.76***
	(4.38)	*(8.48)*	*(11.370*	*(8.70)*	*(11.76)*	*(3.03)*
3	147.93***	128.85***	105.13***	102.15***	76.32***	-71.61***
	(8.25)	*(9.41)*	*(11.48)*	*(13.97)*	*(13.53)*	*(4.09)*
H	136.50***	111.78***	107.44***	91.55***	78.81***	-57.70***
Lowest Default Risk Group	*(8.14)*	*(8.32)*	*(7.92)*	*(8.72)*	*(11.80)*	*(3.80)*

Table 3.4: Fama-Macbeth Regressions, Using Levels and Changes, Panel A

Table 3.4 reports Fama-Macbeth regressions of SPREAD on characteristics and distress measures. In Panel A, all variables are in levels and, in Panel B, all variables are in changes. SPREAD is the firm-level credit spread calculated as described in Section 3.1, 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, CASHMTA is the ratio of cash to the market value of total assets, RETURN is the cumulative return over the past year, IDIOVOL is idiosyncratic volatility, MB is the market-to-book ratio, Log ME is the logarithm of market capitalization (measured in thousands), MERTONDD is the Merton's distance-to-default measure, CHS-Z is the CHS z-score, RATING is the Standard & Poor's corporate rating converted into numeric value (AAA=1, …, C=13), ANALYSTS is the number of analysts (divided by 100) that follow the firm. The computation of these variables is described in the appendix. All variables with the "Δ" prefix are changes from the prior-year values for the variables. p-values are reported below coefficient estimates. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Levels of Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INTERCEPT	0.040***	0.015***	0.021***	0.039***	0.089***	0.010**	0.034***	0.103**
	0.000	0.002	0.001	0.000	0.001	0.035	0.000	0.000
REPUTATION	-0.004***		-0.001***	-0.003***	-0.003***	-0.002***	-0.003***	-0.014**
	0.000		0.002	0.001	0.000	0.002	0.000	0.000
NIMTAVG		-0.124**	-0.105*				-0.107*	-0.067
		0.038	0.097				0.083	0.181
TLMTA		0.007***	0.007***				0.007***	0.007**
		0.001	0.002				0.001	0.000
CASHMTA		-0.0114**	-0.011*				-0.009*	-0.010**
		0.030	0.062				0.081	0.017
RETURN		-0.042*	-0.042*				-0.038*	-0.041*
		0.090	0.083				0.099	0.099
IDIOVOL		0.848***	0.819***				0.798***	0.767**
		0.001	0.001				0.002	0.001
MB		0.000	0.001**				0.001**	0.000
		0.638	0.020				0.017	0.765
Log ME		-0.002***	-0.002***				-0.002***	-0.011**
		0.000	0.000				0.000	0.000
MERTONDD				-0.001***				
				0.000				
CHS-Z					-0.007**			
					0.013			
RATING						0.002***		
						0.001		
ANALYSTS							-0.060**	
							0.015	
REPUTATION							0.010***	
*ANALYSTS							0.006	
REPUTATION								0.001***
*Log ME								0.000
R^2	0.25	0.60	0.63	0.32	0.37	0.51	0.65	0.66

Table 3.4: Fama-Macbeth Regressions, Using Levels and Changes, Panel B

Panel B: Changes in Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
INTERCEPT	0.001	0.000	0.000	0.000	0.016*	0.000	0.000
	0.310	0.450	0.450	0.870	0.070	0.970	0.560
ΔREPUTATION	-0.005***		-0.002***	-0.003***	-0.003***	-0.003***	-0.003**
	0.000		0.000	0.010	0.000	0.000	0.027
ΔNIMTAVG		-0.079*	-0.081				-0.1026
		0.100	0.180				0.880
ΔTLMTA		0.016**	0.026*				0.008
		0.020	0.100				0.710
ΔCASHMTA		-0.009	-0.004				-0.009
		0.310	0.320				0.730
RETURN		-0.016	-0.015				-0.012
		0.250	0.250				0.710
ΔIDIOVOL		0.253***	0.213***				0.198***
		0.000	0.000				0.010
ΔMB		0.000	0.000				-0.000
		0.600	0.390				0.800
ΔMERTONDD				0.000**			
				0.045			
ΔCHS-Z					-0.002*		
					0.070		
ΔRATING						0.003***	
						0.001	
ΔANALYSTS							-0.010**
							0.041
ΔREPUTATION							0.010
*ΔANALYSTS							0.712
R^2	0.09	0.35	0.39	0.16	0.17	0.16	0.47

Table 3.5: OLS Regressions, with Year Fixed Effects and Firm Clustered Errors, Panel A

Table 3.5 reports ordinary least squares regressions of SPREAD on characteristics and distress measures. In Panel A, all variables are in levels and, in Panel B, all variables are in changes. SPREAD is the firm-level credit spread calculated as described in Section 3.1, 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, CASHMTA is the ratio of cash to the market value of total assets, RETURN is the cumulative return over the last year, IDIOVOL is the standard deviation of regression errors obtained from regressing daily excess returns on the Fama and French (1993) factors, MB is the market-to-book ratio, Log ME is log market capitalization (measured in thousands), MERTONDD is the Merton distance-to-default measure, CHS-Z is the CHS z-score, RATING is the Standard & Poor's corporate rating converted to numeric value (AAA=1, …, C=13), DEF is the BAA-AAA corporate bond spread, TERM is the yield spread between long-term (10-year) treasury bonds and the short-term (three-month) treasuries, MKT is the market risk premium, ANALYSTS is the number of analysts (divided by 100) that follow the firm. The computation of these variables is described in the appendix. Except for model (7), all the regressions include fixed yearly effects. All variables with the "Δ" prefix are changes from the prior-year values for the variables. Standard errors are calculated based on firm-level clusters. p-values are reported below coefficient estimates. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Levels of Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INTERCEPT	0.038***	0.0138***	0.0175***	0.0392***	0.0905***	0.0057*	0.0311**	0.0352***	0.0839***
	0.000	0.000	0.000	0.000	0.000	0.073	0.000	0.000	0.000
REPUTATION	-0.004***		-0.0018***	-0.0034***	-0.0030***	-0.0014***	-0.0042***	-0.0034***	-0.0111***
	0.000		0.011	0.000	0.000	0.000	0.000	0.001	0.000
NIMTAVG		-0.168***	-0.1618***					-0.1664***	-0.1365**
		0.005	0.008					0.007	0.018
TLMTA		0.0073***	0.0069***					0.0074***	0.0070***
		0.002	0.002					0.001	0.003
CASHMTA		-0.0197***	-0.0189***					-0.0188***	-0.0184***
		0.001	0.002					0.004	0.004
RETURN		-0.0277	-0.0281					-0.028	-0.0265
		0.197	0.190					0.185	0.203
IDIOVOL		1.0424***	1.0121***					0.9844***	0.9784***
		0.000	0.000					0.000	0.000
MB		0.0003	0.0004					0.0004	0.0002
		0.528	0.389					0.384	0.676
Log ME		-0.0015***	-0.0013***					-0.0014***	-0.0082***
		0.000	0.000					0.000	0.000
MERTONDD				-0.0005***					
				0.000					
CHS-Z					-0.0073***				
					0.000				
RATING						0.0020***			
						0.000			
DEF							1.0657***		
							0.000		
TERM							-0.0037		
							0.863		
MKT							-0.119***		
							0.000		
ANALYSTS								-0.0860***	
								0.012	
REPUTATION *ANALYSTS								0.0137***	
								0.007	
REPUTATION *log ME									0.0011***
									0.000
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Clusters	315	282	282	281	282	279	315	282	282
R^2	0.23	0.54	0.58	0.3	0.36	0.41	0.22	0.56	0.56

Table 3.5: OLS Regressions, with Year Fixed Effects and Firm Clustered Errors, Panel B

Panel B: Changes in Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INTERCEPT	-0.0005	0.0006	0.0005	0.0008**	0.0004	0.0003	-0.0021	0.0004
	0.503	0.140	0.212	0.019	0.304	0.228	0.234	0.262
ΔREPUTATION	-0.0032***		-0.0017***	-0.0034***	-0.0026***	-0.003***	-0.0032***	-0.0016***
	0.000		0.000	0.000	0.000	0.000	0.000	0.000
ΔNIMTAVG		-0.0831***	-0.0808**					-0.0809***
		0.006	0.013					0.011
ΔTLMTA		0.0183***	0.0166***					0.0159***
		0.000	0.000					0.001
ΔCASHMTA		-0.003	-0.0018					-0.0008
		0.636	0.793					0.901
RETURN		-0.0205**	-0.016*					-0.0167
		0.025	0.081					0.072
ΔIDIOVOL		0.3668***	0.337***					0.3447***
		0.001	0.002					0.001
ΔMB		-0.0005	-0.0004					-0.0004
		0.177	0.359					0.297
ΔMERTONDD				-0.0002***				
				0.000				
ΔCHS-Z					-0.0051***			
					0.000			
ΔRATING						0.0009***		
						0.010		
ΔDEF							0.8808***	
							0.000	
ΔTERM							-0.0464	
							0.261	
MKT							0.1631	
							0.350	
ΔANALYSTS								-0.0041*
								0.092
ΔREPUTATION								0.0238**
*ΔANALYSTS								0.021
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Clusters	276	249	249	244	249	243	276	202
R^2	0.17	0.25	0.29	0.21	0.29	0.20	0.17	0.30

Table 3.6: Failure Prediction – CHS Covariates, Merton's Distance to Default & Fortune Scores

Table 3.6 reports results from logit regressions of the failure indicator on predictor variables. 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, CASHMTA is the ratio of cash to the market value of total assets, MB is the market-to-book ratio, and MERTONDD is Merton's distance to default measure. REPUTATION is that year's overall Fortune reputation score. We define a "Failure" event as an S&P rating downgrade to CCC+ or below in the following year. The computation of these variables is described in the appendix. P-values are reported below coefficient estimates. McFadden pseudo R2 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)
Sample Period:	1983-2008	1983-2008	1983-2008	1983-2008	1983-2008
NIMTAAVG	-37.327***	-38.796***	-36.142***		
	0.000	0.000	0.000		
TLMTA	2.597***	3.842***	3.513***		
	0.000	0.000	0.000		
EXRETAVG	-11.385***	-6.403***	-7.478***		
	0.000	0.000	0.000		
SIGMA	2.249***	2.266***	2.022***		
	0.000	0.000	0.000		
CASHMTA	-0.776	-1.116	-1.077		
	0.453	0.438	0.468		
MB	-0.109	-0.119	-0.118		
	0.184	0.433	0.432		
MERTONDD				-0.593***	- 0.556***
				0.000	0.000
REPUTATION			-0.463***		-0.471***
			0.000		0.000
CONSTANT	-6.548***	-6.929***	-3.892***	-0.847***	1.759**
	0.000	0.000	0.000	0.003	0.030
Observations	17350	3689	3689	3479	3479
Failures	302	68	68	63	63
Pseudo R^2	22.2%	22.6%	24.1%	21.6%	23.4%
Sample	All Observations	Observations with Reputation	Observations with Reputation	Observations with Reputation	Observations with Reputation

Table 3.7: Principal Component Analysis of the Reputation Score

Table 3.7 reports results from principal component analysis conducted on the sub-components of the Fortune Reputation survey. v1 is long term investment value, v2 is quality of management, v3 is quality of products or services, v4 is financial soundness, v5 is wise use of assets, v6 is innovativeness, v7 is responsibility to the community and the environment and v8 is the ability to attract, develop, and keep talented people. Comp1 through Comp8 are the principal components.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	6.79633	6.37282	0.8495	0.8495
Comp2	.42351	.0615008	0.0529	0.9025
Comp3	.36201	.196501	0.0453	0.9477
Comp4	.165508	.0487825	0.0207	0.9684
Comp5	.116726	.0640597	0.0146	0.9830
Comp6	.0526662	.00432611	0.0066	0.9896
Comp7	.04834	.0134335	0.0060	0.9956
Comp8	.0349065	.	0.0044	1.0000

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
v1	0.3702	-0.1580	-0.2269	0.0246	0.0598	-0.5066	0.7156	0.1164
v2	0.3654	-0.2846	0.0061	-0.0332	-0.6027	0.0251	-0.2761	0.5867
v3	0.3431	0.2319	0.4642	-0.7711	0.0450	0.0600	0.0960	-0.0608
v4	0.3518	0.0277	-0.5355	-0.1517	0.5934	0.2852	-0.2335	0.2788
v5	0.3671	-0.2313	-0.2462	0.0348	-0.3154	0.5076	0.1638	-0.6049
v6	0.3371	-0.2690	0.6207	0.4816	0.3752	0.2152	0.0541	0.0821
v7	0.3140	0.8437	-0.0202	0.3771	-0.1878	0.0655	0.0558	0.0658
v8	0.3754	-0.0429	-0.0042	0.0730	0.0590	-0.5913	-0.5613	-0.4287