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CORPORATE SOCIAL RESPONSIBILITY AND FINANCIAL DISTRESS

Using both multivariate regressions, simultaneous nonlinear equations and a discrete time hazard model, I find that the level of CSR in a firm is a significant determinant of distress, even after controlling for previously identified drivers of firm distress. The relationship is robust to the endogeneity of CSR investments and free cash flow and suggests that there is informational value in extra financial metrics.

Introduction

Popular support for the notion that companies owe a duty to constituents other than shareholders has grown in recent years. The argument in favour of corporate social responsibility (hereafter CSR) is that corporations must be responsible for the negative externalities they create through their actions. While free market advocates suggest that addressing market failures is the role of government, others point out that the market capitalization of the world's largest multinationals outstrips the GDP of many of the countries in which they operate. Given these dynamics, they argue, it becomes less clear whether governments in fact have the capability to perform this role. Hence, firms are facing increasing pressure to consider both the goals of shareholders as well as broader societal goals.

This idea stands in stark contrast to the standard model of financial economics, where the goal of management is to maximize shareholder wealth. The debate over the goal of the firm is far from new, and can be traced at least to the 1930's with Berle (1931) arguing the neo-liberal position in favour of shareholder primacy and Dodd (1932) advocating the wider "stakeholder" perspective. Arguably, it was the 1984 publication of Freeman's "Strategic Management: A Stakeholder Approach" that ushered in the latest era of interest in stakeholder theory as an alternative framework for viewing the corporation. Freeman defines stakeholders as "any group or individual who can affect or is affected by the achievement of the firm's objectives." In contrast to the shareholder model of financial economics, stakeholder theorists argue that the objective of the firm is not simply shareholder wealth maximization, but the simultaneous maximization of the utility of all stakeholder groups, including employees, customers and the community in which the firms operate.

The resistance to the stakeholder model rests largely on its lack of theoretical underpinning. Once free of the obligation to maximize shareholder wealth, it becomes entirely unclear whose utility managers should maximize, or even how the utility of competing stakeholder groups should be measured. Stakeholder theorists have attempted to reconcile the shareholder and stakeholder models by pointing out that engaging in activities that benefit stakeholders could be equally beneficial to shareholders because shareholders are one of the stakeholders of the firm (e.g. Freeman, Wicks and Parmar (2004), among others). Investing in CSR need not necessarily be done at the expense of shareholders, and some researchers have argued that there is in fact a positive relationship between CSR investments and firm financial performance. Considerable research has been done in an effort to uncover that link. There have been two related, but subtly different approaches to the question of how CSR affects firm performance. The first strand of research, concentrated in the management literature, looks at the link between firm-level social performance and financial performance. To date, the evidence has been mixed. Margolis and Walsh (2001) survey the literature and find little evidence of a link between firm-level social performance and financial performance. However, in another widely cited survey of the same literature, Orlitzky et. al. (2003) do find evidence of a link between CSR and financial performance. The second strand of the research, centred in the finance literature looks at the returns to investors who choose portfolios of firms with high levels of CSR. Here again, results are mixed, although the growing consensus appears to be that while there is no premium to "socially responsible" investing, there is likewise no penalty associated with it (e.g. Statman et. al. (2006)).

Faced with evidence that investments in CSR do not increase risk-adjusted returns, advocates of the stakeholder view have proposed a newer view of CSR, where CSR is viewed as a proxy for general good management. Stakeholder theorists argue that firms that are able to negotiate the intricacies of competing economic, social and governance agendas are likely endowed with higher quality managers. While the link between management quality and CSR rankings is an open question, the link between financial distress and the quality of management is firmly established. Altman and Hotchkiss (2006) report that, "without question, the most pervasive reason for a firm's distress and possible failure is some type of managerial incompetence… Of course, firms fail for multiple reasons, but management inadequacies are usually at the core of the problems." It is this syllogism that provides the motivation for this paper. If CSR is indeed a proxy for management quality, it follows that firms with better management should experience less financial distress than firms with less able managers, ceteris paribus. If the advocates of CSR are correct, there should be a negative and monotonic relationship between CSR scores and financial distress. Of course, finding a significant relationship between CSR and distress (as I do) cannot be used to conclude that firms with high levels of CSR necessarily are endowed with better management. I make no claims in this regard. Instead, I explore the economic question of whether there is a relationship between firms with high (low) levels of CSR and decreased (increased) probability of distress.

There is some support for this notion. Using a set of Canadian CSR risk measures, Boutin-Dufresne and Savaria (2004) find higher CSR scores associated with lower levels of firm idiosyncratic volatility. Turning to the environmental, governance and social components that are subsumed under the umbrella of CSR, Konar and Cohen (2001) use emissions data from the Toxic Release Inventory and find that reductions in emissions are associated with higher firm market values. Blank and Carty (2002) review the performance of stocks ranked highly by the environmental research service Innovest for the 1997-2000 time period. They find that an equal-weighted portfolio of the highest-rated companies outperformed an equal-weighted portfolio of all rated companies. Goktan, Kieschnick and Moussawi (2006) examine the link between governance and distress and find no evidence that corporate governance influences default, but that it does impact the likelihood of takeover. I am unaware of any empirical studies explicitly linking the social dimensions of CSR to the likelihood of distress or default.

The main result of this research can be summarized as follows: Using both multivariate regressions and a discrete time hazard model, I find that the level of CSR in a firm is a significant determinant of distress, even after controlling for previously identified drivers of firm distress. This is a remarkable result, since there is little reason to believe the information collected by CSR rating firms would be unavailable to other interested parties, and it begins to explain some of the interest that banks and pension funds are showing in "extra-financial" information. Using a system of non-linear simultaneous equations, I demonstrate that the relationship is robust to the endogeneity of CSR investments and free cash flow. Finally, using a discrete hazard model with competing risks I show that "good" firms- those in the top quartile of KLD scores- are 11% less likely to experience takeover or default. Those in the bottom quartile are 11% more likely to default or be exposed to the external discipline of the market. The balance of the paper is as follows: Section II provides a brief review of the financial distress literature. Section III describes the data and methodology used in the paper, with the results being discussed in section IV. Section V concludes.

Theory and Conceptual Framework

Corporate distress and default has been an area of active research for over 40 years, following Altman's (1968) seminal work on the determinants of bankruptcy. The bulk of the earlier work relies on accounting-based variables in static models. Shumway (2001) points out that these models generate inconsistent estimates because the researcher can only observe firm variables at the time of default. As defaults are relatively infrequent, there is inherent selection bias. Shumway suggests a hazard model instead of the linear discriminant framework employed by Altman, or the logistic approach of Zmijewski (1984), and proposes additional market variables to produce more accurate bankruptcy forecasts. Another class of models is option-theoretic, and is based on the work of Merton (1974). Under certain assumptions, Merton shows that solving a system of nonlinear equations can yield the probability of default. A final group of empirical studies links distress risk to changes in credit ratings. Blume, Lim and MacKinley (1998) and Molina (2005) are representative of this approach.

Regardless of the model employed, the determinants of default can be largely grouped into 5 classifications: firm liquidity, profitability and leverage; market variables; and macroeconomic or business cycle variables. Several studies have suggested that firms with low levels of liquidity are more likely to experience distress, because cash constrained firms are more vulnerable to exogenous negative shocks to cash flow (e.g. Altman (1968); Ohlson (1980) among others). In the multivariate analysis that follows, I use the ratio of net working capital to total assets to proxy liquidity and expect that it will be negatively related to the probability of default.

Another predictor of distress in past studies is firm profitability. In competitive markets, firms need to generate positive profits in order to survive. Firm profitability will be linked to distress and bankruptcy in two ways. First, firms with poor management will ultimately be driven out of the market by more able management teams. Second, in the absence of a large reserve cushion, the lack of profits will ultimately be associated with low levels of liquidity. Here again, I follow Altman (1968) in using the ratio of operating income to total assets to proxy for firm-level profitability. Recognizing the difference between short term and long-term profitability, I also include the ratio of retained earnings to total assets as a firm-level proxy for long-term profitability.

The third predictor of financial distress is firm leverage. Once again, the theoretical underpinning for leverage as a predictor of distress lies in the fact that leverage limits the ability of the firm to withstand negative shocks to cash flow. Following Ohlson (1980) I use the ratio of total liabilities to total assets to control for the impact of leverage on distress. I also include the ratio of the market value of equity to total liabilities, since market participants should be sensitive to the probability of default and bid down the value of firms as the probability of distress increases.

The recognition that the market performance of firms can provide information about potential distress gives rise to the final class of firm-level variables. If the value of equity is bid down for firms in distress, size is clearly an important predictor of distress. Earlier accounting based studies also captured this effect using the market value of equity scaled by the book value of total assets, but Shumway (2001) demonstrates that both the excess return and volatility of returns are powerful predictors of future distress. I include both variables with excess return being the return for each firm in the previous month minus the value-weighted NYSE/AMEX return from the CRSP tape. Equity volatility is the idiosyncratic standard deviation of stock returns, formed by regressing the returns for each stock on the monthly value weighted index return. The standard deviation of the residual from the regression is the idiosyncratic volatility.

Finally, it is well documented that corporate defaults are clustered in time. One explanation is that all firms are subject to macroeconomic forces that may trigger clusters of defaults (e.g. Lo (1986), Lennox (1999)). Alternatively, there may be a cascade of defaults, as the market "learns" from each event. Das et. al (2007) suggest that the Enron and WorldCom defaults may have revealed the depth of the accounting irregularities in U.S. corporations, thus increasing the conditional default probabilities for other firms. Therefore it is necessary to control for economy wide factors as well as for industry specific shocks. Increases in interest rates would be an example of the former, while sector-specific deregulation would be an example of the latter. I include the Chicago Fed National Activity Indicator (CFNAI) to control for macroeconomic factors that may lead to clustering in the incidence of distress. I also include SIC codes at the 2-digit level to control for industry specific factors contributing to correlated distress or default.

Econometrically, the earlier literature focussed on static models and accounting variables, with the Altman Z score (1968, 1984) models being among the most widely used. After Dichev (1998) demonstrated that Ohlson's (1980) O-score was better able to predict CRSP delisting, it also grew in popularity. Both scores have been widely used in the empirical literature (see for example, Griffon and Lemmon (2002), Dichev (1998) and Stone (1991) among others.) One of the difficulties with models of this type is the selection bias inherent in the research design. The relative infrequency of default necessitates the use of very wide panels of data. At default, the researcher observes firm-level covariates over some arbitrary period. A second concern is that the wide panels introduce the possibility that the explanatory variables will not remain stationary. Shumway (2001) suggests the use of a hazard model to capture the information in the length of time that a firm remains in a panel. The amount of time that a firm remains a going concern is used to predict the likelihood that similar firms will survive. Other researchers have suggested extensions to the Shumway (2001) model to account for the fact that distressed firms may seek out merger partners or be taken over before they experience default. Both merger/takeover and default are possible exit paths for poorly performing firms and examining either in isolation raises the real possibility of model misspecification. Goktan, Kieschnick and Moussawi (2006) use a discrete hazard model with competing risks to examine the effect of corporate governance on the likelihood of firm survival. Bergstrom, et. al. (2005) use a multinomial logit model to account for the same issue when examining a panel of Swedish mergers and bankruptcies.

Data and Methodology

Rankings for social responsibility are available from Kinder, Lydenberg and Domini (KLD). Ranking data are available for approximately 650 companies on the S&P 500 and the Domini 400 index. Annual data sets cover the period from 1991 to 2003. Data for the 1100 companies on the Russell 1000 and DS 400 are available from 2001 to 2003. Firm-level financial information is gathered from Compustat, with stock return data coming from CRSP. The only common element between the KLD, Compustat and CRSP data is the ticker, so matching is done manually to ensure that the appropriate Compustat and CRSP data are matched with the KLD data set. There are 9,852 observations in the KLD data set, representing 1,735 unique tickers[1]. After matching the KLD and Compustat data sets, a filter removes all financial and insurance stocks, and the resulting data is merged with the CRSP stock information by the NCUSIP. This results in observations covering 93,062 firm-months and 1,295 unique firms over the period 1991 to 2003.

[1] The number of firms is overestimated by counting the tickers because the same firm can use multiple tickers over the 13 year panel. After manual matching and removal of financial firms, there were five firms spanning 36 firm/years that were discarded because a positive match could not be made.

Distance to Default

I utilize the distance to default (DD) as the primary measure of distress throughout the paper. As this cannot be observed, it must be calculated from observed firm variables. Using the DD as a measure of distress is conceptually different than observing defaults as in the discrete hazards framework. Solving for the DD produces the probability of future default, and does not depend on default ever occurring. This is an attractive alternative to the hazard model because it sidesteps the sample selection bias that results when firms must default before entering the model. It also solves the merger vs. bankruptcy econometric issue, because it identifies firms that are likely to be in distress, without needing to observe the ultimate resolution of that distress. The calculation of the distress measure deserves some explanation. Distress is defined as the inability of the firm to meet its obligations to debt holders. Suppose a firm has a single zero coupon bond outstanding, with a face value of F, maturing at time T. If the value of the firm (V_T) at time T exceeds the obligation, it is rational for the firm to pay off the debt. If however, V_T <F, then the firm will default. The value of the firm's equity can be written as:

$$E_T = (V_T - F, 0)^+ \qquad (1)$$

Following the work of Merton (1974), the value of the equity of the firm can be viewed as a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. Using the familiar Black-Scholes (1973) option pricing formula, the value of equity is:

$$E = V\mathrm{N}(d_1) - Fe^{-rT}\mathrm{N}(d_2) \qquad (2)$$

where E is the value of the firm's equity, V is the value of the firm's assets, F is the face value of debt, r is the risk free rate, and N(.) is the cumulative standard normal distribution function.

In the Black-Scholes model, N(d_2) represents the risk neutral probability that the option will be exercised, so it follows that N (-d_2) is the risk neutral probability that the option will not be exercised and the firm will default on its obligation. I follow the method of Bharath and Shumway (2004) to determine this value. The advantage of this method is simply that the firm need not actually go bankrupt to be identified as distressed. This methodology is fundamentally different from the discrete hazard model with competing risks that I employ later in the paper. That model depends on the actual default or takeover of the firm as an input into the hazard function.

I use long term and short term debt from the Compustat Quarterly database, winsorized at the 1st and 99th percentile as well as the 90 day t-bill rate from the Federal Reserve Bank of St. Louis as inputs. Daily price data come from CRSP and are used to estimate the equity volatility over a 12-month horizon. The resulting monthly distances to default are then matched to the CSR rankings and firm specific financial variables.

Regression Specification

The dependent variable is the distance to default, which can be thought of as the probability of financial default in the next period. Because the DD measures the probability of a default in the next month, it is not surprising that the majority of firms have DD values close to zero. This does not, however, mean that all firms with zero probability of default in the next month are equally healthy. Many of the firms with zero probability of default in the next month would have positive probabilities of default over longer horizons. Unfortunately, increasing the default estimation horizon decreases the number of available observations because we are constrained by the availability of KLD ranking data. If an annual default horizon is used, it results in the loss of 91% of the observations, as each firm would have a maximum of 13 data points available, instead of the current 156.

The true likelihood of distress that we wish to measure is unobserved because of the construction of the distress measure; therefore we estimate the following censored regression specification, where the KLD score is the main explanatory variable of interest:

$$\begin{aligned}&DD = \alpha + \beta_1^{'}(FIRM) + \beta_2(MACRO) + \beta_3(KLD) + \varepsilon \\ &if \quad DD > 0 \\ &else \quad DD = 0\end{aligned} \tag{3}$$

All explanatory variables are initially lagged 1 year and treated as exogenous variables. The null hypothesis is that KLD scores are not related to the likelihood of default.

The first regression treats the KLD score as a discrete exogenous variable. There are two challenges in using KLD scores as an independent variable. The first is that they are not continuous. There is no reason to expect that the ordinal ranking is equivalent to a continuous indicator. The ordinal nature of the score provides information about the relative social performance of firms, but not the magnitude of the differences between firms with different scores. We know, for example, that a score of +2 is better than a score of +1, but we cannot infer that a score of +2 is twice as good as +1. Likewise, there is no reason to expect that moving from a KLD score of 9 to 10 has the same impact as moving from -9 to -10. The first regression specification utilizes 16 indicator variables for KLD levels are used in addition to the aforementioned firm and macroeconomic controls.

The second potential difficulty in using KLD scores as a proxy for CSR is that there are a number of firms with composite scores very close to zero. The median score is 0 with the highest KLD score being +10 and the lowest score being -11. The mass of scores around zero mean that the proxy will be unable to differentiate between good and bad firms for a large portion of the sample. Indeed, it is this fact that leads to the segmenting of the sample into “good” and “bad” firms, with good firms being in the top quartile of KLD scores and bad firms being in the bottom quartile. Throughout the balance of the paper, I use the following labeling convention: firms in the top quartile are “good” and those in the bottom quartile are “bad”.

Simultaneous Equations

A natural argument against the preceding specifications is the endogeneity of CSR investments and free cash flow. Because these investments are largely discretionary, they may be undertaken when profitability is high or when business prospects are good. Since profitability and the business cycle are also known determinants of distress, the resulting parameter estimates will be biased. To address this concern, the following simultaneous system of nonlinear equations is run:

$$\begin{aligned}&DD = \alpha + \beta_1^{'}(FIRM) + \beta_2(MACRO) + \beta_3(KLD) + \varepsilon \\ &if \quad DD > 0 \\ &else \quad DD = 0\end{aligned} \tag{4}$$

$$\Pr(KLD = 1) = \frac{\exp\left(\alpha + \beta_1(profit) + \beta_2(macro) + \varepsilon\right)}{1 + \exp(\alpha + \beta_1(profit) + \beta_2(macro) + \varepsilon)} \tag{5}$$

where (4) is the aforementioned tobit regression and (5) is a discrete logistic regression with good firms equalling 1 and bad firms equalling zero. This specification results in some loss of data relative to the good and bad indicator variables used in the other regression specifications because the firms that are not in the top and bottom quartile are dropped. This specification is chosen because the computational resources needed to solve simultaneous systems of nonlinear equations demands parsimony. The results are shown in Table 4.

Discrete Hazards Model

Next, I follow the methodology used in Goktan et. al. (2005) and test the main hypothesis using a Cox (1972) discrete hazards model with competing risks. In this model, exits from the data set over the 13 years under observation are coded as defaults, mergers, or share exchanges. Firms that do not exit the panel are coded as going concerns. The regression equation is:

$$h_i(t) = \lambda_0(t)\exp\left(\beta_1(FirmControls)_i + \beta_2(Macro) + \beta_3(KLD)_i\right) \tag{6}$$

where $h_i(t)$ is the hazard rate for firm i at time t and $\lambda_0(t)$ is the baseline hazard rate. Because there are multiple observations on each firm, I compute Lin Wei (1989) standard errors, adjusted for clustered observations across firms. I include 3 specifications, one where mergers and acquisitions are treated as the same type of event and then two models where they are considered separately.

Results

Univariate Analysis

The explanatory variable of interest is the KLD rating. The null hypothesis holds that there is no difference between the probability of distress for good firms or bad firms as measured by the composite KLD score. Because the KLD score is not a continuous variable, I segment the sample into good and bad firms, with good firms having KLD scores greater than 1 and bad firms having KLD scores less than negative 1. While the grouping is somewhat arbitrary, it results in good firms being in the top quartile of KLD scores and bad firms being in the bottom quartile.

Table 1

Summary Statistics for Good and Bad Firms

This table reports the descriptive statistics for the principal variables. The sample consists of 93,026 firm-month observations over the 1991 to 2003 period for non-financial firms. Distance to default is the percentage probability of distress as calculated by Merton (1974). NWCTA is the ratio of net working capital to total assets. OITA is the operating income scaled by total assets. RETA is the retained earnings of the firm scaled by total assets. TLTA is the ratio of total liabilities to total assets. XRET is the monthly excess return for the firm over the value weighted market return. Firm size is the natural logarithm of total assets. Z Score is a proxy for default risk, as computed in Altman (1984). New Z Score uses updated coefficients as computed by Hillegeist et. al. (2004). KLD Total is the cumulative KLD score for the firm before exclusionary screens. KLD Strength is the number of firm strengths identified by KLD. KLD Concern is the number of concerns identified by KLD for each firm. Complete definitions of these variables can be found in the appendix. ***, **, * indicate t-tests of the mean and Wilcoxon tests of the median at 1%, 5%, and 10% levels of significance, respectively.

Variable		N	Mean	Median	Std Dev	Minimum	Maximum
Distance to Default	bad	19823	0.1113	0	0.2586	0	1
	good	23388	0.0505***	0	0.1778	0	1
NWCTA	bad	19823	0.0890	0.0610	0.1636	-0.161	0.7173
	good	23388	0.1543***	0.1230***	0.1959	-0.161	0.7173
OITA	bad	19823	0.1314	0.1260	0.0762	-0.106	0.3999
	good	23388	0.1693***	0.1632***	0.0855	-0.106	0.3999
RETA	bad	19823	0.1611	0.1804	0.2989	-0.786	0.9085
	good	23388	0.3156***	0.3070***	0.2729	-0.786	0.9085
TLTA	bad	19823	0.6381	0.6516	0.1754	0.1076	1.0811
	good	23388	0.5452***	0.5627***	0.1922	0.1076	1.0811
XRET	bad	19823	-0.0050	-0.0034	0.1056	-0.274	0.3275
	good	23388	-0.000***	-0.0014**	0.1008	-0.274	0.3275
Volatility	bad	19823	0.0193	0.0164	0.0113	0.006	0.0698
	good	23388	0.0196***	0.0167	0.0112	0.006	0.0698
SIZE	bad	19823	22.385	22.4980	1.387	17.559	25.119
	good	23388	21.555***	21.5965***	1.7022	17.559	25.119
EBIT	bad	19823	0.0699	0.0794	0.1018	-0.288	0.3712
	good	23388	0.1023***	0.1058***	0.1174	-0.288	0.3712
Z Score	bad	19823	1.5528	1.5405	0.9857	0	4.7976
	good	23388	2.1039***	2.1728***	1.0296	0	4.7976
New Z Score	bad	19823	2.5585	4.3383	2.5199	0	12.738
	good	23388	3.1135***	4.4620***	2.8605	0	12.738
KLD Total	bad	19823	-3.2270	-3	1.5476	-11	-2
	good	23388	3.2696***	3***	1.536	2	13
KLD Strength	bad	19823	0.9651	0	1.4918	0	10
	good	23388	4.2751***	4***	2.089	2	14
KLD Concern	bad	19823	4.1920	3	2.3028	2	15
	good	23388	1.0055***	1***	1.2462	0	9

Comparing the values of the explanatory variables for the good and bad firms is done in Table 1. Supportive of the notion that good firms are less likely to suffer distress, there is a statistically and economically significant difference in the likelihood of default in the next period between the firms in the top quartile (5.05%) and the bottom quartile (11.13%). Bad firms tend to be larger than good firms (22.38 vs. 21.56). Turning to the determinants of distress, we see that liquidity, proxied by the ratio of net working capital to assets (NWCTA) is much lower for the bad firms (8.90% vs. 15.43%). The two proxies for profitability are the ratio of operating income to total assets (OITA) and the ratio of retained earnings to total assets (RETA). The first captures profitability in the current period while the second is a measure of long-term profitability. Both measures are higher for good firms than they are for bad firms, significant at the 1% level. The leverage measure is the ratio of total liabilities to total assets (TLTA). Once again, leverage is higher for the bad firms (63.81%) than it is for the good firms (54.52%). The only unexpected result is that idiosyncratic volatility is lower for bad firms than it is for good firms, although this may be simply a function of the size differential in the two groups. Finally, several of the minimum and maximum values are the same for both good and bad samples. The reason is that the reported results have been winsorized at the 1% and 99% level to control for outliers in the multivariate analysis that follows.

In summary, while the univariate analysis points to good firms being less likely to experience distress, it is premature to ascribe the difference to the CSR performance of the firm. Indeed, with the exception of firm size, every determinant of distress lines up in the direction of CSR. It is not surprising then that the Z score for firms in the bottom quartile is significantly lower than the Z score for firms in the upper quartile. Both the original Z score and the updated specification (from Hillegeist et. al. (2004)) are different at the 1% level (1.55 and 2.56 vs. 2.10 and 3.11 for the original and the updated scores respectively). Without controlling for the firm characteristics that drive the likelihood of distress, any inference about the relationship between CSR and distress is premature. I address this issue in the tests that follow.

Multivariate analysis

The multivariate analysis uses the distance to default as the dependent variable. The first model in Table 2 regresses the KLD score against the accounting-based Z Score and various market based predictors of distress. If the Z score completely captures the likelihood of distress, then the coefficients on the KLD score should be insignificant. Following Goss and Roberts (2007), I use dichotomous indicator variables for each of the KLD levels in the data. The extreme positive and negative KLD classifications are aggregated to ensure that there are sufficient observations in each classification. All continuous variables are winsorized at the 1% and 99% level. As expected, the coefficient on Z score is negative and significant, as is the coefficient on the National Activity Index, suggesting that corporate distress is tied to the business cycle, with more distress occurring during periods of weaker economic activity. Consistent with the predictions of the distress and bankruptcy literature, firms with higher idiosyncratic volatility equity and lower excess returns are more likely to experience distress (e.g. Shumway (2001)).

Table 2

Tobit Regression of Default Probability against KLD Score

This table shows the coefficients from the following regression of the estimated distance to default on KLD score and controls for firm, industry and macroeconomic factors.

$$DD = \alpha + \beta_1^{'}(FIRM) + \beta_2(MACRO) + \beta_3(KLD) + \varepsilon$$
$$if \quad DD > 0$$
$$else \quad DD = 0$$

The dependent variable is the distance to default computed by the Merton (1974) model. Firm size is the natural logarithm of total assets. NWCTA is the ratio of net working capital to total assets. OITA is the operating income scaled by total assets. RETA is the retained earnings of the firm scaled by total assets. TLTA is the ratio of total liabilities to total assets. MVETL is the market value of equity scaled by total liabilities. XRET is the monthly excess return for the firm over the value weighted market return. VOL is the idiosyncratic equity volatility. CFNAI is the Chicago Fed index of economic activity. Z Score is a proxy for default risk, as computed in Altman (1984). Model 1 includes the Z score and indicators for each KLD level (m1 is a score of -8; m7 is -7 etc.0 is the omitted variable). Model 2 replaces the Z score with firm-level determinants of distress. Model 3 replaces the KLD indicators with 2 aggregate "good" and "bad" dummy variables. Estimation is done using the generalized method of moments. Standard errors are in parenthesis. ***, ** and * denote significance level at 1%, 5% and 10% levels respectively. Coefficients on Year and Industry dummies are included in all regressions but are not reported.

Parameter	Model 1	Model 2	Model 3
Intercept	-0.6855	-0.6825	-0.6725
	(0.0928)***	(0.0905)***	(0.0904)***
New Z Score	-0.02		
	(0.0007)***		
SIZE		-0.0067	-0.0069
		(0.0015)***	(0.0015)***
NWCTA		-0.0182	-0.0156
		0.0139	(0.0139)
OITA		-1.8614	-1.8599
		(0.0272)***	(0.0272)***
RETA		-0.0988	-0.0989
		(0.0075)***	(0.0075)***
TLTA		1.044	1.0407
		(0.0144)***	(0.0143)***
MVETL		-0.0024	-0.0025
		(0.0003)***	(0.0003)***
XRET	-0.5013	-0.4398	-0.4407
	(0.0158)***	(0.0151)***	(0.0151)***
Volatility	7.9925	6.7559	6.7746
	(0.1529)***	(0.1549)****	(0.1548)***
CFNAI	-0.0209	-0.0275	-0.027
	(0.0037)***	(0.0036)***	(0.0036)***
KLD –8	0.1709	-0.0031	
	(0.0258)***	(0.0235)	
KLD –7	0.0786	-0.0634	
	(0.0238)***	(0.0219)***	
KLD –6	0.1326	-0.0003	
	(0.0149)***	(0.0139)	
KLD –5	0.2087	0.0779	
	(0.0121)***	(0.0115)***	
KLD –4	0.1279	-0.0031	
	(0.0103)***	(0.0099)	
KLD –3	0.1294	0.0219	
	(0.0087)***	(0.0083)***	
KLD –2	0.106	0.0139	
	(0.0066)***	(0.0063)**	
KLD –1	0.0468	0.0147	
	(0.0058)***	(0.0056)***	
KLD +1	0.0115	0.0293	
	(0.0061)**	(0.0059)***	
KLD +2	-0.0371	-0.013	
	(0.0073)***	(0.007)*	
KLD +3	-0.0554	-0.0205	

	(0.0085)***	(0.0082)**	
KLD +4	-0.0717	-0.0546	
	(0.011)***	(0.0105)***	
KLD +5	-0.0436	-0.04	
	(0.0139)***	(0.0133)***	
KLD +6	-0.0017	-0.0744	
	(0.0188)	(0.0178)***	
KLD +7	-0.0278	-0.1215	
	(0.0256)	(0.0258)***	
KLD +8	0.1452	0.0926	
	(0.0222)***	(0.0208)***	
Good Indicator			-0.0389
			(0.0045)***
Bad Indicator			0.0036
			(0.0043)
N	93062	93062	43211
Log Liklihood	-42443	-39968	-32454

After controlling for the accepted accounting and market based determinants of distress, there remains an almost monotonic negative relationship between KLD scores and the probability of distress. All of the coefficients are significant with the exception of the KLD6 and KLD7 indicators. The signs are consistent with the interpretation that good firms are less likely to experience financial distress, even after controlling for previously identified determinants of distress. A single coefficient, (KLD +8 or more) breaks the pattern of good firms being associated with a lower probability of default. Inferences on this single indicator need to be made with caution given to small number of firm-months in this category. These results are not driven by outliers, and both industry and time effects are controlled in all of the regression specifications in Table 2.

The second model replaces the omnibus Z score variable with the firm-level ratios that are used to predict distress. Not surprisingly, there is an increase in explanatory power using this specification, since the regression is no longer constrained by the coefficients built into the Z score. The firm-level characteristics all have the expected sign and all are significant at the 1% level except for the liquidity proxy, which is not significant. Larger firms are less likely to experience distress, as are firms with higher levels of both short and long term profitability. Firms with higher levels of leverage have a higher probability of experiencing future distress. Once again, the KLD indicators show an overall pattern of low scores being associated with higher probability of default, although the pattern is less clear, with one “bad” firm indicator being significantly positive (KLD-7) and several others being indistinguishable from zero (KLD-8; KLD-6 and KLD-4). As KLD levels increase to KLD+2, the signs flip from positive to negative, consistent with the hypothesis that good firms face lower distress risk. The highest KLD group is once again positive and significant, but as previously noted, this is likely due to the small number of observations in the extreme groups.

In order to reduce the noise induced by using 16 indicators for KLD levels, the final model aggregates the KLD levels and uses one indicator for the top quartile (labeled “Good Indicator”) and another for the bottom quartile (“Bad Indicator”). In this specification (Model 3), the coefficient for bad firms is positive and the good firms have a negative coefficient, and both are significant at the 1% level. All of the control variables are similar in magnitude and significance to the preceding models. As a robustness check the distance to default estimate in all of the regressions is replaced by both the Z score and the O score in unreported linear regressions. The results are qualitatively unchanged.

Table 3

Simultaneous Equation Estimates of Distance to Default on KLD Score

This table shows the coefficients from the following system of simultaneous equations:

$$DD = \alpha + \beta_1^{'}(FIRM) + \beta_2(MACRO) + \beta_3(KLD) + \varepsilon$$
$$if \quad DD > 0$$
$$else \quad DD = 0$$
$$\Pr(KLD = 1) = \frac{\exp(\alpha + \beta_1(profit) + \beta_2(macro) + \varepsilon)}{1 + \exp(\alpha + \beta_1(profit) + \beta_2(macro) + \varepsilon)}$$

The first equation is a censored regression, while the second is a discrete logistic regression of good and bad firms. Firm size is the natural logarithm of total assets. NWCTA is the ratio of net working capital to total assets. OITA is the operating income scaled by total assets. RETA is the retained earnings of the firm scaled by total assets. TLTA is the ratio of total liabilities to total assets. MVETL is the market value of equity scaled by total liabilities. XRET is the monthly excess return for the firm over the value weighted market return. VOL is the idiosyncratic equity volatility. CFNAI is the Chicago Fed index of economic activity. ***, ** and * denote significance level at 1%, 5% and 10% levels respectively. Coefficients on Year dummies are included in all regressions but are not reported.

Parameter	Distance to Default	KLD
Intercept	0.1212	3.1538
	(0.0804)	(0.1502)***
SIZE	-0.0383	-0.2002
	(0.0030)***	(0.0043)***
NWCTA	0.0438	
	(0.0234)*	
OITA	-1.9542	2.1263
	(0.0481)***	(0.0878)***
RETA	-0.1625	0.9791
	(0.0153)***	(0.0268)***
TLTA	1.0523	
	(0.0233)***	
MVETL	-0.0127	
	(0.0009)***	
XRET	-0.5181	
	(0.0254)***	
VOL	4.0094	
	(0.2630)***	
CFNAI	-0.0160	0.0458
	(0.0058)***	(0.0097)***
KLD Indicator	-0.3155	
	(0.0286)***	
n	42749	
Log Liklihood	-40924	

The strength of the preceding results can be questioned because they fail to address potential endogeneity of KLD scores and default risk. Dealing with this problem requires the joint solution of the censored default regression alongside a regression on the determinants of KLD scores. Because KLD scores are discrete, the resulting system of non-linear equations is computationally very demanding. For this reason, a parsimonious specification of KLD scores was chosen, where the probability of being in the top or bottom KLD quartile- a "good" or "bad" firm- is a function of firm size and profitability. The logistic regression of the good/bad KLD indicator on firm-level profitability shows that firm-level investments in CSR are positively related to profitability, as predicted by the "slack resources" theory of McGuire (1988) and the empirical findings of Orlitzky (2003). Consistent with the idea of "slack resources", investments in CSR are increasing both in short term and long term profitability. Smaller firms tend to invest more in CSR, and somewhat surprisingly, firms are more likely to invest in CSR during economic downturns. The coefficients on the Default equation are qualitatively similar to those in the single equation censored regressions in Table 2. Significantly, the coefficient on the KLD dummy remains significant and negative. After controlling for the endogeneity of CSR investments and free cash flow, higher KLD scores are still associated with a lower likelihood of distress, and this result is significant at the 1% level.

Table 4

Estimates of Firm Exit by Discrete Hazard with Competing Risks

This table shows the coefficients from the following discrete hazard regression with competing risks:

$$h_i(t) = \lambda_0(t)\exp\left(\beta_1(FirmControls)_i + \beta_2(Macro) + \beta_3(KLD)_i\right)$$

The first model treats all exits as the same type of event. The second treats defaults as a separate type of event, while the third model treats merger exits as a separate type of event. The dependent variable is the interaction of the duration in the panel and the reason for exit. Firm size is the natural logarithm of total assets. NWCTA is the ratio of net working capital to total assets. OITA is the operating income scaled by total assets. RETA is the retained earnings of the firm scaled by total assets. TLTA is the ratio of total liabilities to total assets. MVETL is the market value of equity scaled by total liabilities. XRET is the monthly excess return for the firm over the value weighted market return. VOL is the idiosyncratic equity volatility. CFNAI is the Chicago Fed index of economic activity. Good Dummy is an indicator equal to 1 if the firm is in the top quartile and 0 otherwise. Standard errors are in parenthesis and are adjusted for clustering. ***, ** and * denote significance level at 1%, 5% and 10% levels respectively. Coefficients on Year and Industry dummies are included in all regressions but are not reported.

Parameter	**All Exits**	**Hazard**	**Exit by Default**	**Hazard**	**Exit by Merger**	**Hazard**
SIZE	-0.1679		-0.3735		-0.1311	
	(0.0064)***	0.845	(0.0173)***	0.688	(0.0069)***	0.877
NWCTA	0.7118		1.5301		0.5024	
	(0.0592)***	2.038	(0.1405)***	4.619	(0.0640)***	1.653
OITA	-2.2004		-5.2894		-1.6729	
	(0.1192)***	0.111	(0.2990)***	0.005	(0.1376)***	0.188

RETA	-0.4403		-0.8966		-0.3376	
	(0.0386)***	0.644	(0.1166)***	0.408	(0.0409)***	0.713
TLTA	0.9307		4.4251		0.0746	
	(0.0836)***	2.536	(0.2013)***	83.523	(0.0960)	1.077
MVETL	-0.0199		-0.0012		-0.0280	
	(0.0032)***	0.98	(0.0027)	0.999	(0.0045)***	0.972
XRET	-0.2972		-0.5525		-0.2108	
	(0.0773)***	0.743	(0.1840)***	0.575	(0.0851)**	0.81
Volatility	15.0437		14.8858		13.4682	
	(0.7883)***	3415194	(1.7523)***	2916162	(0.8749)***	706614.3
CFNAI	-0.0949		-0.0422		-0.0959	
	(0.0154)***	0.909	(0.0415)	0.959	(0.0167)***	0.909
Good Indicator	-0.1252		-0.3917		-0.0772	
	(0.0186)***	0.882	(0.0558)***	0.676	(0.0198)***	0.926
Bad Indicator	0.1059		0.1056		0.1249	
	(0.0196)***	1.112	(0.0503)*	1.111	(0.0213)***	1.133
n	92049		92049		92049	
AIC	389970		52496		33064	

The advantage of the preceding analysis is that it uses the probability of default as a dependent variable. This is conceptually convenient because we can infer distress in all firms without waiting for any of them to actually default. This is important because financial distress can occur without ever triggering default. Gilson, John and Lang (1990) point out that formal bankruptcy proceedings are often avoided through negotiated restructuring with creditors. Our distress proxy is unaffected by the actions of managers. Indeed, none of the analysis to this point has utilized the actual default experience of firms as an input into the analysis. I now turn to a set of tests that incorporates the information in the actual default experience of firms.

This discrete hazard approach offers two significant advantages over the tobit regressions used to this point. The first is that the interpretation of the coefficients is more intuitive than the coefficients of the Tobit regressions. Second, by specifying a discrete model with competing risks and observing how firms exit the data set, we can see whether CSR related investments have differing impacts on mergers vs. bankruptcies. Table 5 contains the results of the Cox discrete hazards regression with competing risks. In these regressions, the dependent variable is a dummy coded to indicate the reason for the firm leaving the data set- either default, takeover, or going concern. The first model does not discriminate between mergers and defaults, and treats ongoing concerns as censoring events. The results are remarkably consistent with the previous analysis, and of central importance are the coefficients on the KLD indicators, which is negative for good firms and positive for bad firms. - good firms are 11% less likely to exit the data set, holding all other variables constant. Bad firms- those in the bottom quartile of KLD scores- are 11% more likely to leave the data set. Looking at the explanatory variables, larger firms are less likely to exit the data set for any reason. Not surprisingly, more profitable firms (OITA and RETA) are less likely to exit, and firms with higher levels of leverage, as measured by the ratio of total liabilities to total assets are more likely to exit. Turning to the market-based variables, higher equity volatility increases the likelihood of exit, as do low excess returns. In this model, the coefficient on liquidity is the opposite of expectations, and the coefficient on market leverage is not significant. Finally, the economic activity coefficient is negative and significant, suggesting that the likelihood of exit is inversely related to macroeconomic conditions. The true value of the model can be seen when defaults are separated from mergers as we do in the 2nd and 3rd models. There we see that defaults are not nearly as sensitive to the business cycle as are mergers.

The second model shows the coefficients where exit is by default and all other types are treated as censoring events. Once again, bad firms are 11% more likely to exit by default, consistent with all of the previous analysis, but firms in the top quartile of KLD scores are 32% less likely to exit by default than other firms, ceteris paribus. The Chicago Fed economic indicator is insignificant, suggesting that firm specific variables dominate the event of default/bankruptcy, and not the prevailing economic conditions. Consistent with Kuehn (1975), smaller firms with lower levels of profitability are more likely to default, although it must be noted that the short term profitability hazard coefficient (0.005) dominates the long term profitability coefficient (0.408). The most sensitive ratio based predictors of exit by default are leverage (TLTA), liquidity (NWCTA) and short term profitability (OITA), suggesting that it is the inability to meet contractual obligations that most often precipitates default. In contrast, the third model shows that takeovers are much less sensitive to leverage. While the results fail to confirm the theoretical prediction that leverage deters mergers (Palepu (1986)), they do point out the benefits of the discrete hazard specification. Mergers are also much more sensitive to the level of economic activity, with more mergers occurring during economic downturns.

Perhaps the most interesting finding in the 3rd model is that while being a bad firm results in a 13% increase in the likelihood of takeover, being good only lowers that likelihood by 7.4%. This stands in stark contrast to the 32.4% decrease in exit by default. It appears that while being among the most socially responsible firms lowers the probability of default, it does little to lower the probability of takeover. Without further tests, we cannot provide any definitive explanations for this finding. However, recent work by Barnea and Rubin (2005) suggests that there may be agency issues driving managers to pursue CSR to the detriment of shareholders. If so, the fact those good firms are much less likely to default than be taken over, may be indirect evidence of the external discipline of the market. Alternatively, it could be that good firms make attractive takeover targets for reasons of reputation.

Conclusion

This paper is motivated by the shift within the socially responsible investment/ CSR community toward a belief that environmental, social and governance performance serves as a proxy and leading indicator of overall management quality. Measuring “management quality” directly is an enormously difficult task, but there is a well-documented link between management quality and financial distress. It follows naturally, that if CSR proxies for good management, and good managers experience less financial distress, then firms with high levels of CSR should experience lower levels of distress. This provides an interesting opportunity to explore the power of CSR rankings as a determinant of distress.

Using CSR rankings from KLD Analytics over a period from 1991 to 2003, I find a robust and negative relationship between KLD scores and distress, as measured by the probability of default from the Merton (1974) model. The result is initially presented using a censored tobit regression model. The result is robust to the endogeneity of CSR investments and firm profitability, with KLD scores remaining negatively related to the probability of default in a system of simultaneous nonlinear equations. I employ an entirely different discrete hazard methodology with competing risks and generate similarly significant results. Once again, CSR investments decrease the likelihood of exit, but there is a substantial difference in the impact of CSR for defaults and mergers. Furthermore, high and low levels of CSR have different impacts depending on the type of exit. Firms with poor social performance face largely the same risk of exit by default or takeover, but good firms are much less likely to default than they are to be taken over.

The contribution of this paper is twofold. First, the identification of additional determinants of distress will interest academics and practitioners involved in the study and prediction of corporate financial distress and bankruptcy. The findings suggest that the information embodied in “extra-financial” metrics has the potential to improve distress and bankruptcy prediction. Second, the result will be of interest to researchers in corporate social responsibility and socially responsible investing. The results highlight the importance of examining both risk and return when assessing the impact of CSR on financial performance. My results suggest that instead of focussing on returns, researchers need to consider the impact of CSR initiatives on the risk profiles of the firms they examine.

References

Altman, E. “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy” Journal of Finance 23 (1968) 589-609

_________ “A Further investigation of the bankruptcy cost question.” The Journal of Finance 39. 1067-1089.

_________ and E. Hodgkiss. Corporate Financial Distress and Bankruptcy, Third Edition. Hoboken, New Jersey:John Wiley and Sons (2006)

Bergstrom, C., T. Eisenberg, S. Sundgren and M. T. Wells. “The Fate of Firms: Explaining Mergers and Bankruptcies” Journal of Empirical Legal Studies 2(1) (2005) pp. 49-85

Barnea, A. and A. Rubin. “Corporate Social Responsibility as a Conflict Between Owners” Working Paper, Simon Fraser University (2005)

Berle, A.A. “Corporate powers as powers in trust” Harvard Business Review 44 (1931) pp. 1049-1074

Bharath, S. and T. Shumway. “Forecasting Default with the KMV-Merton Model” Working Paper, University of Michigan (2004)

Black, F., and M. Scholes. “The Pricing of Options and Corporate Liabilities”’ Journal of Political Economy 81 (1973) pp 637-659

Blank, Herbert D. and C. Michael Carty. "The Eco-Efficiency Anomaly." Innovest Working Paper, June (2002)

Blume. M. E., F. Lim and A. C. MacKinlay. “The declining credit quality of U.S. corporate debt: Myth or reality?” Journal of Finance 53 (1998) pp 1389- 1413

Boutin-Dufresne, F. and P. Savaria. “Corporate Social Responsibility and Financial Risk” Journal of Investing Spring (2004) pp 57-66

Cox, D. “Regression Models and Life Tables” Journal of the Royal Statistical Society, Series B (1972)

Das, S., D. Duffie, N. Kapadia and L. Saito. “Common Failings: How Corporate Defaults are Correlated” Journal of Finance 62(1) (2007) pp. 93-117

Dichev, I. D. “Is the risk of bankruptcy a systematic risk?” Journal of Finance 53 (1998) pp. 1131-1147

Dodd, E. M. “For whom are corporate managers trustees?” Harvard Law Review 45 (1932). Pp. 1145-1163

Freeman, R.E. “Strategic Management: A Stakeholder Approach” Boston:Pitman (1984)

Freeman, R.E., A. Wicks and B. Parmar. “Stakeholder Theory and ‘The Corporate Objective Revisited’” Organization Science 15 (3) (2004) pp. 364- 369

Goktan, M.S., R. Kieschnick, and R. Moussawi. “Corporate Governance and Firm Survival” Working Paper, University of Pennsylvania (2006)

Griffin, J.M. and M.L. Lemmon. “Book-to-Market Equity, Distress Risk, and Stock Returns” Journal of Finance (2002) pp. 2317-2336

Hillegeist, S., E. Keating, D. Cram and K.Lundstedt. “Assessing the Probability of Bankruptcy” Review of Accounting Studies 9 (2004) pp 5-34

International Finance Corporation. “Who Cares Wins”, http://www.unepfi.org/fileadmin/events/2004/stocks/who_cares_wins_global_compact_2004.pdf

Kuehn, D. Takeovers and the Theory of the Firm (1975) MacMillan

Konar, S. and M. Cohen. “Does the Market Value Environmental Performance?” Review of Economics and Statistics 83(2) (2001) pp 281-309

Lennox, C.”Identifying failing companies: A reevaluation of the logit, probit and DA approaches”. Journal of Economics and Business 51 (1999) pp151-178

Lo, A. “ Logit vs. Discriminant Analysis: Specification test and application to corporate bankruptcies, Journal of Econometrics 31 (1986) pp151- 178

Margolis, J.D., and Walsh, J.P. People and Profits? The search for a link between a company's social and financial performance. Mahwah, NJ: Erlbaum. (2001).

McGuire, J.B., T. Schneeweiss, and B. Branch. "Perceptions of Firm Quality: A Cause or Result of Firm Performance." Journal of Management, 16 (1), (1990).

Merton, Robert C. “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates,” Journal of Finance, (1974) 449-470.

Molina, C., “Are firms underleveraged? An examination of the effect of leverage on default probabilities.” Journal of Finance 60, (2005) pp 1427-1459

Ohlson, J. “Financial Ratios and the Probabilistic Prediction of Bankruptcy” Journal of Accounting Research 18 (1980) pp 109

Orlitzky, Marc, Frank L. Schmidt, and Sara L. Rynes. "Corporate social and financial performance: A meta-analysis." Organization Studies, 24, (2003).

Shumway, T. “ Forecasting Bankruptcy More Accurately: A Simple Hazard Model”, Journal of Business 74 (2001) pp 101-124

Stone, M. “Firm Financial Stress and Pension Plan Continuation/ Replacement Decisions” Journal of Accounting and Public Policy (1991) pp175-206

Wei, L.J., D.Y. Lin and L. Weissfeld. “Regression Analysis of Multivariate Incomplete Failure Time Data by Modeling Marginal Distribution,” Journal of the American Statistical Association 84 (1989) pp.1065-1073

Zmijewski, M. “Methodological issues related to the estimation of financial distress,” Journal of Accounting Research 22 (1984) pp 59-82