Corporate Social Responsibility and the Cost of Debt Financing

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This study examines the link between corporate social responsibility and bank debt. Our focus on banks exploits their specialized role as quasi-insider delegated monitors. We find that firms with the worst social responsibility scores pay higher spreads (16 bps) but firms with average or good social scores benefit very little from increasing them further. The modest premium charged the worst firms together with the absence of a payoff for the best firms suggest that banks do not regard corporate social responsibility as significantly value enhancing or risk reducing.

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I. INTRODUCTION

How do financial markets view socially responsible companies? Among financial economists, the accepted view of the firm has managers working to maximize the utility of the shareholders. To the extent that the interests of other stakeholders are considered, the goal must be shareholder wealth maximization. Classical finance theorists remain steadfast in their belief that if corporate social responsibility (CSR) initiatives do not maximize firm value, they represent a costly diversion of scarce firm resources. The traditional shareholder view recognizes that the unfettered pursuit of profit may result in negative externalities for other constituents, but holds that the burden of dealing with these social issues is best left to governments, who have both the means and the jurisdiction to deal with them.

However, the sovereignty of the shareholder has come under attack from management and strategy researchers who argue that the firm has multiple stakeholders, including employees, suppliers, and the larger community in which it operates and that the proper goal of management must be to meet the objectives of all stakeholder groups simultaneously. According to advocates of the stakeholder view, corporate social responsibility goes beyond simply staying within the rules of the game, and has been defined as "actions that appear to further some social good, beyond the interest of the firm and that which is required by law" (McWilliams and Segal (2001)). A recent survey by the Center for Corporate Citizenship at Boston College finds the majority of U.S. business executives sharing this view. They describe the role of management as balancing the goals of investors, employees, consumers, communities and the environment. Recent work by Faleye et. al. (2006) documents the impact of an additional stakeholder on corporate behaviour in the United States. They find labor controlled firms deviate from strict shareholder wealth maximization, investing less in long term assets and taking less risk. Support for the stakeholder view is even stronger outside of the United States, with employees being the stakeholder group most often given explicit consideration.

In an attempt to reconcile CSR with the shareholder view of the firm, stakeholder theorists suggest that pursuing multiple objectives need not be detrimental to shareholder interests. In fact, they argue that satisfying multiple constituencies may actually increase financial performance (e.g., Clarkson (1995); Waddock and Graves (1997)). This argument posits that companies paying attention to issues of sustainability and social responsibility are more likely to perform well in all dimensions, including financial performance. If the company strives to satisfy all stakeholders, the stakeholders will reciprocate by supporting the firm. Employees will be more loyal. Outside stakeholders will be more supportive. Ultimately (although perhaps not immediately) this is manifest in superior performance. A related argument is that socially responsible companies will be less prone to extreme negative events. By including environmental, social and governance considerations into business plans, firms reduce the risk of financial fallout that accompanies lapses in ethical behavior.

The debate between the shareholder and stakeholder views revolves around whether investments in CSR are value enhancing, or whether they are examples of agency conflicts between managers and shareholders (Jensen and Meckling (1976)). This tension is illustrated by a Financial Times article in January 2004 that criticized the chairman of Royal Dutch Shell PLC, claiming that he "spent more time trying to convince environmentalists of Shell's commitment to sustainable development than reassuring investors that he was aware of the growing gap between Shell's performance and that of its peers."[1] Barnea and Rubin (2005) suggest that CSR investments are

[1] "Unsure of Shell: shareholders call for change after 4bn barrels of oil and gas are cut from proved reserves," *Financial Times of London.* January 23, page 21.

motivated by the desire of managers to burnish their reputations as responsible stewards of industry at the expense of shareholders. This represents an agency cost of equity similar to the purchase of unnecessary corporate jets (Yermack (2006)) or other excessive perquisite consumption.

This paper approaches the question from a fresh perspective. Instead of focusing on equity, we look at the impact of CSR on the cost of private debt. Exploiting the unique role of banks as "quasi-insiders" of the firm, we explore whether banks discriminate between firms with low levels of CSR and those with higher levels. The banking literature has long established that banks are fundamentally different from other stakeholders. In their roles as delegated monitors (Diamond (1984); Fama (1985)), banks are given access to information about the firm that may not be available to outsiders. They use this information to make initial decisions about the ability of the firm to honor its loan obligations and, after the loan agreement is struck, to monitor the firm to ensure repayment[2]. Among the options available to banks to mitigate risk are demands for security, shortened maturity or increasing the spread charged on the loan to reflect the risk[3].

Of interest here is whether loan contract terms, and in particular, loan spreads are influenced by the social performance of the firm. Consistent with the loan pricing literature, our dependent variable is the loan spread over LIBOR on private bank debt. Our proxy for CSR is the Kinder, Lydenberg and

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[2] There is some support for the monitoring role of banks in the context of environmental issues. Aintablian *et. al.* (2004) find higher positive abnormal returns when new bank loans are announced for firms with higher potential for spills compared to those with more benign environmental profiles. While results are not presented in that paper, one suspects that banks compensated for the risk inherent in lending to companies with questionable environmental practices by charging higher yields.

[3] Dennis, Nandy and Sharpe (2000) provide a thorough review of the determinants of loan contract terms.

Domini & Co. (hereafter KLD) rankings for U.S. firms. Notwithstanding the difficulties inherent in measuring corporate social performance, KLD rankings are the most widely recognized and accepted measures of firm-level corporate social responsibility. In examining loan spreads for evidence of a "social responsibility" premium, we assume that banks have no social agenda to promote. We take banks as being neutral, favoring neither the shareholder, nor the multiple stakeholder view of the corporation. Instead, we assume that banks are interested solely in the ability of the borrower to repay its loan obligations. If investments in CSR lead to lower risk and improved financial performance (as suggested by stakeholder theory), then banks will provide more attractive terms on loans to socially responsible corporations. Alternatively, if socially responsible firms are at a disadvantage because they take on costs that would otherwise be borne by outsiders and governments, there should be a positive relationship between social responsibility and spreads.

Recognizing the potential for endogeneity to confound results, we use multiple econometric methods, including both multivariate regressions and matched firms. We find a statistically significant premium of between 2 and 16 basis points for firms with poor environmental, social and governance records. The differential is conditional on the current CSR score of the firm, with the firms having the lowest scores being subject to the highest premiums. Companies with poor records can lower their cost of debt financing by improving their social performance, but banks provide no incentive for the majority of firms to invest in CSR.

To our knowledge, this paper is the first to examine the impact of social responsibility on the cost of debt financing. In doing so, we exploit the unique role of banks as "quasi-insiders" of the firm. Because they have access to firm information unavailable to outsiders, banks are in a position to judge whether the CSR related investments of the firm lower risk or improve the financial position of the company. Their determination is manifest in the loan contract terms offered to the firm. With the exception of firms with the worst CSR records, we find that the cost of private debt does not vary with CSR.

The balance of the paper is as follows. Section II provides a brief literature review. Section III outlines the data and provides a discussion of the regression and the matching firm results. Section IV concludes.

II. REVIEW OF EXISTING EVIDENCE

The link between financial performance and social performance has been examined in both the management and the finance literatures. The bulk of the finance literature views the question through the lens of socially responsible investing (SRI). Often used interchangeably, SRI and CSR are related but subtly different concepts. CSR researchers look for links between social performance and financial performance at the firm level. SRI research focuses on the returns to investing in portfolios of companies that are identified as socially responsible. The SRI industry is sizeable, with $2.71 trillion in assets under management in 2007 according to the Social Investment Forum.

The consensus view in the SRI literature is that there is no observed link between CSR and equity returns. The finding of mixed results is supportive of the shareholder view. There is no observed premium for social responsibility since any corporate actions (regardless of the motivation) are immediately reflected in stock prices. Therefore, any observed relationships between corporate social responsibility and financial performance will disappear as soon as they are viewed on a risk-adjusted basis. It follows that any attempt to impose "positive" screens (where only suitably identified "socially responsible" companies are chosen) is a futile exercise. Further, opponents of SRI argue that portfolios subjected to "negative" social responsibility screens will actually underperform, since the investible universe is being artificially constrained and all risks are impounded in returns before the screening takes place.

Earlier research by Malkiel (1991) is supportive of this view. He looked at return performance of portfolios that boycotted companies doing business with South Africa and found that the stocks that were removed outperformed the other holdings by an average of 3% per year over an 18-year period. It follows that those portfolios that did not invest in South African businesses, underperformed those that did. The argument is a simple application of the Markowitz (1952) model of portfolio choice. Restricting the investible set must lead to lower risk adjusted returns. However, Milevsky et. al. (2006) present an optimization algorithm and demonstrate that when passive index portfolios are appropriately rebalanced, the penalty for imposing negative screens may be economically insignificant.

Alternatively, stakeholder theorists point to research that finds ethically screened portfolios actually outperform screened portfolios. Contrary to Malkiel's evidence of underperformance, Statman (2000) finds that the Domini Social Index[4] outperforms the S&P 500 over the 1990- 1998 period. However, superior performance of socially responsible portfolios is relatively rare. More often, the research finds neither outperformance nor return underperformance for investors in screened portfolios. Examining Canadian ethical mutual funds, Asmundson and Foerster (2001) find that relative to the broader market, there is no return underperformance, and some weak evidence of lower risk for screened funds. Statman (2006), Goldreyer and Diltz (1999), Bauer, et. al. (2002) and Guerard

[4] Created by the social research firm of KLD Research & Analytics, the Domini 400 Social Index is a market capitalization-weighted common stock index. It monitors the performance of 400 U.S. corporations that pass multiple, broad-based social screens. The Index consists of approximately 250 companies included in the Standard & Poor's 500 Index, approximately 100 additional large companies not included in the S&P 500 but providing industry representation, and approximately 50 additional companies with particularly strong social characteristics.

(1997) provide similar evidence.

At the firm level, the argument against CSR is that engaging in such activity is costly, and ceteris paribus, those firms that choose to behave ethically will bear higher costs, which will in turn result in lower performance levels. Generally, the extant research on CSR and firm performance has been concentrated in the management and policy areas. The first strand of this literature looks at short-term effects of unethical behavior. Standard event study methodology is used to uncover abnormal returns in the period surrounding the unethical behavior. An examination of the South African boycott during apartheid, by Teoh et. al.(1999) is representative of this type of research. However, McWillams et. al. (1999) suggest that that the potential for confounding events to contaminate results compromises this line of attack.

The second strand looks at long term performance based on accounting or market-based ratios. Both Margolis and Walsh (2001) and Orlitzky, et. al. (2003) provide thorough reviews. Not unlike the SRI literature, results are mixed, with researchers documenting positive (Orlitzky, et. al. (2003)), neutral (McWilliams and Siegel (2000)), and negative relationships (Wright and Ferris (1997)) between CSR and financial performance. Of particular relevance to this paper is the paucity of research on the CSR/performance link from the perspective of debt. Of the 52 studies reviewed by Orlitzky et. al., none of them examines the link between CSR and corporate debt. Of the 103 papers reviewed by Margolis and Walsh (2001), none of them examines debt. The lack of any research in the debt area is somewhat surprising, given the size of the corporate debt market relative to the equity market. According to Thomson Financial, the worldwide syndicated loan market totaled $3.8 trillion U.S. dollars in 2004, while the size of the equity markets was $845 billion.

The corporate debt market is an excellent arena in which to look for a link between social performance and financial performance because of the unique intermediation role played by banks. The primary advantage to using the debt market for the study derives from its informational efficiency. For example, Altman et. al. (2004) find that syndicated loan markets are more informationally efficient than bond markets, with the loan market reflecting the probability of default before the bond markets. Allen et. al. (2004) find that negative earnings announcements are anticipated by the loan market before they are reflected in the equity market. Our hypothesis is that banks are uniquely suited to assess the impact of CSR related investments, and their assessment will be manifest in the spreads charged to their customers. Controlling for previously identified determinants of loan spreads, we ask whether banks discriminate between firms with low levels of CSR and those with higher levels. It is to that question that we now turn.

III EMPIRICAL FRAMEWORK AND RESULTS

A. Data Description and Univariate Analysis

Any study of the links between CSR and financial performance must begin with a clear definition of both terms. Because we are interested in loans, our metric for financial performance will be the interest charged on corporate loans, measured as the initial all-in-drawn spread over the London InterBank Offer Rate, or LIBOR (hereafter referred to as the spread). The spread is the amount the borrower pays in basis points over LIBOR for each loan dollar drawn down. It includes the spread of the loan and any annual (or facility) fee paid to the bank group.

More problematic is the quantification of social responsibility. On examining previous studies, there appear to be several methods of defining socially responsible business practices. Carroll (1991) introduces the Carroll Concern for Society Index, while Aupperle (1991) suggests the use of aggregate measures of corporate principles and values. The use of multiple measures gathered through surveys is a common method of quantifying responsibility (e.g., Hansen and Wernerfelt (1989)). Published rankings (e.g., Waddock and Graves (1997)) are also common, with Fortune ethical rankings, the Transparency International Corruption[5] index and the Kinder, Lydenberg and Domini &

[5] Lee and Ng (2002) find that Transparency International's ratings of national corruption have significant power to

Co. rankings being among the more popular. While we acknowledge the difficulty inherent in the measurement of CSR, we use the KLD rankings as our measure of corporate social responsibility. The KLD data are widely accepted by practitioners and academics as an objective measure of corporate social responsibility, being referenced in over 40 peer reviewed articles and we use them as the main explanatory variable in regressions on yield spreads. The KLD score is lagged 1 year and initially treated as an exogenous variable.

KLD ranks companies on 13 dimensions of CSR, using surveys, financial statement information, reports from mainstream media, government documents and peer-reviewed legal journals. The 13 dimensions are community, corporate governance, diversity, employee relations, environment, human rights, product, alcohol, gambling, firearms, military, tobacco and nuclear power. Companies may have strengths and concerns in the first 7 dimensions, while the final 6 dimensions are purely exclusionary screens and companies can only register concerns in those categories. For example, a company can receive credit for a strong environmental policy at the same time a concern is registered for its environmental record. We do not include the exclusionary concerns as part of the total KLD score, and we also report strengths and concerns separately. The total of the strengths minus the concerns is the composite KLD score. Sharfman (1996) provides a review of the construct validity of the KLD measure.

Loan information is collected from the Loan Pricing Corporation Dealscan database. Rankings for social responsibility are available for approximately 650 companies on the S&P 500 and the Domini 400 index 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 institutional ownership data coming from the Thompson CDA/Spectrum (13f) database. The only common element between the KLD, Dealscan, Compustat and Thompson CDA/Spectrum (13f) data is the ticker.

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explain price/book ratios for the 1995-1998 time period.

Therefore, the KLD data are matched with the Dealscan loan data by ticker and name. There are 9,852 observations in the KLD data set, representing 1,735 unique firms. Only if both match is the observation kept. After matching with Compustat, there are 9,263 observations covering 1,295 firms. There are 66,472 U.S. loan facilities in the Dealscan database over the same period. Matching the KLD data with the loan data yields a final data set of 4,730 observations. The final filter removes all financial and insurance stocks, resulting in a final sample of 4,120 loans extended to 732 firms over the period from 1991 to 2003.

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 -10 to -9.

Second, there is a large 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. Fully 1,995 of the 4,120 firms in the sample have KLD scores from negative to positive one. The mass of scores around zero means 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 quartiles. For ease of exposition, we label firms in the top quartile "good" and those in the bottom quartile "bad" throughout the balance of the paper.

Insert Table 1 here

Turning to the summary statistics in Table 1we see that loans in this sample have average (mean) all-in drawn spreads of 96.15 basis points[6]. There is positive skewness in the data, which is not unexpected since firms are unlikely to receive loans having spreads less than LIBOR. This skewness is the motivation for the logarithmic transformation of the dependent variable in the regressions that follow.

Insert Table 2 Here

The comparison between the good and bad firms in Table 2 reveals a statistically significant difference of 32.41 basis points between the spreads charged to bad firms and those charged to good firms. However, ascribing this difference to corporate social performance in the firms would be premature. There are several firm level characteristics that differ between the two groups that also drive yield spreads. Specifically, the high KLD group of companies has higher market to book ratios (2.36 vs. 1.55), lower market value of debt to equity (0.30 vs. 0.77) and higher Altman Z scores (1.96 vs. 1.38). The good firms tend to be smaller than the bad firms as measured by the logarithm of total assets (22.52 vs. 23.07). There is little difference in the maturity of the loans between the two groups, but the good firms tend to take larger loans (as a percentage of total debt outstanding). Diamond (1991) posits that firms borrow from banks to build reputations as good repayers. As the relationship between the firm and

[6] This is lower than the amount reported in similar studies in the banking literature (for example, Coleman, Escho and Sharpe (2004) report average all in drawn spreads of 126.8 basis points). The majority of the KLD scores are applied to the constituents of the S&P 500 or the Domini index. Because the goal of the Domini index is to be broadly consistent with the S&P500, it is not surprising that the sample over-represents the largest firms in the US economy.

the bank grows, the bank is willing to lend more funds. The stronger banking relationships enjoyed by good firms allows them to get larger loans than bad firms.

Finally, there are differences in ownership structure between the good firms and the bad firms with the latter having fewer institutional shareholders. This result is intriguing, and it is unclear whether the presence of institutional ownership motivates socially responsible behavior, or whether responsible business practices attract institutional investors. On a related note, the concentration of institutional ownership, defined as the percentage of the average shares outstanding held by institutions also differs between firms. Good firms have lower concentration of institutional ownership (60% vs. 64%), significant at the 1% level. Because many of these characteristics are also known determinants of yield spreads, it points to the need for multivariate analysis to correctly control for the observed variation between firms. We turn to these results next.

B. Regression Design

The literature on the determinants of loan spreads is well developed, with the majority of studies using a single equation regression approach (e.g., Berger and Udell (1995); Guedes and Oppler (1996)). We follow in that tradition, but also run a system of simultaneous equations to confirm our results. We control both firm and loan characteristics, as both have been shown to be determinants of spreads. Lender characteristics are considered in a robustness check. Because the KLD data are only available on US firms, there is no need to control for country effects.

Firm controls include:

Size: Ln (Total Assets). Larger firms are better able to withstand negative shocks to cash flow and are thus less likely to default. In addition, there are reputation effects that increase with firm size (Diamond (1989), (1991)). Hence, larger firms are viewed as less risky by banks and should enjoy lower yields on debt.

Market/Book: Depending on the context, M/B has been used as a control for risk, growth opportunities and market mispricing. It is also included because of its relationship to CSR (firms with high social responsibility ratings are generally found to have higher market-to-book ratios).

Long-term Debt/Equity: It has been demonstrated both theoretically and empirically that firms with higher leverage are expected to pay higher spreads.

Secured status: A dichotomous indicator variable equal to one if the loan is secured, zero otherwise. Where available, the actual indicator is used. Where it is missing the predicted value from a first stage logistic regression is substituted.

EBIT: We include earnings before interest and taxes scaled by total assets to control for the possibility that any relationship between the spread and the KLD variable is actually being driven by free cash flow in the firm. The temporal sequencing issue has been identified in the CSR literature. It is not clear whether CSR leads to improved financial performance or whether improved performance frees up funds that can be used on CSR related projects. Because investments in CSR are largely discretionary, the "slack resources" theory (McGuire et al. (1990)) argues that the initiation or cancellation of CSR related projects depend on the availability of excess funds.

Z Score: a proxy for credit risk, Altman's (1984) Z score is a measure of distress risk, with higher scores indicating a lower likelihood of default. It is included in the regressions to control for the possibility that KLD scores are proxying general default risk.

Bond Rating: S&P long-term debt rating on the signing date, it is an omnibus indicator capturing various risks. It is equal to 1 if the long-term debt of the firm is rated and equal to zero if it is not. We expect that the absence of a rating will imply a higher spread.

Investment Grade: Conditional on the presence of a rating, we categorize debt as investment grade if it has a rating higher than BB+. The variable is equal to unity if the debt is of investment grade and we expect that investment grade debt will have lower spreads.

Institutional Shareholders: Equal to the natural logarithm of (1+ the number of institutional owners). Research by Barnea and Rubin (2005) suggests that investments in CSR may be an agency conflict between managers who benefit from burnishing their reputations as champions of social responsibility, and shareholders who bear the cost of the investments. Bhojraj and Sengupta (2003) find that institutional ownership is negatively associated with yields on public bonds. Roberts and Yuan (2006) document a negative non-linear relationship between institutional ownership and loan yield spreads because of the monitoring they provide.

Institutional Concentration: The ratio of shares held by institutions to the average shares outstanding. The overall impact of ownership structure on investments in CSR is unclear. If CSR investments are value enhancing, then the presence of more institutional owners could increase observed levels of CSR. If however, CSR investments are value destroying, the cost (to institutions) of pursuing them will increase with institutional ownership. This is a simple application of the agency cost of equity argument put forward by Jensen and Meckling (1976).

Industry Dummies based on 2-digit SIC codes. Following the U.S. Department of Labor, we control for differences across industries. DiBartolomeo and Kurtz (1999) demonstrate the importance of controlling for industry effects in studies of socially responsible investing.

In addition to firm characteristics driving loan costs, the actual features of the loan are known to be determinants in its cost. Banks can trade off several loan features, including maturity, security and commitment fees (in the case of revolving loans). We include the following controls for loan characteristics:

Maturity: The duration of the loan, measured in years. There is mixed evidence on how the maturity of the loan impacts the spread. The "trade-off" hypothesis suggests that banks will charge higher spreads on loans with longer maturities, to cover the risk of lending over longer periods. The "credit quality" hypothesis predicts a negative relationship because high-risk lenders are crowded out of the long debt market. As a result, riskier borrowers can only obtain shorter-maturity loans at higher yields (Dennis, Nandy and Sharpe (2000) and Gottesman and Roberts (2004)).

Loan Concentration: Measured as the log of the package amount / (loan package amount + total debt). Following Dennis, Nandy and Sharpe (2000) we use loan concentration as a proxy for the strength of the relationship between the bank and the borrower. Berger and Udell (1995) find evidence that stronger relationships lead to lower spreads.

Loan Type: Since costs vary depending on the type of loan negotiated, (Preece and Mullineaux (1996)), we include dummies for revolvers, bridge loans and miscellaneous other loans, with term loans being the omitted variable.

Loan Purpose: As above, the purpose of the loan affects its cost. We control for differing loan purposes with dummies for takeovers, repayments, corporate purposes and other purposes.

Syndicate: A dummy variable equal to unity if the loan is syndicated. Esty (2001) and Dennis and Mullineaux (2000) document fundamental differences between conventional and syndicated loans, with syndicated loans having higher yields.

Finally, we include the 1-month US dollar LIBOR rate at the time of the loan as an independent variable to control for prevailing macroeconomic conditions. Coupled with the fact that the dependent variable is a spread over a floating rate, the addition of the LIBOR variable should capture the effects of any intertemporal economic shocks. Nonetheless, we also include year dummies in the regression specifications. All continuous variables are winsorized at the 1% and 99% level to control for outliers.

At first blush, OLS regressions would appear to be appropriate, with the standard errors adjusted for heteroskedasticity. However, because we do not know the form of any potential heteroskedasticity ex ante, we utilize the generalized method of moments for estimation of the regression equations. The resulting t-statistics are robust to heteroskedasticity.

The general form of the regression equations is:

$$\ln(SPREAD) = f\,(\,firm\ \ characteristics,\ \ loan\ \ characteristics,\ \ KLD) \tag{1}$$

C. Single Equation Results

The first regression (Model 1) in Table 3 treats the KLD score as a discrete exogenous variable. Sixteen KLD dummies are used in addition to the firm and loan controls described above. The extreme positive and negative KLD classifications are aggregated to ensure that there are sufficient observations in each classification. Specifically, all KLD scores equal to or greater than 8 are represented by a single indicator variable. Likewise, all scores equal to or less than –8 are aggregated. A second specification (Model 3) aggregates the KLD scores into the top and bottom quartiles— the aforementioned "good" and "bad" firms.

Insert Table 3 Here

Because the dependent variable is log transformed, the coefficient of the independent variable represents the percentage change in the mean of the dependent variable given a one-unit change in the explanatory variable. After controlling for firm and loan characteristics, the regression suggests that firms with KLD scores of -8 or lower pay an additional 16.01 basis points relative to firms with a KLD score of 0 (25.7% of the mean of the log spread of 4.132). This result is significant at the 5% level. As the level of concern falls, as measured by the composite KLD score, the additional compensation demanded by banks falls, both in magnitude and statistical significance. When the KLD score rises to -5, the additional spread demanded is indistinguishable from zero.

Because the Dealscan database is missing secured status for 2,028 observations, an (unreported) logistic regression is used to fit the missing data in estimating model 1. An alternative specification uses only the observations where the secured status is known. This lowers the sample size to 1830. The goal is to ensure that the "errors-in-variables" introduced by the fitting process is not biasing the regression coefficients. Model 2 shows the regression results. As can be seen, the coefficient on the lowest scoring firms is no longer significantly different from zero. This is likely because this specification, while it reduces errors-in-variables, suffers from selection bias. The firms where the secured dummy is observed tend to be larger firms. The positive coefficients on KLD-6 and KLD-7 retain their significance.

Perhaps of more interest is the behavior of the KLD coefficient when the KLD score is greater than 0. These are the most socially responsible firms and, if the stakeholder view is correct, should be rewarded with a lower yield spread. Instead, the impact of higher scores is indistinguishable from zero. Somewhat surprisingly, firms with the highest KLD scores (KLD>8) actually pay 17 basis points ($0.279(e^{4.1319})$) more than firms with lower scores. Outliers do not drive this result, and both industry and time effects are controlled in the regression specification. It may be evidence that lenders punish firms that squander resources on social responsibility when those initiatives have negative net present values.

One possible interpretation is that as firms increase the number of stakeholders that they try to accommodate in their business mission, they lose focus because the goals of competing stakeholders may not be perfectly aligned. The ability of the firm to focus on multiple missions has been explored in a related context by Dewatripont et. al. (1999). Their theoretical model predicts that firms with "fuzzy" missions will have poor managerial incentives, impairing the effectiveness of the organization. On the other hand, there are very few firms with scores of 8 or higher and inferences must be made with caution. It is equally possible that this result is sample specific. Indeed, that is the biggest drawback to using a specification where each KLD level has its own indicator. An alternative is to aggregate the levels and have one indicator for the top quartile and another for the bottom quartile. In this specification (Model 3) however, neither coefficient is statistically significant, perhaps because the effects are concentrated only in the extreme tails of the distribution of KLD scores.

D. Two-Stage Estimates

The preceding specifications suffer from potential endogeneity of the KLD score with other determinants of yield spreads. It is possible that the variables that determine loan spreads are also determining lagged KLD scores. If so, there will be correlation between the coefficients of the explanatory variable and the error term leading to biased estimates. In order to circumvent this problem, we employ a two-stage estimation process. We continue to aggregate firms into good and bad categories, with the remaining firms labelled "neutral" for convenience. We run the following ordered logistic regression on ex ante firm characteristics:

$$(2) \qquad \text{Prob} \left\{ \begin{array}{c} \text{Good} \\ \text{Neutral} \\ \text{Bad} \end{array} \right\} = \text{f (firm characteristics)}$$

We then use this fitted probability as a single explanatory variable in a second pass regression of yield spreads. The advantage of a two-step process is that the endogeneity of the KLD score and yield spread is controlled and the resulting variable is a continuous probability instead of an ordinal score. The ordered logistic specification yields two probabilities. The first (Predicted KLD(1)) is the probability of being good or neutral against being bad. The second, (Predicted KLD(2)) is the probability of being good against being neutral or being a bad firm. We insert the two probabilities generated by the ordered logistic regression into our yield spread regression.

Insert Table 4 Here

Model 1 in Table 4 presents the results of the ordered logistic regression. Smaller firms tend to have higher KLD scores, as do higher Market-to-Book firms. Good firms are also more likely to have lower leverage. Higher levels of EBIT are associated with higher scores. Whether these firm level attributes are caused by the CSR investments of the firm, or the CSR investments caused the characteristics, is beyond the scope of this paper and is an area left to future research.

While the ordered logistic specification is theoretically the most appropriate specification because it uses all of the observations, the chi squared test of proportional odds is significant, indicating poor model fit. The poor fit of the model arises because of the inability of the KLD proxy to discriminate except in the top and bottom quartiles. Furthermore, there is the potential for multicollinearity to confound the interpretation of these coefficients because they are highly negatively correlated[7]. Therefore, we run an alternative dichotomous specification where bad firms are 0 and good firms are 1. This specification (Model 2) yields similar coefficients to the first model with the notable difference being the Z score, which is significant in Model 1 but not in Model 2. Two final alternative models are tested. Model 3 removes institutional ownership and the increase in AIC suggests that it is important in explaining the variation in KLD scores. Finally, the Investment Grade dummy is added to the regressions, conditional on the presence of a bond rating. Neither Investment Grade nor the level of intangible assets is significant in this specification.

Insert Table 5 Here

Table 5 shows the results of the spread regressions where the KLD variable is endogenized, drawing on Model 1 from Table 4. Model 1 uses all of the observations in the sample and two sets of

[7] The possibility exists for multicollinearity to be affecting control variables as well. VIF tests on earlier versions of the regression specification did not indicate significant problems, but the interpretation of the coefficients on control variables needs to be done with caution. We thank Lawrence Kryzanowski for pointing out this issue.

KLD probabilities. The first probability (KLD(1)) measures the probability of being good or neutral against the probability of being bad. The second probability (KLD(2)) measures the probability of being good against the probability of being neutral or bad. Both coefficients are negative and significant. At first blush, these results would seem to vindicate the stakeholder view. However, the economic significance is modest.

The first coefficient can also be viewed as the cost of being a bad firm by reversing the sign on the coefficient. A one standard deviation increase in the probability of being bad increases the yield spread by 7.5 basis points[8]. The second coefficient measures the benefit of being a good firm. A one standard deviation increase in the probability of being good lowers the spread by 4.1 basis points. These results can be reconciled with the 16 basis point increase in yields found in Table 3 by recognizing that the effects in Table 5 cover the entire sample, while the effects in Table 3 are for just the worst performers (KLD<-7). The second specification yields results of similar magnitude. A one standard deviation increase in the probability of being good lowers the spread by 6.5 basis points. The reason that none of the regressions yield economically significant results is again tied to the distribution of KLD scores. The predicted KLD scores generated by the logistic regression fall mainly between 40% and 60%, mimicking the distribution seen in the actual data. This tight range means that the coefficient, which can be interpreted as the percentage change in the mean of the dependent variable when the probability of

[8] Interpreting the coefficient is complicated by the log transformation. The standard deviation of the predicted KLD score is 0.126 so the standardized regression coefficient is -1.828 x .126/0.89= -0.257. The normal interpretation is that a one standard deviation change in the probability of being good or neutral (i.e., not bad) lowers the standard deviation of the log spread by 0.257. However the reported standard deviation in Table 3.2 is log transformed. An approximate conversion is to compute the coefficient of variation and apply it to the raw mean spread.

$$0.257\left[\exp(4.132)\times\frac{1}{1+\exp(0.89-1)}\right]\approx 7.5bps\,.$$

being good goes from 0% to 100%, is never observed in the data. No firms have KLD probabilities approaching either of the two extremes.

One final specification is presented in Table 5, to mitigate any errors in variables bias. Model 3 restricts the second stage regression to include only the good and bad firms that were used in the first pass regression. Restricting the sample mitigates the errors-in-variables problem because the only observations used in the second stage are those that are used in the first stage logistic regression. However, dropping the middle 50% of the distribution introduces sample selection bias. To control for this, we use Heckman's two-stage correction and include the inverse Mill's ratio to control for explanatory power attributed to the KLD score that is actually a function of sample selection. The coefficient of fitted KLD in the final specification is now larger, at 10.6 basis points.

E. Endogeneity of Loan Contract Terms

One criticism of the preceding regressions could be that the endogeneity of maturity and yield spread has not been adequately controlled. Dennis, Nandy and Sharpe (2000) demonstrate how the failure to account for this can lead to improper inference. To verify the results of the preceding regressions, we re-estimate the following system of equations using three stage least squares.

$$\ln(SPREAD) = f(maturity,\ \ firm\ characteristics,\ loan\ characteristics,\ KLD) \tag{3}$$

$$Maturity = f(\ln(SPREAD),\ \ firm\ characteristics,\ loan\ characteristics,) \tag{4}$$

Insert Table 6 Here

The results are presented in Table 6. Compared to the results in Table 5, the coefficient on maturity has changed signs and is now significantly negative. Generally, the remaining coefficients are not changed. In particular, the KLD coefficient maintains its statistical significance, while remaining economically insignificant (4.7 basis points).

F. Unobserved Heterogeneity of Lead Lenders

While the foregoing analysis has controlled for borrower and loan characteristics, there exists the possibility that our results may be impacted by unobserved heterogeneity among the lenders. Several recent papers on the determinants of loan contract terms have controlled for lead lenders' characteristics (Coleman, Esho and Sharpe (2004) and Hubbard, Kuttner and Palia (2002), among others). Coleman, Esho and Sharpe (2004) demonstrate that banks with better monitoring abilities are able to demand higher initial loan spreads. They also find that high-risk banks charge higher yields, a result that is also reported by Hubbard, Kuttner and Palia (2002), who note a negative association between the health of the lender and the spread charged to the borrower. They find that capital-constrained banks charge higher spreads, especially when the borrowers have higher levels of information opacity.

Following the line of reasoning promoted by Coleman, Esho and Sharpe, our results could be explained by bank monitoring. If the firms with the lowest KLD scores also require the most monitoring, then the positive relationship between poor scores and yields could be due to the superior monitoring abilities of the banks that hold those loans and not due to the KLD score. We control for unobserved lender heterogeneity by adding bank fixed effects to our model. The administration agent in each deal is identified as the lead bank in the syndicate. We identify the ultimate parent of each lead bank, and include indicator dummies in the regressions.

Insert Table 7 Here

Table 7 reproduces the result of Model 1 in Table 5, and repeats the results after controlling for bank fixed effects. Of primary interest are the KLD coefficients. Recall that the first coefficient, KLD(1) measures the cost of having a low KLD score (after changing the sign on the coefficient estimate). The cost of being a poor performer increases from –1.828 to –2.578, meaning that a one standard deviation change in the KLD(1) score would result in an increase of 12 basis points in the cost of borrowing. The results suggest that there are bank monitoring effects present in the sample. The coefficient of determination increases (63.3% vs. 70.1%) in the fixed effects model. Because the cost of borrowing increases when bank characteristics are controlled, one interpretation is that banks with good monitoring abilities avoid firms with environmental social and governance concerns.

The second coefficient KLD(2) can be interpreted as the benefit of having good CSR performance. Here, the coefficient is smaller (-0.891 vs. –0.462), yielding a decrease in yield spreads of only 2 basis points. The result is not economically significant, and has only marginal statistical significance. After controlling for bank fixed effects, there appears to be little incentive provided by banks for the pursuit of high KLD scores. This does not mean that banks do not recognize the impact of proactive CSR investments, simply that they do not reward high CSR related investments when they are not accompanied by similar levels of concerns. These results are consistent with the preceding analysis and reinforce the idea that firms with very low KLD scores pay higher yields, but very high KLD scores are not rewarded with lower yields. Taken together, the regression results point to a statistically significant effect that is economically significant only for firms with the very worst KLD scores. A more direct test is possible. To confirm the regression results, we turn now to matched firm tests of differences in yield spreads.

G. Matched Firms

An alternative to the regression approach is to use matched pairs to examine if there is a yield differential between firms with high scores and those with low scores. Traditionally, researchers attempt to isolate the variable of interest by matching firms based on other characteristics that also drive the dependent variable. Following the work of Fama and French (1993) matching is often done on the basis of size and book to market ratio. Control firms are sorted into bins based on size and then further subdivided based on their book-to-market ratio. Each firm in the treatment group is then matched to the firm (or portfolio of firms) whose characteristics most closely match its own[9]. The difficulty with this approach is that it is sensitive to the number of criteria used and the size of each bin. In order to minimize the likelihood of mismatching firms confounding the results, we borrow from the biostatistics literature and utilize propensity scoring as the method for matching. A propensity score is the conditional probability of a firm being assigned to a particular treatment group given its observable characteristics.[10]

The predicted probability from a logistic regression is used as the single matching criterion between the treatment group and the control group. Propensity score matching is done by sampling from a large reservoir of potential firms (the controls) and finds those whose characteristics lead to them having the same propensity score as the firm in the treatment group. The advantage of this method is that it produces matched pairs that are similar on multiple dimensions. Our methodology is as follows: first, we calculate the propensity score for all firms. Then, we sort both the treatment group and the control group by the propensity score. We start with the first firm in the treatment group and match it with the first firm in the control group whose propensity score matches to four significant digits. If more than one control firm is a potential match, the control firm is randomly selected from among the possible controls. Both the treatment and the control firm are then placed in a file of matched firms, so no control is matched to more than one treatment firm. If no control firm matches to four significant digits, the treatment firm is not matched and the selection process moves to the next firm. Matching continues until all treatment firms have been matched or discarded. We expect the two sets of empirical distributions of yield spreads to be identical under the null with respect to the mean. The foregoing is

[9] Barber and Lyon (1996) provide an econometric review.

[10] See Rosenbaum and Rubin (1983) for the original discussion and Hillion and Vermaelen (2004) and Li and Zhao (2006) for applications in a finance context.

known as the "greedy match" propensity scoring algorithm.

Insert Table 8 Here

The results of firm matching are presented in Table 8. The regression results presented in the previous section point to the possibility that the poorest performing firms, specifically those with KLD scores less than negative 4, may pay higher yields. The matching algorithm isolates these firms and uses propensity score matching to find a group of control firms that share the same firm and loan characteristics, but have higher KLD scores. Of the 253 firms in the sample of "bad" firms with KLD scores less than -4, 91 were successfully matched to control firms that have higher KLD scores. As can be seen, firms with lower KLD scores pay 14.47 basis points more than matched firms (exp(4.3594)-exp(4.1548)). The result is significant at the 10% level (p=0.0945) using the non-parametric rank sum test[11]. While the results are not shown, the propensity score also controls for industry and year of the loan.

None of the other variates are significantly different from zero with the exception of market/book. This gives pause, since the direction of the market/book difference is consistent with higher yields in the univariate results, although it is unclear whether the M/B difference would have a significant economic impact on the observed loan spreads. However, further tightening of the matching criteria lowers the number of matched firms below 40 observations rendering any inference suspect. As it stands, it should be noted that the 14.47 basis points is very close to the 16 basis points from the regression specification.

[11] The rank sum test is chosen over the t-test because it is robust to violations of the normality assumption of the t-test.

The second specification looks at the aforementioned "bad" firms, those in the lowest quartile of KLD scores with 153 firms successfully matched. The spread difference is now much smaller, at 6.71 basis points, consistent with the weaker relationship observed in the regression results. Once again, the matched pair results are very close to the 7.5 basis points estimated in the previous section. There is a single firm characteristic (bond rating) that has a different distribution in the control group relative to the treatment group. It is possible that the bond rating and not the KLD score is driving this difference, although it seems unlikely, since the difference is small, notwithstanding its statistical significance.

The third specification (Model 3 in Table 8) looks at the "good" firms. Given the regression results previously reported, it is not surprising that the premium for having a high KLD score is not economically (4.57 bps.) significant. This difference is just short of significance at the 10% level (p=.1182). Note however, the concordance between the two methodologies (4.1 basis points in the previous section).

The final model (Model 4 in Table 8) explores whether lenders penalize firms with very high KLD scores. If so, it would be evidence supportive of Barnea and Rubin's conjecture that investments in CSR are agency costs, where managers burnish their reputations at the expense of shareholders. Unfortunately, there are too few firms with very high (KLD>7) scores to use the "greedy match" algorithm previously described. The "greedy match" propensity-matching algorithm trades off accuracy in matching against the number of observations lost. Higher precision in matching means fewer successful matches. With only 34 firms having KLD scores greater than 7, we turn to the "optimal matching" algorithm for the final model.

The methodology is as follows: The propensity score for each firm is calculated and calipers are set at +/- 0.25 of the standard deviation of the propensity score. All control firms falling within this range are potential matches. If only a single firm falls within the calipers, it is selected as the match. If multiple firms fall within +/- 0.25 standard deviations, then the algorithm chooses the control firm that minimizes the Euclidean distance between the treatment firm characteristics and those of the control firm. The optimal matching algorithm is appropriate when the number of treatments or controls is small.

The optimal matching algorithm is able to find control firms that match the treatment firms across multiple dimensions, and the log spread is considerably higher for the good firms. However, the result is not statistically significant at traditional levels, so we are unable to comment on the agency argument. Whether high levels of CSR represent agency costs remains an open question. Our results suggest that if such costs are being borne by shareholders, they are not being reflected in the cost of borrowing.

IV. CONCLUSION

The CSR phenomenon has firmly taken root across corporate America, if not within the academic finance community. MBA candidates can now specialize in Corporate Social Responsibility. Firm resources are employed to produce reports on CSR initiatives. Scarce advertising dollars are spent trumpeting social records. And, while there is a growing body of literature on corporate social responsibility, there has been little research on the effect of CSR on the cost of debt financing.

This paper attempts to fill that gap in the empirical literature. Exploiting the unique position of banks as quasi-insiders of the firm with access to information about the value of CSR projects, we examine whether CSR investments lower the cost of debt financing. Stakeholder theorists argue that CSR investments are value enhancing. Our results provide little support for this view. Instead, we observe banks charging higher yields to firms with numerous concerns, but making no discrimination among the majority of firms with few or no concerns. Using two different econometric techniques, we document the penalty for being among the worst laggards at less than 20 basis points. Further, banks do not reward firms identified as leaders in social responsibility. In fact, there is weak evidence that banks may actually punish firms with very high levels of CSR, consistent with these investments being value destroying agency costs of the firm.

Our findings have interesting policy implications. If firms are being punished for paying too much attention to stakeholder groups, it suggests that there is a role for government in mitigating negative externalities, since rational firms will not engage in socially responsible behaviors if they are punished by the market for doing so. These are not new issues. They go to the heart of the CSR debate. Lenders are providing incentives for firms to correct the most egregious behavior by demanding higher yield spreads from firms with the worst records in social responsibility. But the market is not providing any incentives to do more than that. The lack of very high scores is consistent with the idea that there is a threshold beyond which further investments in CSR are evidence of value destroying agency costs. Further research may help shed light on those aspects of CSR that add value and those that do not.

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Table 1
Summary Statistics

This table reports the descriptive statistics for the principal variables. The sample consists of 4,120 loans collected from Dealscan over the 1991to 2003 period for non-financial firms. Spread is defined as the initial all-in-drawn spread over LIBOR for the loan, expressed in basis points. Maturity is the length of the loan, in years. Loan Amount is the natural logarithm of the loan amount, scaled by total assets. Firm size is the natural logarithm of total assets. Z Score is a proxy for default risk, as computed in Altman (1984). LIBOR is the 1 month USD London Interbank Offer Rate at the end of the deal month. 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.

Variable	N	Mean	Median	Std Dev	Minimum	Maximum
Log Spread	4069	4.16	4.14	0.89	2.40	6.96
Spread	4069	96.15	62.50	99.24	11.00	1050.00
Maturity	3960	3.01	3.00	2.09	0.08	23.00
Market/Book	4057	1.94	1.53	1.39	0.63	39.12
Debt/Equity	4057	0.52	0.26	0.96	0.00	12.97
Loan Concentration	3867	-2.19	-2.05	1.08	-10.87	-0.01
Size	4063	22.47	22.46	1.33	14.68	27.20
LIBOR	4120	3.40	3.14	2.00	1.09	6.83
Z Score	4120	1.73	1.72	1.03	0.00	5.64
EBIT	4004	0.09	0.09	0.10	-0.77	0.90
Inst. Shareholders	3971	5.54	5.53	0.62	0.69	7.40
Inst. Concentration	3970	0.63	0.64	0.17	0.06	1.49
KLD Total	4120	-0.19	0	2.84	-11	10
KLD Strength	4120	2.22	2	2.36	0	14
KLD Concern	4120	2.40	2	2.41	0	15

Table 2
Summary Statistics for Good and Bad Firms

This table reports the descriptive statistics for the principal variables. The sample consists of 4120 loans collected from Dealscan over the 1991 to 2003 period. Spread is defined as the initial all-in-drawn spread over LIBOR for the loan, expressed in basis points. Maturity is the length of the loan, in years. Loan Concentration is the natural logarithm of the loan amount, scaled by total assets. Firm size is the natural logarithm of total assets. Z Score is a proxy for default risk, as computed in Altman (1984). LIBOR is the 1-month USD London Interbank Offer Rate at the end of the deal month. 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. Differences in means are measured by a t-test. Median differences are measured by non-parametric Wilcoxon test. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.

Variable		**N**	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
Spread	Bad	1109	103.47***	62.5***	106.06	12.50	1050.00
	Good	981	71.06	40.00	80.86	12.00	1000.00
Maturity	Bad	1098	2.97**	3.00***	2.06	0.08	10.00
	Good	948	2.78	2.00	2.07	0.08	23.00
Market/Book	Bad	1116	1.55***	1.32***	0.77	0.63	8.69
	Good	981	2.36	1.82	1.69	0.81	14.58
Debt/Equity	Bad	1116	0.77***	0.40***	1.22	0.00	12.97
	Good	981	0.30	0.16	0.39	0.00	3.34
Loan Concentration	Bad	1047	-2.50***	-2.35***	1.11	-8.80	-0.25
	Good	941	-2.14	-1.99	1.14	-10.87	-0.10
Firm Size	Bad	1119	23.07***	23.10***	1.18	19.63	27.08
	Good	982	22.52	22.59	1.42	17.25	27.20
LIBOR	Bad	1134	3.17***	2.15***	1.98	1.09	6.83
	Good	991	3.81	4.06	1.97	1.09	6.83
Z Score	Bad	1134	1.38***	1.36***	0.92	0.00	4.97
	Good	991	1.96	2.00	1.01	0.00	5.18
EBIT	Bad	1102	0.07***	0.07***	0.08	-0.41	0.83
	Good	964	0.12	0.11	0.10	-0.37	0.86
Inst. Shareholders	Bad	1090	5.65*	5.62***	0.56	3.76	7.09
	Good	955	5.70	5.74	0.69	0.69	7.40
Inst. Concentration	Bad	1090	0.64***	0.65***	0.18	0.09	1.49
	Good	954	0.60	0.60	0.15	0.14	1.13
KLD Total	Bad	1134	-3.56***	-3.00***	1.78	-11.00	-2.00
	Good	991	3.42	3.00	1.64	2.00	10.00
KLD Strength	Bad	1134	1.27***	1.00***	1.72	0.00	9.00
	Good	991	4.84	4.00	2.47	2.00	14.00
KLD Concern	Bad	1134	4.83***	4.00***	2.66	2.00	15.00
	Good	991	1.41	1.00	1.53	0.00	9.00

Table 3
Regression of Spread against KLD Score

This table shows the coefficients from a regression of the log-spread on KLD score and controls for borrower characteristics and loan features. The dependent variable is the natural logarithm of the all-in-drawn spread. Descriptions of the explanatory variables are provided in the appendix. Model 2 tests for bias due to the estimation of the secured variable by using only observations for which the secured status is observed. 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 dummies are included in all regressions but are not reported.

	Model 1	**Model 2**	**Model 3**
Intercept	9.765	6.880	9.543
	(0.445)***	(0.443)***	(0.443)***
Maturity	0.008	0.007	0.008
	(0.006)	(0.008)	(0.006)
Market/Book	-0.094	-0.066	-0.096
	(0.010)***	(0.014)***	(0.010)***
Debt/Equity	0.280	0.240	0.278
	(0.019)***	(0.020)***	(0.011)***
Loan Concentration	-0.048	-0.051	-0.048
	(0.012)***	(0.016)***	(0.012)***
Firm Size	-0.185	-0.124	-0.176
	(0.011)***	(0.015)***	(0.010)***
LIBOR	-0.033	-0.021	-0.033
	(0.020)*	(0.028)	(0.020)*
Z Score	-0.052	-0.036	-0.051
	(0.014)***	(0.018)**	(0.014)***
Revolver	-0.140	0.214	-0.146
	(0.092)	(0.260)	(0.094)
Other	0.182	0.336	0.182
	(0.128)	(0.275)	(0.130)
Bridge	0.226	0.710	0.233
	(0.132)*	(0.288)**	(0.134)*
Repay	-1.019	-0.248	-0.992
	(0.162)***	(0.089)***	(0.158)***
Syndicate	0.019	0.055	0.020
	(0.065)	(0.084)	(0.064)
Takeover	-0.902	-0.179	-0.881
	(0.163)***	(0.089)**	(0.160)***
Corporate Purpose	-1.023	-0.209	-0.996
	(0.160)***	(0.081)***	(0.157)***
Other Purpose	-1.278	-0.493	-1.256
	(0.161)***	(0.089)***	(0.158)***
Secured	0.712	0.840	0.718
	(0.034)***	(0.038)***	(0.034)***
Bond Rating	-0.127	-0.104	-0.130
	(0.040)***	(0.041)**	(0.039)***
CSR Indicator (Low)			0.035
			(0.022)

CSR Indicator (High)			-0.023
			(0.023)
KLD negative 8 or less	0.257	-0.017	
	(0.103)**	(0.197)	
KLD negative 7	0.230	0.342	
	(0.095)**	(0.163)**	
KLD negative 6	0.179	0.216	
	(0.067)***	(0.079)***	
KLD negative 5	0.080	-0.006	
	(0.056)	(0.087)	
KLD negative 4	0.046	0.084	
	(0.043)	(0.077)	
KLD negative 3	0.046	0.073	
	(0.042)	(0.054)	
KLD negative 2	0.009	0.033	
	(0.033)	(0.045)	
KLD negative 1	0.064	0.073	
	(0.030)**	(0.038)*	
KLD positive 1	-0.011	0.026	
	(0.032)	(0.043)	
KLD positive 2	0.021	0.063	
	(0.036)	(0.049)	
KLD positive 3	-0.052	-0.140	
	(0.041)	(0.060)**	
KLD positive 4	-0.013	0.012	
	(0.050)	(0.081)	
KLD positive 5	-0.045	0.178	
	(0.063)	(0.111)	
KLD positive 6	0.007	-0.081	
	(0.071)	(0.104)	
KLD positive 7	-0.013	-0.166	
	(0.128)	(0.160)	
KLD positive 8 or greater	0.279	0.368	
	(0.139)**	(0.160)**	
Adjusted R^2	0.637	0.682	0.635
Number of Observations	3858	1830	3858
Year Dummies	yes	yes	yes
Industry Dummies	yes	yes	yes

Table 4
First Stage Logistic Regression of KLD Score

This table shows the coefficients from a first stage logistic regression of the KLD score against borrower characteristics and loan features. 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. In model 1, the dependent variable equals 2 if the firm has a KLD score greater than 1,and 1 if the KLD score is between -1 and +1, and 0 if the KLD score is less than negative 1. Intercept 2 applies to the probability of KLD scores greater than 1, over KLD scores less than 1. The remaining models are dichotomous, with the dependent variable equal to 1 if the firm has a KLD score greater than 1, and 0 if the KLD score is less than negative 1. The first and second specifications include institutional ownership. The third model uses the bond rating while the fourth specification adds investment grade, conditional on the firm having a bond rating. All specifications include year dummies but coefficients are not reported.

	Model 1	Model 2	Model 3	Model 4
Intercept	6.953	11.675	10.287	9.892
	(4.206)*	(1.893)***	(1.717)***	(1.967)***
Intercept 2	9.344			
	(4.207)**			
Firm Size	-0.508	-0.705	-0.187	-0.202
	(0.063)***	(0.106)***	(0.045)***	(0.055)***
Market/Book	0.112	0.21	0.482	0.612
	(0.042)***	(0.077)***	(0.072)***	(0.093)***
Debt/Equity	-0.182	-0.43	-0.64	-0.71
	(0.061)***	(0.118)***	(0.116)***	(0.136)***
EBIT	1.695	2.296	1.856	1.821
	(0.473)***	(0.784)***	(0.768)**	(0.936)*
Z Score	-0.140	-0.059	0.035	-0.135
	(0.050)***	(0.089)	(0.085)	(0.100)
Bond Rating	0.076	0.031	0.001	
	(0.051)	(0.093)	(0.089)	
Inst. Shareholders	0.769	1.129		
	(0.124)***	(0.212)***		
Inst. Concentration	-1.066	-2.107		
	(0.204)***	(0.335)***		
Investment Grade				0.09
				(0.066)
Intangible Assets				-0.467
				(0.418)
Mining	-0.566	0.049	0.106	-0.254
	(0.682)	(0.252)	(0.252)	(0.277)
Construction	-0.519	-0.958	-1.067	-1.147
	(0.689)	(0.558)*	(0.561)*	(0.567)**
Manufacturing	-0.124	0.75	0.756	0.564
	(0.678)	(0.215)***	(0.217)***	(0.226)**

Transportation, Commercial, Gas and Electricity	-0.116	0.787	0.908	0.744
	-0.679	(0.212)***	(0.216)***	(0.223)***
Wholesale Trade	-0.211	0.355	0.386	0.278
	(0.686)	(0.305)	(0.296)	(0.323)
Retail Trade	-0.034	0.901	0.914	0.831
	(0.680)	(0.240)***	(0.240)***	(0.257)***
Services	-0.191	0.697	0.745	0.57
	(0.679)	(0.227)***	(0.230)***	(0.245)**
Percent Concordant	0.681	0.77	0.779	0.788
Percent Discordant	0.315	0.228	0.219	0.21
Max Rescaled RSq	0.158	0.286	0.296	0.312
Good	970	970	1007	767
Neutral	1973			
Bad	1112	1112	1156	949
AIC	7950	2407	2498	1957

Table 5
Regression of Log-Spread against Endogenized KLD Score

This table shows the coefficients from a regression of the log-spread on KLD score and controls for borrower characteristics and loan features. The dependent variable is the natural logarithm of the all-in-drawn spread. Model 1 uses the predicted KLD coefficient from the ordered logistic regression (Model 1- Table 4). Predicted KLD in model 1 is the probability of having a KLD score greater than negative 1. Predicted KLD(2) is the probability of having a KLD score greater than positive 1. Model 2 uses the predicted KLD score from the dichotomous logistic regression (Model 2-Table 4) Model 3 tests for bias due to the estimation of the KLD variable by using Heckman's two stage correction. 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 dummies are included in all regressions but are not reported.

	Model 1	**Model 2**	**Model 3**
Intercept	12.175	10.595	11.848
	(0.407)***	(0.440)***	(0.463)***
Maturity	0.016	0.007	0.005
	(0.006)***	(0.006)	(0.008)
Market/Book	0.037	0.038	0.142
	(0.019)**	(0.016)**	(0.030)***
Debt/Equity	0.101	0.153	0.026
	(0.024)***	(0.022)***	(0.036)
Loan Concentration	-0.066	-0.042	-0.015
	(0.013)***	(0.012)***	(0.017)
Firm Size	-0.266	-0.227	-0.234
	(0.013)***	(0.012)***	(0.017)***
LIBOR	-0.038	-0.032	-0.017
	(0.020)*	(0.02)	(0.028)
Z Score	-0.048	-0.016	-0.044
	(0.014)***	(0.014)	(0.022)**
Revolver	0.580	-0.16	-0.305
	(0.103)***	(0.091)*	(0.119)**
Other	0.854	0.168	0.054
	(0.137)***	(0.127)	(0.16)
Bridge	0.949	0.203	-0.019
	(0.135)***	(0.131)	(0.174)
Repay	-0.809	-1.014	-2.106
	(0.184)***	(0.157)***	(0.136)***
Syndicate	-0.002	0.007	-0.067
	(0.065)	(0.063)	(0.111)
Takeover	-0.625	-0.889	-1.903
	(0.185)***	(0.159)***	(0.135)***
Corporate Purpose	-0.794	-1.016	-2.129
	(0.183)***	(0.156)***	(0.127)***
Other Purpose	-1.028	-1.263	-2.34

	(0.184)***	(0.157)***	(0.126)***
Secured	0.689	0.699	0.683
	(0.036)***	(0.034)***	(0.057)***
Bond Rating	-0.014	-0.113	
	(0.040)	(0.038)***	
Predicted KLD(1)	-1.828	-1.399	-2.275
	(0.237)***	(0.127)***	(0.217)***
Predicted KLD(2)	-0.891		
	(0.279)***		
Inverse Mills			0.005
			(0.016)
Adjusted R2	0.633	0.69	0.689
Number of Observations	3800	3858	1686

Table 6
Simultaneous Equations of Yield Spread and Maturity

This table shows the coefficients from a simultaneous system of equations of spread and maturity on KLD score and controls for borrower characteristics and loan features. The dependent variable in the first equation is the natural logarithm of the all-in-drawn spread. The dependent variable in the second equation is the loan maturity in years. Descriptions for all explanatory variables are given in the Appendix. Predicted KLD in the Spread equation is the predicted KLD score from the dichotomous logistic regression (Model 2-Table 3). Estimation is done by three stage least squares. 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.

	Spread	**Maturity**
Intercept	11.529	10.808
	(0.432)***	(6.281)*
Log Spread		-0.506
		(0.619)
Maturity	-0.287	
	(0.024)***	
Market/Book	0.015	-0.001
	(0.015)	(0.064)
Debt/Equity	0.188	0.096
	(0.024)***	(0.246)
Loan Concentration	-0.038	0.052
	(0.014)***	(0.053)
Firm Size	-0.245	-0.125
	(0.014)***	(0.157)
Revolver	0.206	-0.872
	(0.083)**	(0.357)**
Other	0.633	-0.348
	(0.138)***	(0.619)
Bridge	0.057	-2.393
	(0.145)	(0.552)***
Repay	-1.024	-0.905
	(0.156)***	(0.732)
Syndicate	0.076	0.225
	(0.091)	(0.208)
Takeover	-1.080	-1.659
	(0.161)***	(0.633)***
Corporate Purpose	-1.320	-1.984
	(0.159)***	(0.738)***
Other Purpose	-1.728	-2.632
	(0.168)***	(0.927)***
Secured	0.717	0.881
	(0.041)***	(0.090)***

Z Score	-0.041	-0.074
	(0.019)**	(0.062)
LIBOR	-0.062	
	(0.007)***	
Bond Rating	-0.084	
	(0.054)	
Predicted KLD	-1.016	
	(0.077)***	
Adjusted R2	0.476	
Number of Observations	3858	

Table 7

Regression of Log-Spread against Endogenized KLD Score Allowing for Fixed Bank Effects

This table shows the coefficients from a regression of the log-spread on KLD score and controls for borrower characteristics and loan features. The dependent variable is the natural logarithm of the all-in-drawn spread. Descriptions for all explanatory variables are given in the Appendix. Model 1 uses the predicted KLD coefficient from the ordered logistic regression (Model 1- Table 4). Predicted KLD in model 1 is the probability of having a KLD score greater than negative 1. Predicted KLD(2) is the probability of having a KLD score greater than positive 1. Bank fixed effects are controlled in model 2 through identifying each facility's administration agent and its ultimate parent. The different number of observations is caused by the removal of the loan facilities that show up in the sample fewer than 10 times. 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 Industry and Year dummies are included in all regressions but are not reported.

	Model 1 (From Table 5- Model 1)	**Model 2 Bank Fixed Effects added**
Intercept	12.175	13.726
	(0.407)***	(0.416)***
Maturity	0.016	0.007
	(0.006)***	(0.006)
Market/Book	0.037	0.023
	(0.019)**	(0.017)
Debt/Equity	0.101	0.008
	(0.024)***	(0.017)
Loan Concentration	-0.066	-0.140
	(0.013)***	(0.015)***
Firm Size	-0.266	-0.288
	(0.013)***	(0.013)***
LIBOR	-0.038	-0.019
	(0.020)*	(0.021)
Z Score	-0.048	-0.079
	(0.014)***	(0.014)***
Revolver	0.580	-0.240
	(0.103)***	(0.039)***
Other	0.854	-0.278
	(0.137)***	(0.097)***
Bridge	0.949	0.108
	(0.135)***	(0.097)
Repay	-0.809	-0.627
	(0.184)***	(0.144)***
Syndicate	-0.002	0.020
	(0.065)	(0.110)
Takeover	-0.625	-0.425
	(0.185)***	(0.146)***
Corporate Purpose	-0.794	-0.617
	(0.183)***	(0.142)***

Other Purpose	-1.028	-0.847
	(0.184)***	(0.144)***
Secured	0.689	0.698
	(0.036)***	(0.035)***
Bond Rating	-0.014	-0.017
	(0.040)	(0.038)
Predicted KLD(1)	-1.828	-2.578
	(0.237)***	(0.240)***
Predicted KLD(2)	-0.891	-0.462
	(0.279)***	(0.276)*
Adjusted R2	0.633	0.701
Number of Observations	3800	2975

Table 8
Spread Differences using Matched Firms

Differences in log-spread are measured by matching firms using propensity scoring. The predicted KLD score from Table 3-model 2 is used as the single matching criterion. The propensity score of the treatment firm is matched (to four significant digits) to a firm in the control group. If more than one control firm matches, the control firm is randomly selected. If no control firms match to four significant digits, the treatment firm is dropped. The table displays the mean and standard deviation for each variable of interest. The p-value of the non-parametric Wilcoxon rank sum test measures the difference between the samples. In Model 1, the treatment group is firms with KLD scores less than negative 4. In Model 2, the treatment group is firms with KLD scores less than negative 1. The third model uses firms with KLD scores greater than 1. The final model uses firms with KLD scores greater than 7 as the treatment.

		Model 1			**Model 2**			**Model 3**			**Model 4**		
		KLD<-4 is Treatment			**“Bad” is treatment**			**“Good” is treatment**			**KLD>7 is Treatment**		
Variable	**Group**	**Mean**	**Std**	**Wilcoxon p-value**	**Mean**	**Std**	**Wilcoxon p-value**	**Mean**	**Std**	**Wilcoxon p-value**	**Mean**	**Std**	**Wilcoxon p-value**
Log Spread	Control	4.155	0.989		4.019	0.899		4.067	0.831		3.773	0.928	
	Treatment	4.359	1.048		4.133	0.744		3.986	0.813		4.175	1.278	
	Difference	-0.205		0.095	-0.114		0.045	0.082		0.118	-0.402		0.130
Size	Control	23.039	0.902		22.471	1.022		22.438	1.281		23.400	1.551	
	Treatment	23.006	0.995		22.386	1.000		22.438	1.301		23.821	1.441	
	Difference	0.033		0.470	0.085		0.419	0.000		0.468	-0.421		0.251
Debt/Equity	Control	0.775	1.028		0.441	0.547		0.373	0.391		0.537	0.881	
	Treatment	0.840	1.156		0.401	0.405		0.367	0.389		0.385	0.624	
	Difference	-0.065		0.424	0.040		0.488	0.007		0.419	0.153		0.412
Market/Book	Control	1.623	0.673		1.763	0.790		1.855	0.941		2.017	1.197	
	Treatment	1.492	0.681		1.742	0.757		1.888	0.926		2.329	0.812	
	Difference	0.131		0.052	0.021		0.392	-0.033		0.193	-0.312		0.213
Bond Rating	Control	0.923	0.268		0.928	0.259		0.865	0.343		0.941	0.239	
	Treatment	0.912	0.285		0.843	0.365		0.881	0.324		1.000	0.000	
	Difference	0.011		0.395	0.085		0.010	-0.017		0.271	-0.059		0.160

		Model 1			Model 2			Model 3			Model 4		
		KLD<-4 is Treatment			"Bad" is treatment			"Good" is treatment			KLD>7 is Treatment		
Variable	**Group**	**Mean**	**Std**	**Wilcoxon p-value**	**Mean**	**Std**	**Wilcoxon p-value**	**Mean**	**Std**	**Wilcoxon p-value**	**Mean**	**Std**	**Wilcoxon p-value**
Z Score	Treatment	1.148	0.825		1.401	0.831		1.451	1.020		1.747	0.714	
	Control	1.210	0.910		1.349	0.897		1.382	0.903		1.665	0.990	
	Difference	0.061		0.453	-0.052		0.224	-0.070		0.328	-0.082		0.698
KLD Score	Control	-0.044	2.724		0.895	1.934		-1.215	2.029		-2.206	3.796	
	Treatment	-5.923	0.846		-3.098	1.508		3.198	1.393		8.529	0.615	
	Difference	5.879		<0.001	3.994		<0.001	-4.413		<0.001	-10.740		<.0001
N		91			153			303			34		