Accounting Transparency and the Term Structure of Credit Spreads

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Abstract

Theory predicts that the quality of a firm's information disclosure can affect the term structure of its corporate bond yield spreads. Using cross-sectional regression and Nelson-Siegel yield curve estimation, I find that firms with higher AIMR disclosure rankings tend to have lower credit spreads. Moreover, this "transparency spread" is especially large among short-term bonds. These findings are consistent with the theory of discretionary disclosure as well as the incomplete accounting information model of Duffie and Lando (2001). The presence of a sizable short-term transparency spread can attenuate some of the empirical problems associated with structural credit risk models.

One of the most important questions in credit risk research is what constitute the corporate bond yield spread. Ever since the seminal work of Merton (1974) that pioneered the structural paradigm in credit risk modeling, researchers have attempted to justify the size of the credit spread, apparently without much success. For example, the early study by Jones, Mason and Rosenfeld (1984) shows that the Merton model severely underpredicts spreads across a large sample of bonds. While the latest variants of the Merton model have managed to raise the level of the predicted spread, systematic pricing errors remain. Eom, Helwege and Huang (2001), for instance, note that many of the structural models still underpredict the spreads on short-term and safer bonds.

Researchers have also come to the realization that a substantial part of the credit spread is, in fact, due to factors other than the default risk of the bond issuer. Direct and indirect evidences abound, with a number of recent studies highlighting the role of state taxes and liquidity premium. For example, for investment-grade corporate bonds, Elton et al. (2001) estimate a state tax premium on the order of 40 bp, and Perraudin and Taylor (2002) and Houweling, Mentink and Vorst (2002) estimate a liquidity premium on the order of 20 bp. Huang and Huang (2002) calibrate several structural models to historical default probabilities. Applying standard estimates of the equity risk premium, they conclude that less than 25% of the credit spread is actually due to credit risk, with the percentage higher for junk bonds and less for short-term bonds. Alternatively, using a reduced-form model with standard credit risk premium adjustments, Jarrow, Lando and Yu (2001) find that bond-implied conditional default probabilities are in line with historical estimates at long maturities, but are too high at short maturities. If anything, these studies indicate that our understanding of the credit spread is far from complete. In particular, the behavior of the credit spread at short maturities should be a focal point of future research.

This paper contributes to the extant literature by empirically identifying and analyzing a heretofore ignored component of the default spread—in this case due to the imperfect observation of firm value. It is well-known that reported total assets, as reflected through mandatory or voluntary corporate disclosures, are at best an imprecise measure of the true firm value.[1] Yet virtually all of the existing structural credit risk models continue to define default as the first passage of a

[1]Recent corporate accounting scandals, such as those involving Enron, Authur Andersen, Worldcom, Adelphia, Global Crossing, Tyco, and Xerox, only serve to perpetuate this belief. Perhaps as further evidence of shoddy audit work, the Wall Street Journal recently publicized a study that shows of the 228 publicly traded companies that filed for Chapter 11 bankruptcy protection between 2001 and 2002, 42 percent were given a clean bill of health by auditors within a year of the filing.

perfectly measured firm value to a default boundary. Duffie and Lando (2001, DL) is a notable exception—they show that the lack of precise knowledge of a firm's value process can lead to a different prediction on the shape of the term structure of credit spreads.[2] The most dramatic implication is that firms with perfect asset reports have zero credit spreads as maturity approaches zero, while firms with noisy asset reports have positive credit spreads under the same limit. With conventional parameters, this gap becomes substantial only when maturity is less than approximately 3 years. Therefore, a "transparency spread" could conceivably help to resolve the short-end credit spread puzzle in structural models.[3]

Following an extensive accounting literature on corporate disclosure quality, I use the annual AIMR corporate disclosure rankings to proxy for the perceived precision of the reported firm value. This ranking represents financial analysts' assessments of the completeness, clarity, and timeliness of firms' disclosure policies. It is the most extensive measure of disclosure quality that one can find, spanning the period from 1979 to 1996 and covering hundreds of firms and more than 30 industries each year.

Two methods are used to estimate the effect of perceived accounting transparency on the term structure of credit spreads. In the first approach, I adopt a cross-sectional regression framework, where the dependent variable, the credit spread, is defined as the difference between the yield to maturity on a corporate bond and the interpolated constant maturity Treasury yields. This is regressed on disclosure ranking, controlling for structural variables such as equity volatility and debt to equity ratio, and liquidity proxies such as issue size and bond age. Term structure effects of disclosure quality are specified by a piecewise linear function of bond maturity, allowing for differential impact at short, medium, and long horizons. Although panel data are available, a cross-sectional regression approach is preferred because disclosure quality does not vary much in the time-series. More importantly, credit spread changes in the time-series are mostly driven by market factors that tend to overwhelm the effect of firm-level characteristics.[4]

[2] DL assume the reported assets as the true firm value plus a normal noise term. However, imprecisely observed firm value can also be modeled in other ways. For example, Cetin et al. (2002) assume that investors can only access a coarsened version of the manager's information set. Giesecke (2001) models an imperfectly observed default boundary. Collin-Dufresne, Goldstein and Helwege (2002) assume that firm values are observed with a lag. In CreditGrades (2002), an industry implementation of the Merton model, short-term spreads are almost entirely generated by the default barrier uncertainty.

[3] Unlike liquidity and tax spreads, the transparency component is a part of the *default* spread. It therefore does not help to boost spreads in a reduced-form model that takes the physically observed default rate as a given input.

[4] Collin-Dufresne, Goldstein and Martin (2001) suggest, and King and Khang (2002) confirm, that the time-series

While the regression framework offers flexible specifications and efficient use of the data, its scope for estimating potentially nonlinear term structure effects is limited, and neither is its use of yield to maturity a clean way to measure the true bond risk for a given horizon. On the other hand, the Nelson and Siegel (1987) yield curve estimation procedure is particularly suitable for this purpose. Hence, in the second approach, I sort bonds into groups by their issuers' leverage ratio, equity volatility, and disclosure ranking, and then estimate Nelson-Siegel yield curves for each group. A similarly estimated Treasury yield curve is subtracted from these, giving rise to a collection of spread curves. A comparison of the spread curves across, say, the high and low disclosure groups with the same leverage ratio and equity volatility groupings, allows one to see the impact of perceived accounting transparency on the entire credit spread term structure in a graphical way.

I do not use credit rating to control for the cross-sectional determinants of credit spreads other than disclosure quality. This is because the major rating agencies claim to have incorporated the quality of information disclosure in their credit ratings. It is possible, however, to test the validity of this claim. While the two are certainly related, I show that credit rating does not fully absorb the effect of information disclosure—among issuers with the same credit rating, those with higher disclosure rankings have lower credit spreads.

Despite the availability of analytic formulas for zero-coupon bond prices, I do not attempt to conduct any structural estimation of the DL model. Instead, only qualitative predictions of the model are taken to the data. This is because the DL model is based on many stylized assumptions that abstract away from realistic features of credit spreads.[5] However, the intuition that a firm is close to instantaneously default-free if one is reasonably sure that its value is above some type of default boundary should survive even in more complex settings.[6] Ultimately, how strongly the term

variation in credit spreads is determined primarily by bond market factors. On the other hand, King and Khang show that the cross-sectional variation in credit spreads is mostly explained by leverage ratio, equity volatility, issue size, and bond age. The first two play an important role in structural credit risk models, while the last two are thought to be proxying for a liquidity component.

[5] For example, the term structures of credit spreads in DL are downward-sloping for all but short maturities while estimations show that they are typically upward-sloping [see Helwege and Turner (1999)]. This can be rectified if we assume stationary leverage ratios so that the default boundary migrates upward over time along with firm value [see Collin-Dufresne and Goldstein (2001)]. The DL model also ignores stochastic interest rate and other determinants of bond spreads, such as liquidity, taxes, and variables proxying for general bond market conditions.

[6] An exception is when firm value contains a jump component [see Zhou (2001)]. However, it is conceivable that there could be a negative association between the AIMR disclosure score and the likelihood and magnitude of downward jumps in firm value. In this case, a similar relationship between disclosure quality and the credit spread term structure remains. This question is addressed in a companion paper by linking disclosure quality with the

structure of credit spreads relates to perceived accounting transparency is an empirical question.

This paper is closely related to a large body of accounting literature employing the same AIMR disclosure rankings data. Motivated by the theoretical work on discretionary disclosure, accounting researchers have focused on the effect of corporate disclosure quality on the cost of capital. The theory of discretionary disclosure, starting with Verrecchia (1983), Darrough and Stoughton (1990), and Feltham and Xie (1994), predicts that firms will withhold private information when disclosure is costly. More recently, Shin (2003) shows that a "sanitization" policy, in which only good news is disseminated, can be supported in equilibrium.[7] This theory suggests that the reported firm value is upward-biased, with the extent of the bias negatively related to disclosure quality. As a result, investors will penalize a lower disclosure quality by charging a higher spread on the firm's debt. In contrast, in the DL incomplete accounting information model where a similar conclusion is reached for only the short-end of the term structure, accounting reports are an unbiased version of firm value.

While studies such as Sengupta (1998) and Mazumdar, Sarin and Sengupta (2002) have identified a negative relation with the cost of debt, they differ from this paper in several key aspects. First, by ignoring the maturity dimension of bonds and bank loans, these studies are silent on potential term structure effects that can be quite dramatic according to DL. Second, the focus on the cost of capital leads to the use of offering yields in these studies, while this paper uses secondary market yields due to its focus on bond pricing. To the extent that security issuances, often accompanied by self-interested disclosures, are plagued by adverse selection and the lemons problem, offering yields will be much more sensitive than secondary yields to the perceived accounting transparency. Therefore, in some sense, this paper provides a lower bound on the effect of disclosure quality on the term structure of credit spreads.[8]

The main part of this paper is organized as follows. Section 1 presents a brief description of the DL model and uses comparative statics to illustrate the term structure effects of perceived accounting transparency. Section 2 documents the major variables used in later analysis and explains the construction of the data sample. Section 3 discusses regression and yield curve estimation results.

option-implied volatility skew.

[7] Consistent with theory, Lang and Lundholm (1993) find that the AIMR disclosure score is increasing in firm size and performance, and higher for firms issuing securities.

[8] To be sure, adverse selection in secondary market trading can also affect the required return on a security. For a simple theoretical model and some numerical illustrations of the size of the effect, see Gârleanu and Pedersen (2003).

Section 4 concludes.

1 Testable Hypotheses

Duffie and Lando (2001, DL) are the first to investigate the role of incomplete accounting information in structural credit risk models. Their intuition is a strikingly simple one. In traditional structural models, the firm value is a perfectly observable diffusion process. Conditional on the firm value being a finite distance above a suitably defined default boundary, the probability that it will cross this boundary in the next Δt is $o(\Delta t)$, implying that credit spreads will disappear as bond maturity shrinks to zero.

In contrast, if firm value is periodically reported with noise, investors can compute a distribution of total assets conditional on the noisy reports plus whether the firm is currently in default. The distinguishing feature is that now there is a small probability that the true firm value actually lies close to the default boundary and can cross over within a short period of time. According to DL, this simple mechanism is enough to produce a default probability within the next Δt that is $O(\Delta t)$, giving rise to a positive credit spread at zero maturity.

[Insert Figure 1 here]

These insights are borne out in Figure 1, which reproduces the base case of DL.[9] The first panel presents the term structure of credit spreads, and the second panel the distribution of firm value conditional on the reported assets and survival, for various accounting precisions (the parameter a measures the standard deviation of the normal noise added to the true firm value). When $a = 0.01$, firm value is reported with an almost perfect precision. We see that the credit spread approaches zero as maturity shortens to zero. With almost perfectly observed firm value above the default threshold, the probability that the firm value is in fact near the boundary and can cross it in a short period of time is minuscule. As a assumes larger values, this probability becomes more substantial, resulting in positive limits instead.

[Insert Figure 2 here]

[9] To generate Figures 1 and 2, I use a slighted modified DL model with a recovery of Treasury assumption. This avoids their double integral and preserves all essential results. Specific formulas and numerical values used in these figures are available upon request.

Additional implications are illustrated in Figure 2. The first panel is the DL base case, the second assumes a lower asset volatility, and the third assumes higher lagged and current reported assets, capturing the effect of lower firm leverage. Since credit spreads always have to reach zero at the short-end under prefect transparency, Panels 2 and 3 are a "compressed" version of Panel 1, which indicates that the absolute magnitude of the effect of transparency is lower for higher quality debt.

Realistic credit spread term structures may depart from those of the DL model in several ways. First, they are usually upward-sloping. As mentioned earlier, this can be justified by changing the flat default barrier in the DL model into one that grows at the same rate as the firm value, maintaining a stationary leverage ratio. Second, since the credit spread may contain liquidity and tax premiums, even in the case of perfect transparency one still may not have zero credit spread in the short-end. Assuming that liquidity and tax premiums are relatively insensitive to the cross-sectional variation in credit quality, this would suggest that transparency premium is proportionally more important for lower quality debt. Third, the theory of discretionary disclosure may produce different results from the DL model, which assumes an exogenous level of transparency.

Panel 4 of Figure 2 presents a scenario which illustrates the difference between the DL model and one that considers discretionary disclosure. In this scenario, the current report is substantially lower than the lagged report, which leads to the counterintuitive result that a higher transparency is associated with higher spreads for most of the term structure. To understand this result, I note that in the first three cases, the conditional distribution of firm value is more or less centered around the current report (see the conditional density panel in Figure 1). One can therefore consider the true firm value as an approximately "unbiased version" of the current report. Since bond price is a concave function of firm value under complete information, Jensen's inequality implies that bond price (credit spread) would decrease (increase) when accounting reports become less precise. In the last case, firm value starts relatively high and is subsequently reported to be low. With a high accounting precision of $a = 0.01$, the starting firm value is irrelevant.[10] However, as a increases, the current report becomes more of an aberration due to accounting noise than a measure of true firm value. The mass of the conditional distribution would then shift to higher firm values, causing credit spreads to decrease. With discretionary disclosure, this case would not arise because firms will

[10] Note that the term structures in Panel 1 and Panel 4 corresponding to $a = 0.01$ are almost identical.

optimally choose not to reveal the bad news in the first place. In other words, this case highlights the importance of an extension of the DL model where the quality and timing of disclosures become an endogenous choice on the part of the firm.

The complexities of the issue, as illustrated in the preceding discussion, suggest that fitting the pricing formulas of the DL model may not be the most suitable approach here. To avoid potential misspecifications of the model, it seems appropriate to follow a more flexible approach such as linear regression or yield curve estimation. To this end, one first needs to formulate testable hypotheses that bring out the qualitative predictions of the various theories on disclosure. The main hypotheses considered in this paper are:

H1 Firms with higher perceived accounting transparency have lower levels of credit spreads.

H2 This "transparency spread" is more pronounced at short maturities.

Of the above hypotheses, H2 is unique to the DL analysis. It is an untested hypothesis that can potentially be a step toward the resolution of a bigger puzzle in credit risk research. Hypothesis H1, attributed to the theory of discretionary disclosure, has found some empirical support from the accounting literature on the cost of debt. The term structure effect of discretionary disclosure, however, is less obvious. One can imagine that it would very much depend on the nature of information that a firm tries to conceal. A temporary shock to firm value, such as a one-time charge due to legal settlement or trading loss, affects the spreads on short-term debt more than those on long-term debt. A more permanent shock to firm value, such as a negative outlook on the firm's earnings growth rate, hardly affects its short-term debt spreads, but causes its long-term debt spreads to increase. The positive networth requirement, effectively part of the short-term debt covenant, suggests that firms have little incentive to conceal information that they may soon be forced to disclose.[11] This seems to indicate that discretionary disclosure would mostly affect long-term credit spreads.

One must note that these hypotheses should be understood with the qualification "other things equal," meaning that one ought to control for other cross-sectional determinants of credit spreads such as asset volatility, distance to default, bond liquidity, etc. Asset volatility and distance to de-

[11] For discussions on short-term debt and positive networth requirements, see Leland (1994) and Toft and Prucyk (1997).

fault are crucial ingredients of any structural credit risk models, including DL. The term structure of liquidity spreads may be downward-sloping according to Ericsson and Renault (2001), and thus could partly be responsible for the short-end credit spread puzzle. These control variables are especially important as corporate disclosure quality has been shown to depend on firm characteristics such as size and stock return performance.

I do not use credit ratings as a control variable because rating agencies specifically list the quality of information disclosure as a determinant of ratings. One can, of course, examine whether credit rating and disclosure quality are related and whether the former is a sufficient statistic for the latter in explaining credit spreads.

2 Data

To test the effect of accounting transparency on credit spreads, three separate data sources are required. First, an extensive data set of corporate and Treasury bond prices is needed to compute credit spreads. Second, there must be a way to reliably measure the accuracy of accounting information. Last but not least, one needs to control for issuer and issue characteristics that can affect credit spreads in the cross-section. In this section, I document the major variables used in later analysis and present some useful summary statistics of the sample.

1. Credit spreads (CS).

   I compute CS as the difference in yield to maturity between a corporate bond and a U.S. Treasury bond with the same maturity. Corporate bond yields are obtained from the Lehman Brothers Fixed Income Database described in Warga (1998). This database contains month-end bid quotes and other characteristics of individual corporate bonds, spanning the period 1973-1998. The associated Treasury yields are obtained by linearly interpolating Benchmark Treasury yields from Datastream for maturities of 1, 3, 5, 7, 10, and 30 years. These are available at the beginning of each month from 1986 onward.

2. Accounting transparency (DISC).

   Following an extensive accounting literature,[12] I use the annual ranking of corporate disclosure

[12] For more detailed accounts of this data, see Lang and Lundholm (1993, 1996), Welker (1995), Sengupta (1998), and Bushee and Noe (2000).

practices published by the Association for Investment and Management Research (AIMR) to measure the transparency of accounting information. The complete data set covers the period 1979-1996, with 8,735 firm-year observations.

Each year, the AIMR selects leading analysts to serve on industry subcommittees. These committees first meet to decide on the set of firms to be evaluated and the criteria for the assessment. Then, each member scores a firm on the basis of the adequacy, timeliness and clarity of its information disclosure on a scale of 0 to 100 in three categories: annual reports, quarterly reports, and investor relations. These scores are averaged across committee members and aggregated into a total disclosure score. To ensure a somewhat uniform standard, AIMR provides each committee with a comprehensive checklist of scoring criteria and guidelines on the weights for each disclosure category. The use of industry specialists and the consensus scoring process reduces the idiosyncratic element of the rankings. Furthermore, individual analyst scores are never made public, diminishing the incentive to manipulate rankings for personal gain.

Since bond investors are likely to be interested in all types of disclosures, I use total disclosure scores in subsequent analyses. I also follow Bushee and Noe (2000) and others in converting the raw total scores into industry percentile ranks using

$$\text{DISC} = \frac{100 \times (\text{number of firms in industry} - \text{rank of score})}{\text{number of firms in industry } - 1}. \tag{1}$$

As the scores given by different industry subcommittees may not be directly comparable, this is one way to "align" the scores across different industries.[13] For the purpose of matching with other data, including month-end credit spreads, I assume that the ranking for year t applies to the period from July 1 in year $t-1$ to June 30 in year t.

3. Maturity and duration (MAT and DUR).

   I include the maturity of a bond in order to describe the shape of the credit spread term structure. On average, the term structure of credit spreads is upward-sloping [see Helwege

[13] This method of "alignment" eliminates any industry differences in the disclosure scores. Another approach is to interpret the industry differences as actually meaningful. For example, appealing to the care that AIMR exercises in ensuring the uniformity of the scoring process across industries, Sengupta (1998) and Welker (1995) use raw total scores in their analyses. In Section 3, I compare the industry percentile ranks with the raw scores and use the latter as a robustness check on the regression results. The coverage of the raw scores is only half as large as that of the industry percentile ranks, however.

and Turner (1999)]. Therefore, longer maturity should be associated with higher yield spreads. However, in subsequent analyses I will mostly use modifications of the maturity variable in order to define a piecewise linear term structure.

Also as a robustness check in Section 3, I use the duration, instead of maturity, of a bond to account for the fact that most of the bonds used in the yield spread regressions bear coupons. Although the Nelson-Siegel yield curve estimation is a more satisfying alternative, the use of bond duration may present a partial fix to this problem in a regression setting.

4. Leverage (LEV).

Structural credit risk models predict that the distance between current firm value and the default boundary is positively related to credit spreads. This "distance to default" can be proxied by the firm's leverage ratio. In this paper I define firm leverage as

$$\text{LEV} = \frac{\text{book value of debt}}{\text{market value of equity} + \text{book value of debt}}. \tag{2}$$

For each month in the sample period, the market value of equity is obtained by multiplying the month-end stock price and the number of shares outstanding, both available from CRSP. The book value of debt is taken to be total debt from COMPUSTAT, reported annually prior to 1992 and quarterly since then. Because debt levels are fairly stable over time, I linearly interpolate monthly figures.

5. Equity volatility (VOL).

Structural models also predict that the volatility of firm value is positively related to credit spreads. In the absence of a market-based measure of firm value, I choose equity volatility instead. This would be a function of both asset volatility and leverage, but the link to asset volatility is monotonic. Specifically, for each month in the sample period I compute the annualized standard deviation of daily stock returns over the preceding 12 months. The daily stock returns from CRSP are used to compute this historical measure of volatility.

6. Bond age and amount outstanding (AGE and LSIZE).

As liquidity proxies, I obtain bond age and issue size from the Lehman database. AGE is defined as the difference (in years) between the settlement date and the issuing date. LSIZE is defined as the logarithm of the dollar amount outstanding of the bond issue (in million dollars). Bond age has been shown to relate positively, and issue size negatively, to credit spreads [see Warga (1992) and Perraudin and Taylor (2002)]. Generally speaking, the older a bond becomes, the less often it will transact, implying a lower price and a higher spread. On the other hand, a larger issue size is associated with more investor interest, more secondary market trading, and consequently, lower spreads. A larger issue size may also benefit from the economy of scale in underwriting costs.

7. Credit rating (RTNG).

   For each month-end observation in the Lehman database, credit rating information is provided. This is given in numerical grades: 1-Aaa+, 2-Aaa, 3-Aa1, 4-Aa2, 5-Aa3, 6-A1, 7-A2, 8-A3, 9-Baa1, 10-Baa2, 11-Baa3, etc. I use Moody's rating unless it is not available, in which case S&P's rating is substituted. In Section 3 I test whether credit rating subsumes the explanatory power of disclosure for credit spreads.

These major variables can be classified as follows:

Dependent variable—CS

Issuer characteristics—DISC, LEV, VOL

Issue characteristics—MAT, DUR, AGE, LSIZE, RTNG

To construct the sample, I first select a subset of corporate bonds from the Lehman database. Following common practice, for each month in the database I choose industrial corporates, excluding callable, putable, and sinkable bonds as well as those with matrix quotes, or with maturities less than 1 year or greater than 30 years.[14] I then merge the subset of corporate bond yields and issue characteristics with the data on disclosure, leverage ratio, equity volatility, and Treasury yields. To ensure sufficient dispersion in disclosure quality in the survived sample of firms, those industries (AIMR classification) with a zero dispersion in disclosure quality are eliminated. I also find that

[14]Financial bonds are typically treated separately from industrial bonds due to substantial differences in the capital structures of financial and industrial firms. However, there are not enough financial bonds after merging with the disclosure data. I exclude bonds with less than one year in maturity because their prices are less reliable. For example, bonds are automatically dropped from Lehman bond indices when their maturities are less than one year. See Duffee (1999) and Elton, Gruber, Agrawal and Mann (2001) for more details on the selection criteria.

prior to 1991 the data do not provide enough complete observations on all major variables (fewer than 100 bonds surviving). Therefore, I focus on January 1991 to June 1996, a period of 66 months.

[Insert Table 1 here.]

Table 1 presents the total sample size over time as well as the breakdown into credit rating and maturity subsamples. These figures are noted because subsequent regression and yield curve analyses are often performed for these subgroups. We see that the sample size generally increases over time, starting with just over 100 bonds at the beginning of 1991 and ending with about 250 bonds in 1996. These bonds are more or less evenly distributed among short-term (maturity less than 5 years), medium-term (between 5 and 10 years), and long-term (between 10 and 30 years) subgroups. In addition, close to half of the bonds are rated A, and the rest are evenly split between Aa or above and Baa bonds. Very few are rated below investment-grade.

[Insert Table 2 here.]

[Insert Table 3 here.]

Summary statistics of the major variables are presented below. As shown in Table 2, the average bond issue in the entire sample period is associated with a credit spread of 90 bp, a maturity of 10.7 years, a total disclosure score (industry percentile rank) of 65.4, a leverage ratio of 32.5%, an annualized stock return volatility of 25.8%, an age of 2.7 years, an amount outstanding of $210 million, and a Moody's credit rating of A2 (numerical grade of 7 in the Lehman data set). Table 3 presents the average monthly correlations among the major variables in the entire sample period. Notably, the correlations between credit spread and the explanatory variables are mostly in agreement with theory. Furthermore, disclosure quality is negatively related to both leverage and asset volatility.

3 Empirical Tests

In this section I test the main hypotheses H1 and H2 using cross-sectional regressions and Nelson-Siegel yield curve estimations.

3.1 Cross-Sectional Regressions

3.1.1 The Level Effect

An important difference between this study and Sengupta (1998) is the use of secondary market yields versus the use of offering yields. The theory of discretionary disclosure suggests that accounting transparency would make a larger impact on offering yields due to a greater degree of information asymmetry around security issuances. Using a smaller sample from 1987 to 1991, Sengupta (1998) estimates that a 100 point increase in the raw AIMR disclosure score is accompanied by a 120 bp reduction in the offering yield. For secondary market yields one would expect the impact to be much less. After all, firms tend to disclose information prior to security offerings, while the Lehman bond database provides regular monthly quotes that are not anchored to any particular corporate event. To highlight this difference, I replicate Sengupta's study by estimating the following cross-sectional regression for each month in the sample period:

$$\mathrm{CS}_i = \alpha + \beta_1 \mathrm{DISC}_i + \beta_2 \mathrm{MAT}_i + \beta_3 \mathrm{LEV}_i + \beta_4 \mathrm{VOL}_i + \beta_5 \mathrm{AGE}_i + \beta_6 \mathrm{LSIZE}_i + \varepsilon_i, \qquad (3)$$

where DISC can be the raw AIMR disclosure score or a disclosure dummy variable that equals 1 if a firm's disclosure score ranks above the median of its industry cohort and 0 otherwise. The use of different definitions of the DISC variable facilitates comparison between existing studies and later analyses in this paper that use the disclosure dummy.

[Insert Table 4 here.]

Table 4 presents the estimation of equation (3) for the whole sample as well as for two subsamples. First, I note that the traditional structural variables, leverage ratio LEV and equity volatility VOL, are highly significant and quite stable across different sample periods and definitions of DISC. One of the liquidity proxies, AGE, is also highly significant. The other liquidity proxy, LSIZE, is of the right sign (negative) when statistically significant. I also note that the term structure is generally upward-sloping. There is no surprise here—the results merely confirm the finding by others that these variables can account for a major portion of the cross-sectional variation in credit spreads.

More importantly, Table 4 shows that the effect of disclosure on the overall level of secondary market yields is significantly weaker than that identified from offering yields. For example, a 100 point increase in the raw disclosure score is only associated with between 30 and 50 bp reduction in the yield spreads, depending on which sample period is used in the estimation. The effect is weaker in the first half of the sample and stronger in the second half. When the disclosure dummy is used in lieu of the raw score, the results are similar. Other things equal, over the second half of the sample high disclosure firms yield 19 bp less than low disclosure firms. Over the entire sample this gap is reduced by half, only because the effect is absent in the first half of the sample.

While these findings are consistent with the differences between primary and secondary bond markets, the regression equation (3) ignores the potentially unequal impact of disclosure quality on different parts of the term structure. It is unlikely to uncover the true extent of the relationship given what one knows from the DL analysis.

3.1.2 Term Structure Effects

To capture a potentially nonlinear term structure, I construct a piecewise linear function of bond maturity. This function has four "knots", respectively, at maturity equal to 0, 5, 10, and 30 years, essentially dividing the set of all bonds into short-term, medium-term, and long-term subsets. Denoting bond maturity by MAT, I define

$$\begin{aligned} z_1 &= \begin{cases} \text{MAT}, & 5 \geq \text{MAT} \geq 0, \\ 5, & 30 \geq \text{MAT} > 5, \end{cases} \\ z_2 &= \begin{cases} 0, & 5 \geq \text{MAT} \geq 0, \\ \text{MAT} - 5, & 10 \geq \text{MAT} > 5, \\ 5, & 30 \geq \text{MAT} > 10, \end{cases} \\ \text{and } z_3 &= \begin{cases} 0, & 10 \geq \text{MAT} \geq 0, \\ \text{MAT} - 10, & 30 \geq \text{MAT} > 10. \end{cases} \end{aligned} \tag{4}$$

A linear combination

$$a_0 + k_1 z_1 + k_2 z_2 + k_3 z_3 \tag{5}$$

represents a piecewise linear term structure, where a_0 is the intercept and k_1, k_2, and k_3 are the slope of the term structure between the knots.

A modified formulation allows easier identification of the transparency spread at various maturities. Let

$$\begin{aligned} m_0 &= 1 - \frac{z_1}{5}, \\ m_1 &= \frac{z_1}{5} - \frac{z_2}{5}, \\ m_2 &= \frac{z_2}{5} - \frac{z_3}{20}, \\ \text{and } m_3 &= \frac{z_3}{20}. \end{aligned} \tag{6}$$

A piecewise linear term structure with the same set of knots can be equivalently represented by

$$a_0 m_0 + a_1 m_1 + a_2 m_2 + a_3 m_3, \tag{7}$$

where a_0, a_1, a_2, and a_3 are the level of the term structure at the knots (respectively, 0-, 5-, 10-, and 30-year maturity).[15]

[Insert Figure 3 here.]

To see the effect of perceived transparency on the term structure, I define dm_n as the product of the disclosure dummy DISC and m_n, where $n = 0, \ldots, 3$, which gives the interaction effect between these two variables. The regression coefficients in front of these terms can be directly interpreted as the transparency spread, i.e. the gap between the high transparency and the low transparency term structures at the respective knot points. A graphical representation of (7) for the high and low transparency term structures is given in Figure 3.

According to the main hypotheses H1 and H2, we would expect to see a significant gap between the term structures of high and low disclosure firms at zero maturity, as reflected in a negative coefficient on dm_0. However, as maturity increases, their differences will diminish due to a higher term structure slope for more transparent firms at the short-end (see Figure 1). This is captured by a coefficient on dm_1 that is still negative, but somewhat smaller in magnitude than the coefficient on dm_0. At maturities beyond 5 years, the DL model predicts no difference between the two term structures. A transparency gap, however, is still expected at longer maturities due to Hypothesis H1. One would therefore expect to see negative coefficients on dm_2 and dm_3. However, the size of the transparency spread at longer maturities is still very much an open question. Theory, if any,

[15] To facilitate interpretation, this equation does not contain an intercept term. As a result, the usual adjusted R^2 is not reported when this equation is estimated.

provides little guidance on this issue.

[Insert Table 5 here.]

Hence, for each month in the sample period, I run the following cross-sectional regression:

$$\begin{aligned} \mathrm{CS}_i &= \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \\ &\quad \beta_8 \mathrm{LEV}_i + \beta_9 \mathrm{VOL}_i + \beta_{10} \mathrm{AGE}_i + \beta_{11} \mathrm{LSIZE}_i + \varepsilon_i. \end{aligned} \tag{8}$$

Apart from the disclosure and term structure related variables, I have included a set of regressors with the most explanatory power for credit spreads in the cross-section [see King and Khang (2002)]. The predicted relation between credit spreads and the independent variables is listed in Table 5.

[Insert Table 6 here.]

Table 6 summarizes the results of the cross-sectional regression (8). Similar to the results reported in Table 4, the effect of disclosure is absent during the first half of the sample, but becomes much stronger in the second half. Focusing on the third column of the table, the estimated term structure parameters imply that the difference between low and high disclosure term structures is 31 bp at maturity zero, 11 bp at 5 years, 14 bp at 10 years, and 34 bp at 30 years.[16] All of these estimates are significant at the 1 percent level. The 31 bp spread at zero maturity represents a significant increase over the 19 bp overall level effect estimated in Table 4. Its size is substantial considering that the average credit spread in the sample period is only 90 bp. Certainly, the magnitude indicates that this is a source of investment-grade credit spread perhaps no less important than those identified by other researchers, such as liquidity and tax components.

It is also noted that the somewhat smaller estimates at the 5-year and 10-year maturity are consistent with the DL prediction that the transparency spread would narrow at longer maturities. However, that the gap widens at the 30-year maturity, reaching a magnitude of 34 bp, is a pattern not predicted by the DL analysis.[17] I note that this is consistent with the hypothesis that firms hide information that would adversely affect their long-term outlook.

[16] For the entire sample, the transparency spread is a weaker 11 bp at maturity zero, 3 bp at 5 years, 9 bp at 10 years, and 13 bp at 30 years. For the first half of the sample, the effect is ambiguous, at -12 bp at maturity zero, -6 bp at 5 years, 4 bp at 10 years, and -11 bp at 30 years.

[17] Of course, since 30 years is the maximum maturity in the data set, the transparency spread at 30 years generally overstates the effect of transparency on long-term bonds (10-30 year maturity). A better gauge for this is perhaps the average of the transparency spreads at 10 and 30 years, which closely approximates the transparency spread at the median of the maturities in this maturity bucket.

To the extent that there is a term structure of liquidity spreads, the estimated term structures may be sensitive to the inclusion/exclusion of liquidity proxies. In principle this should affect the short-end more since with a smaller maturity the sample should mostly consist of older bonds approaching the end of their lives (hence homogeneous in having higher liquidity risk). Yet Table 6 shows no significant change in the transparency gaps and only parallel shifts in the term structure estimates when excluding AGE and LSIZE. Combined with the fact that these liquidity proxies are significant when included, I conclude that the term structure of liquidity spreads is flat and unlikely to affect the main inference.

A related complication for short-term bonds is that their greater age potentially allows investors more time to learn about the quality of their issuers, in turn leading to higher sensitivity to disclosure quality. To address this concern, I note that short-term bonds (with maturity less than 5 years) in the sample have an average age of 3.3 years compared to 2.7 years for all bonds. It seems unlikely that this small difference is responsible for the substantially larger short-term transparency spread. Furthermore, this explanation is inconsistent with offering yields being even more sensitive to disclosure quality, as it implies that investors would have had no time to learn the relevant parameters.

3.1.3 Nonlinear Effects

There are several reasons to believe that the relationship between disclosure and credit spreads should be conditioned on the credit quality of the issuer. Take firm leverage and volatility for example. Figure 2 shows that disclosure quality has a smaller effect on credit spreads for low leverage and volatility firms simply because the overall level of the spread is lower. Furthermore, structural models tend to impart a nonlinear relation between key inputs, such as leverage and volatility, and credit spread. Therefore, for each month in the sample period, I separate the firms into high and low leverage and volatility groups by the respective medians, and then perform the regression in equation (8) for each group.[18]

[Insert Table 7 here.]

An obvious conclusion from Table 7 is that disclosure quality has no effect on higher quality

[18] Since the effect of disclosure is stronger in the second half of the sample period, the remaining analyses focus on the period from July 1993 to June 1996.

issuers. For example, for the low leverage group the estimates imply a transparency spread of -5 bp at zero maturity, 6 bp at 5 years, 6 bp at 10 years, and 2 bp at 30 years. For the low volatility group the numbers are, respectively, 1, 5, -3, and 15 bp. Some of these estimates, in particular those closer to zero, are not significant at conventional significance levels. The average credit spread for these groups is about 60 bp, between the typical level of spreads on Aa- and A-rated bonds. It seems that very little of this average spread is caused by differences in disclosure quality.

In contrast, for the high leverage and volatility groups the effect of disclosure quality is dramatic. For the high leverage group, the transparency spread is 102 bp at zero maturity, 28 bp at 5 years, 25 bp at 10 years, and 63 bp at 30 years. For the high volatility group the numbers are, respectively, 60, 9, 19, and 39 bp. Compared with the cases with low leverage and low volatility, these estimates have much higher t-statistics, and are all significant at the 1 percent level. The average credit spread for these groups is about 110 bp, between the typical level of spreads on A- and Baa-rated bonds. Therefore, transparency spread is a major component of short-term credit spreads for a significant portion of investment-grade bonds.

It is possible that the lack of significance of the transparency gap in low leverage and volatility groups is due to less variation in the disclosure variable among these groups. In an extreme case, firms with below-median leverage or volatility all have perfect disclosure scores, and a regression would not be able to identify any relation between disclosure and credit spread. I check summary statistics each month and look for differences in the dispersion of disclosure scores between the low and the high groups. As expected from the small correlation between DISC and VOL (see Table 3), there is virtually no difference when sorting by volatility. There is a large difference when sorting by leverage, but the low leverage group still exhibits substantial variations in disclosure scores with a typical mean of 80 and standard deviation of 20, in contrast with 60 and 30 for the low group.

3.1.4 Credit Rating

In the previous regressions I do not use credit rating in any way. This is because rating agencies claim that credit rating already contains information regarding perceived accounting transparency. The validity of this claim can be tested in two ways. First, one can conduct a cross-sectional regression with credit rating (RTNG) as the dependent variable. Since it is conceivable that firms with bad accounting quality and zero leverage will probably have a high credit rating and never go bankrupt, I condition the estimation on firm leverage and equity volatility as in Table 7. Second, one can replicate the cross-sectional credit spread regressions with RTNG as an additional independent variable. This allows one to check whether disclosure quality continues to have the same impact on credit spreads when credit rating is included.

[Insert Table 8 here.]

Table 8 presents the estimation of the following regression equation:

$$\text{RTNG}_i = \alpha + \beta_1 \text{DISC}_i + \beta_2 \text{MAT}_i + \beta_3 \text{LEV}_i + \beta_4 \text{VOL}_i + \beta_5 \text{AGE}_i + \beta_6 \text{LSIZE}_i + \varepsilon_i, \tag{9}$$

where DISC is the disclosure dummy variable and RTNG is credit rating in numerical grades following the convention of the Lehman database. Overall, the results show that the disclosure quality of an issuer indeed influences the credit rating of its debt. The unconditional regression, presented in the first column, shows that a firm can improve its credit rating by about half a notch (-0.45) if it can elevate its disclosure quality above the industry median. A closer look also reveals that the results are conditional on the credit quality of the issuer. For low quality issuers, represented by the high leverage or high equity volatility groups, the effect doubles (-1.27 or -0.82). On the other hand, for high quality issuers disclosure quality has no effect on credit ratings (-0.05 or -0.006, neither significant at conventional significance levels).

[Insert Table 9 here.]

Table 9 presents the estimation of the following regression equation:

$$\begin{aligned} \text{CS}_i \quad = \quad & \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \\ & \beta_8 \text{LEV}_i + \beta_9 \text{VOL}_i + \beta_{10} \text{AGE}_i + \beta_{11} \text{LSIZE}_i + \beta_{12} \text{RTNG}_i + \varepsilon_i. \end{aligned} \tag{10}$$

When using linearly transformed versions of equations (10) and (8) that include an intercept term, the adjusted R^2 has increased substantially with the inclusion of the RTNG variable. Simultaneously, however, the explanatory power of leverage and volatility has been reduced. This is consistent with credit rating being determined from traditional structural variables plus information not captured by the major variables included in this study. I also note that the inclusion of credit rating has not rendered the disclosure measure irrelevant for the low quality issuers. In fact, for the high leverage group the transparency spread is 51 bp at zero maturity, 12 bp at 5 years, 16 bp at 10 years, and a wider 46 bp at 30 years. For the high volatility group, these figures are, respectively, 52, 2, 8, and 32 bp. The effects appear to be weaker than those identified in Table 7. But with the exception of the two closest to zero, all estimates are significant at the 1 percent level. In summary, credit rating is indeed correlated with the disclosure quality of the issuer. However, the term structure effect of disclosure quality on credit spreads remains even after considering the information contained in credit ratings.

3.1.5 Robustness of the Results

To the extent that industry differences in the disclosure scores represent actual differences in industry-wide disclosure practice rather than the idiosyncracies of the industry subcommittees, the raw scores may be a better starting point for the preceding analysis. Over the period where the two data sets overlap (1986-1996), the fraction of variation in the raw scores attributed to industry differences is 47 percent, suggesting significant difference in the two measures. The average correlation between the two over the same period is only 64 percent, reinforcing this point. Therefore, I re-run the regressions in Tables 6 and 7 with disclosure dummies constructed from raw scores instead of percentile ranks.

In addition, I repeat the previous analysis with term structure variables defined from duration rather than the maturity of the bond. As mentioned in Section 2, this can help to alleviate problems caused by coupon bonds and yield to maturity as the risk measure.

[Insert Table 10 here.]

Both sets of results are presented in Table 10 in the form of the transparency spread at various maturities/durations. The original results, summarized from Tables 6 and 7, are presented in Panel 1 for comparison. The transparency spread at the 30-year maturity/duration is not included because only a small fraction (less than 15 percent) of bonds have duration between 10 and 30 years, which leads to low power on the estimates for dm_3.

Overall, Table 10 supports the same patterns documented above: 1) There is a large and significant transparency spread at zero maturity, which narrows at longer maturities. 2) This transparency spread is more significant for issuers with higher credit risk. Although the estimates in Panels 2 and 3 are somewhat smaller in magnitude than those in Panel 1, their statistical significance remains. In the case of bond duration (Panel 2), the transparency spread clearly decreases at the 5-year duration and then widens at the 10-year duration. The widening spread at longer maturities is not robust, however, when raw disclosure scores are used instead of industry percentile ranks (Panel 3).

As a last robustness check of the regression results, I include the default probability metric as used by Vassalou and Xing (2003) in addition to firm leverage and equity volatility in the cross-sectional regressions.[19] This is essentially a nonlinear transformation of the leverage and volatility variables as prescribed by the Merton (1974) structural model. While this may understandably reduce the explanatory power of leverage and volatility, results not presented here show that the transparency spreads are not affected.

3.2 Nelson-Siegel Yield Curve Estimation

As a further robustness check of the regression results, in this subsection I extract Nelson-Siegel yield curves from the monthly subsamples.

3.2.1 Methodology

Although I have adapted the linear regression framework to the estimation of an inherently nonlinear object and uncovered some serious evidence supporting the major hypotheses H1 and H2, there are more appropriate tools to address the same problem. The main advantages of the Nelson and Siegel (1987) approach are: 1) an entire yield curve is estimated instead of the piecewise linear approximation obtained with regressions; 2) the discount function is used in the estimation instead of yield to maturity, which can complicate regression results due to coupon effects. The disadvantage of yield curve fitting is that one must have a large number of bonds with relatively homogeneous characteristics.

To estimate the effect of transparency, one must have yield curves from two groups of bonds that differ only in their quality of disclosure. If one simply sorts bonds according to their disclosure scores, the resulting low disclosure group may have higher yields not because of lower disclosure, but higher credit risk due to the negative association between disclosure and the structural variables.

[19] This data is downloaded from Yuhang Xing's website: http://www.ruf.rice.edu/~yxing/.

To avoid this pitfall, one can sort bonds into bins by other determinants of the credit spread, split each bin into high and low disclosure groups, and then estimate a yield curve for each disclosure group in each bin.

If the sorting is too fine and the resulting bins too small, one risks not having enough dispersion of disclosure quality in the bins. This problem can be serious since the disclosure dummies are defined at the industry level, further reducing the sample size and dispersion that one can work with. As a compromise I use only two variables in the initial sort and only two subgroups each (low and high) are formed, resulting in a total of 4 bins. I use leverage and volatility as the two sorting variables since they consistently have high predictive power in all of the cross-sectional regressions.

A typical application of the Nelson-Siegel procedure is to extract yield curves for bonds with the same credit rating [see Elton et al. (2001)]. Since ratings may contain information about disclosure quality, this is not a good way to study the effect of transparency on credit spreads. However, this application can provide an economic measure of accounting transparency that is not fully captured by agency ratings, thus may be of some practical value.

In addition to the major variables summarized in Section 2, I obtain bond coupon, first coupon date, bid price and accrued interest from the Lehman database. With a discount function, one can then compute the theoretical price of the bond. Nelson and Siegel (1987) assume that the discount function takes the form

$$R(t) = a + b\left(\frac{1 - e^{-dt}}{dt}\right) - ce^{-dt}, \tag{11}$$

where a, b, c and d are constants. Each month, I fit this four-parameter discount function by minimizing the sum of squared pricing errors. Each group of bonds, by disclosure or by credit rating, thus provides its own fitted discount function and yield curve.

One issue with the Nelson-Siegel procedure is that it fits a relatively simple discount function, which may not have the flexibility to capture the shape of the yield curve out to a maturity of 30 years. There are more complex specifications, of which Nelson-Siegel is a special case, that have been extensively studied [see Dahlquist and Svensson (1996)]. However, since the interest here is primarily the behavior of the term structure at shorter maturities, a Nelson-Siegel fit out to a maturity of 10 years should be sufficient.

Another issue is the influence of the default-free term structure on the corporate bond yield curve. Since the testable hypotheses are formulated on credit spreads, not bond yields, I construct monthly Nelson-Siegel yield curves from Treasury bonds in the Lehman database and subtract them from the corporate yield curves to obtain the credit spread term structures.

3.2.2 Results by Leverage and Volatility Groups

In order to ensure the stability of the estimation, I first sort the monthly sample by either leverage or volatility (but not both) into two bins. In each bin there are more than 80 bonds, which would be further split into groups of about 50 bonds for each disclosure group. This is a reasonable size for yield curve estimations.[20]

[Insert Figure 4 here.]

[Insert Figure 5 here.]

Figures 4 and 5 present the spread curves for leverage and volatility groups, respectively. To facilitate comparison between the high and low disclosure spread curves, these figures include error bands that are one standard deviation above or below the average term structure. For the low volatility and the low leverage groups, the spread curves for high and low disclosure firms are not very different. On the other hand, for the high groups one can see differences in the level of the spread curves and a noticeable widening of the gap at the short-end. In particular, one can infer a gap at one-year maturity of about 70 bp when sorting the high leverage group, and 60 bp when sorting the high volatility group, both of which appear to be significant judging from the error bands.

[Insert Figure 6 here.]

I also estimate spread curves for HH (high leverage, high volatility) and LL (low leverage, low volatility) groups, with qualitatively the same findings (see Figure 6). In this case, the short-end gap is close to 200 bp. One might notice in Figures 4-6 that the transparency spread also widens slightly as maturity approaches 10 years. While this is less dramatic than the transparency gap at

[20] The high and low disclosure groups overlap for firms with median disclosure scores. Due to the small sample, I do so to ensure that the two groups are balanced in size. The downside is that the difference between the two yield curves would not be as great as when the two groups are mutually exclusive. Generally speaking, the corporate yield curve estimations involve groups of 10 to 70 bonds, depending on the specific definition and monthly period of the group (see Table 1). The Treasury yield curve estimation typically involves about 125 Treasury notes and bonds.

short maturities, this observation is consistent with the findings of the cross-sectional regressions. Recall, for example, that in Table 7 the transparency spread starts at 102 bp, drops to 28 bp at 5-year maturity and 25 bp at 10-year maturity, and finally reaches 63 bp at 30-year maturity. This pattern is very similar to that of Figures 4-6.

3.2.3 Results by Credit Ratings

Instead of controlling for the degree of credit risk using firm leverage and equity volatility, one can also sort the bonds using their credit ratings. In this paper, the size of the monthly subsample is sufficient to allow the distinction among Aa-, A-, and Baa-rated bonds. The estimation of yield curves for these bonds shows that the average RMSE is in all cases lower than those estimated by Elton et al. (2001). For example, for the high disclosure group the RMSE is 28¢ for Aa-rated bonds, 63¢ for A-rated bonds, and 97¢ for Baa-rated bonds. For the low disclosure group these figures are 17¢, 71¢, and $1.14, respectively.[21]

[Insert Figure 7 here]

Figure 7 presents the results for the three rating categories. The differences between the two disclosure groups are much smaller than when one uses structural control variables. This is to be expected as rating agencies claim to have incorporated disclosure quality in their credit rating designations. For Baa-rated bonds, those with higher disclosure still enjoy a lower spread (though not by much). For Aa- and A-rated bonds, those with higher disclosure may or may not have a lower spread depending on the maturity of the bond. In all cases, the statistical significance of the transparency spread is weak. This finding appears to be in conflict with Table 9, which shows that the inclusion of credit rating in yield spread regressions only marginally diminishes the size of the transparency spread. Since the rating variable is included in equation (10) only to induce a parallel shift of the term structure, the results presented here are likely to be more robust.

4 Conclusion

In this paper I examine the relationship between the term structure of credit spreads and the perceived quality of accounting information.

[21] The RMSE for the leverage and volatility groups can be as low as 64¢ (LL group with high disclosure) and as high as $2.71 (HH group with low disclosure). The RMSE for Treasury securities is 15¢.

To the extent that the perceived lack of transparency may signal hidden bad news about a company, the quality of accounting information may have an impact on its cost of debt or offering yields. This paper extends the existing accounting literature to secondary market bond price data, and identifies a weaker effect, consistent with the secondary market being less affected than the primary market by adverse selection and the lemons problem.

More importantly, this paper notes the recent work by Duffie and Lando (2001), who study the effect of incomplete but unbiased accounting information on credit spreads. In addition to the "level effect" implied by firms' policy of discretionary disclosure, I empirically test the term structure effect, which holds that firms with more accurate information disclosure have lower *short-term* credit spreads.

The results, based on monthly cross-sectional regressions of credit spreads on a measure of disclosure derived from the annual AIMR corporate disclosure quality rankings, confirm the presence of both effects. These results are robust when controlling for other determinants of credit spreads, and when using alternative specifications that take into account potentially nonlinear dependencies. An explicit construction of the spread curves also supports the findings. The presence of a short-end transparency spread, which can reach as much as 100 bp for investment-grade issuers with above-average leverage or volatility, underscores the importance of incomplete information in structural credit risk models.

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	1991	1992	1993	1994	1995	1996
Total	109	179	212	207	247	238
Aa or above	2	15	24	35	42	34
A	73	102	113	109	126	103
Baa	16	40	43	39	32	58
Non-investment-grade	0	0	0	0	4	15
Short-term	33	43	51	54	76	73
Medium-term	34	62	79	71	79	79
Long-term	26	55	74	76	89	81

Table 1: **Sample size.** The sample period is monthly between January 1991 and June 1996. Figures are for January in the given year. Short-term bonds have maturity shorter than 5 years, medium-term bonds between 5 and 10 years, and long-term bonds between 10 and 30 years. The subgroups do not add up to the total because industries in each subgroup with no dispersion in disclosure quality are deleted.

Variable	Mean	Std Dev	Min	Max
CS	0.90	0.54	-0.12	11.95
DISC	65.42	28.04	0.00	100.00
MAT	10.66	8.43	1.00	29.96
LEV	0.32	0.16	0.01	0.79
VOL	0.26	0.06	0.13	0.61
AGE	2.75	2.04	0.05	11.30
LSIZE	5.35	0.49	3.91	6.91
RTNG	7.24	2.24	2.00	24.00

Table 2: **Summary statistics of major variables.** The sample period is between January 1991 and June 1996.

	CS	DISC	MAT	LEV	VOL	AGE	LSIZE
DISC	-0.24						
MAT	0.27	-0.10					
LEV	0.48	-0.22	0.04				
VOL	0.34	-0.08	-0.07	0.25			
AGE	0.04	0.06	-0.19	0.05	-0.06		
LSIZE	-0.12	0.23	-0.01	0.05	-0.19	-0.09	
RTNG	0.69	-0.26	0.07	0.57	0.32	0.07	-0.15

Table 3: **Average correlations among major variables.** For each month in the sample period of January 1991 to June 1996, correlations among the major variables are computed. The average correlations across the 66 months are presented.

	Raw Disclosure Score			Disclosure Dummy		
	1/91-6/96	1/91-6/93	7/93-6/96	1/91-6/96	1/91-6/93	7/93-6/96
Intercept	0.13	0.55	-0.22	-0.093	0.44	-0.54
	1.08	4.96	-1.25	-0.75	4.17	-3.02
DISC	-0.0044	-0.0034	-0.0053	-0.085	0.04	-0.19
	-14.01	-7.57	-13.45	-4.44	2.63	-8.94
MAT	0.014	0.0093	0.018	0.013	0.0086	0.017
	19.65	12.44	30.67	19.22	12.39	30.60
LEV	0.98	1.13	0.85	1.08	1.13	1.04
	17.74	13.55	12.65	23.89	20.07	15.21
VOL	2.80	2.04	3.43	2.53	1.74	3.18
	10.68	7.49	8.65	9.91	8.67	7.79
AGE	0.025	0.024	0.026	0.018	0.016	0.019
	14.98	9.14	11.95	11.88	9.75	8.14
LSIZE	-0.023	-0.064	0.010	-0.023	-0.078	0.023
	-2.46	-5.46	0.90	-1.98	-6.63	1.47
Adj. R^2	0.438	0.358	0.504	0.423	0.338	0.493

Table 4: **Effect of disclosure quality on the level of credit spreads.** For each month in the sample period, I estimate the following regression: $\mathrm{CS}_i = \alpha + \beta_1 \mathrm{DISC}_i + \beta_2 \mathrm{MAT}_i + \beta_3 \mathrm{LEV}_i + \beta_4 \mathrm{VOL}_i + \beta_5 \mathrm{AGE}_i + \beta_6 \mathrm{LSIZE}_i + \varepsilon_i$. The disclosure quality variable DISC is the raw AIMR total corporate disclosure score or the disclosure dummy. Average OLS estimates across the monthly regressions are reported. The t-statistic for each average appears immediately beneath.

Variables	Description	Relation with spread
CS	Credit spread	dependent variable
dm_0	Transparency spread at zero maturity	$-$
dm_1	Transparency spread at 5-year maturity	$-$, but magnitude less than dm_0
dm_2	Transparency spread at 10-year maturity	$-$, relative magnitude unclear
dm_3	Transparency spread at 30-year maturity	$-$, relative magnitude unclear
LEV	Firm leverage ratio	$+$
VOL	Equity volatility	$+$
AGE	Bond age	$+$
LSIZE	Log of amount outstanding	$-$

Table 5: **Predicted effects of disclosure quality and other variables on the term structure of credit spreads.** The cross-sectional regression equation is $\text{CS}_i = \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \beta_8 \text{LEV}_i + \beta_9 \text{VOL}_i + \beta_{10} \text{AGE}_i + \beta_{11} \text{LSIZE}_i + \varepsilon_i$.

	With liquidity adjustments			Without liquidity adjustments		
	1/91-6/96	1/91-6/93	7/93-6/96	1/91-6/96	1/91-6/93	7/93-6/96
m_0	-0.15	0.35	-0.57	-0.11	0.028	-0.22
	-1.28	2.51	-3.72	-1.88	0.31	-3.14
m_1	-0.14	0.41	-0.60	-0.16	0.041	-0.33
	-1.10	4.94	-3.10	-2.30	0.80	-2.88
m_2	0.062	0.58	-0.37	0.057	0.22	-0.076
	0.51	5.31	-2.16	0.92	3.39	-0.81
m_3	0.24	0.61	-0.059	0.22	0.23	0.21
	2.18	5.19	-0.35	3.81	3.17	2.40
dm_0	-0.11	0.12	-0.31	-0.12	0.11	-0.31
	-2.37	3.38	-4.72	-2.58	2.93	-5.07
dm_1	-0.031	0.063	-0.11	-0.028	0.057	-0.10
	-1.81	2.69	-7.38	-1.68	2.47	-5.92
dm_2	-0.094	-0.041	-0.14	-0.10	-0.047	-0.15
	-4.66	-2.49	-4.22	-5.20	-2.67	-4.77
dm_3	-0.13	0.11	-0.34	-0.13	0.11	-0.32
	-3.71	3.75	-9.69	-3.58	3.51	-10.11
LEV	1.07	1.14	1.02	1.09	1.11	1.07
	23.07	19.28	14.74	22.48	17.95	14.68
VOL	2.52	1.67	3.23	2.45	1.83	2.97
	9.85	8.69	7.93	10.29	9.96	7.60
AGE	0.019	0.016	0.022	–	–	–
	12.68	9.94	9.39			
LSIZE	-0.014	-0.069	0.031	–	–	–
	-1.25	-6.56	2.04			

Table 6: **Effect of disclosure quality on the term structure of credit spreads.** For each month in the sample period, I estimate the following regression: $\text{CS}_i = \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \beta_8 \text{LEV}_i + \beta_9 \text{VOL}_i + \beta_{10} \text{AGE}_i + \beta_{11} \text{LSIZE}_i + \varepsilon_i$, with and without the liquidity proxies AGE and LSIZE. Average OLS estimates across the monthly regressions are reported. The t-statistic for each average appears immediately beneath.

	Leverage		Volatility	
	Low	High	Low	High
m_0	0.10	0.076	-0.40	-0.82
	1.56	0.37	-5.79	-2.55
m_1	0.37	-0.50	-0.22	-1.07
	4.76	-1.86	-3.39	-2.96
m_2	0.50	-0.21	-0.076	-0.72
	7.03	-1.06	-1.27	-2.08
m_3	0.65	0.21	0.26	-0.46
	8.91	1.05	4.13	-1.35
dm_0	0.050	-1.02	-0.0059	-0.60
	2.68	-5.49	-0.36	-3.97
dm_1	-0.055	-0.28	-0.045	-0.089
	-2.98	-5.53	-2.61	-3.11
dm_2	-0.059	-0.25	0.030	-0.19
	-2.36	-7.67	2.34	-3.89
dm_3	-0.022	-0.63	-0.15	-0.39
	-1.16	-13.52	-9.62	-7.28
LEV	0.99	0.89	0.72	1.36
	14.40	7.43	13.86	9.73
VOL	1.41	3.46	1.54	3.69
	9.41	6.85	7.03	4.51
AGE	0.021	0.020	0.014	0.030
	8.97	4.83	6.89	6.36
LSIZE	-0.061	0.016	0.048	0.046
	-6.62	1.04	5.57	2.18

Table 7: **Nonlinear effect of disclosure quality on the term structure of credit spreads.** For each month in July 1993 to June 1996, I estimate the following regression: $\mathrm{CS}_i = \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \beta_8 \mathrm{LEV}_i + \beta_9 \mathrm{VOL}_i + \beta_{10} \mathrm{AGE}_i + \beta_{11} \mathrm{LSIZE}_i + \varepsilon_i$. Average OLS estimates across the monthly regressions are reported. The t-statistic for each average appears immediately beneath.

	All	Leverage		Volatility	
		Low	High	Low	High
Intercept	5.38	9.13	6.80	0.95	6.45
	18.86	20.61	18.27	2.46	7.53
DISC	-0.45	-0.054	-1.27	-0.0063	-0.82
	-10.35	-0.71	-14.38	-0.11	-9.64
MAT	0.010	-0.0061	-0.0038	0.024	0.0045
	5.85	-1.29	-1.63	7.81	1.69
LEV	9.35	15.81	2.32	9.90	9.71
	85.70	39.26	7.75	33.51	62.05
VOL	8.33	3.10	8.76	13.83	8.85
	12.58	3.42	11.34	6.21	4.18
AGE	0.089	0.10	-0.033	0.055	0.14
	8.54	6.62	-2.08	5.36	7.35
LSIZE	-0.58	-1.34	-0.10	-0.031	-0.85
	-14.39	-21.52	-1.22	-0.42	-9.57
Adj. R^2	0.485	0.423	0.317	0.479	0.555

Table 8: **Effect of disclosure quality on credit rating.** For each month in July 1993 to June 1996, I estimate the following regression: $\mathrm{RTNG}_i = \alpha + \beta_1 \mathrm{DISC}_i + \beta_2 \mathrm{MAT}_i + \beta_3 \mathrm{LEV}_i + \beta_4 \mathrm{VOL}_i + \beta_5 \mathrm{AGE}_i + \beta_6 \mathrm{LSIZE}_i + \varepsilon_i$. Average OLS estimates across the monthly regressions are reported. The t-statistic for each average appears immediately beneath.

	All	Leverage		Volatility	
		Low	High	Low	High
m_0	-0.93	-0.42	-0.93	-0.32	-1.32
	-6.51	-6.74	-4.31	-5.66	-4.03
m_1	-1.08	-0.42	-1.26	-0.25	-1.66
	-5.83	-5.96	-4.73	-5.13	-4.41
m_2	-0.87	-0.28	-0.99	-0.15	-1.34
	-5.51	-4.46	-4.68	-3.17	-3.82
m_3	-0.52	-0.054	-0.52	0.20	-1.04
	-3.49	-0.87	-2.58	4.25	-2.99
dm_0	-0.31	-0.14	-0.51	-0.10	-0.52
	-5.44	-5.67	-4.53	-5.57	-4.00
dm_1	-0.055	-0.014	-0.12	-0.043	-0.021
	-3.35	-0.96	-2.61	-2.24	-0.81
dm_2	-0.088	0.011	-0.16	0.048	-0.076
	-2.47	0.51	-4.32	4.08	-1.47
dm_3	-0.30	-0.026	-0.46	-0.12	-0.32
	-8.68	-1.97	-9.46	-10.76	-6.23
LEV	0.13	-0.25	0.60	0.082	0.26
	1.97	-4.92	4.91	1.68	1.73
VOL	2.39	1.26	2.40	0.65	2.41
	6.15	11.56	5.35	4.63	3.22
AGE	0.012	0.0093	0.026	0.010	0.013
	4.63	3.61	5.62	6.20	2.54
LSIZE	0.079	0.041	0.0074	0.039	0.13
	6.19	4.77	0.61	6.76	5.54
RTNG	0.095	0.084	0.13	0.067	0.11
	19.20	32.15	15.01	20.88	13.80

Table 9: **Does credit rating subsume the effect of disclosure quality on the term structure of credit spreads?** For each month in July 1993 to June 1996, I estimate the following regression: $\text{CS}_i = \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \beta_8 \text{LEV}_i + \beta_9 \text{VOL}_i + \beta_{10} \text{AGE}_i + \beta_{11} \text{LSIZE}_i + \beta_{12} \text{RTNG}_i + \varepsilon_i$. Average OLS estimates across the monthly regressions are reported. The t-statistic for each average appears immediately beneath.

	All	Leverage		Volatility	
		Low	High	Low	High
Panel 1: Percentile rank and maturity					
dm_0	-0.31	0.050	-1.02	-0.0059	-0.60
	-4.72	2.68	-5.49	-0.36	-3.97
dm_1	-0.11	-0.055	-0.28	-0.045	-0.089
	-7.38	-2.98	-5.53	-2.61	-3.11
dm_2	-0.14	-0.059	-0.25	0.030	-0.19
	-4.22	-2.36	-7.67	2.34	-3.89
Panel 2: Percentile rank and duration					
dm_0	-0.32	0.049	-0.99	-0.081	-0.50
	-5.55	2.18	-6.00	-4.70	-3.60
dm_1	-0.082	-0.062	-0.17	0.033	-0.073
	-3.97	-3.09	-4.68	1.96	-1.92
dm_2	-0.29	-0.086	-0.48	-0.16	-0.39
	-6.55	-3.48	-8.75	-6.04	-5.37
Panel 3: Raw score and maturity					
dm_0	-0.18	0.060	-0.76	-0.023	-0.35
	-3.30	2.73	-5.20	-1.28	-2.81
dm_1	-0.18	-0.16	-0.087	-0.066	-0.25
	-14.07	-16.22	-2.39	-4.99	-10.39
dm_2	0.025	-0.078	0.17	0.047	-0.0030
	1.15	-2.78	4.11	2.52	-0.076

Table 10: **Further robustness checks on the transparency spread.** For each month in July 1993 to June 1996, I estimate the following regression: $\text{CS}_i = \beta_0 m_{0i} + \beta_1 m_{1i} + \beta_2 m_{2i} + \beta_3 m_{3i} + \beta_4 dm_{0i} + \beta_5 dm_{1i} + \beta_6 dm_{2i} + \beta_7 dm_{3i} + \beta_8 \text{LEV}_i + \beta_9 \text{VOL}_i + \beta_{10} \text{AGE}_i + \beta_{11} \text{LSIZE}_i + \varepsilon_i$. Panel 1 reproduces the results from Tables 6 and 7. Panel 2 uses bond duration instead of maturity in defining the term structure variables. Panel 3 defines the disclosure dummy using raw disclosure scores instead of industry percentile ranks. Average OLS estimates across the monthly regressions are reported. The t-statistic for each average appears immediately beneath.

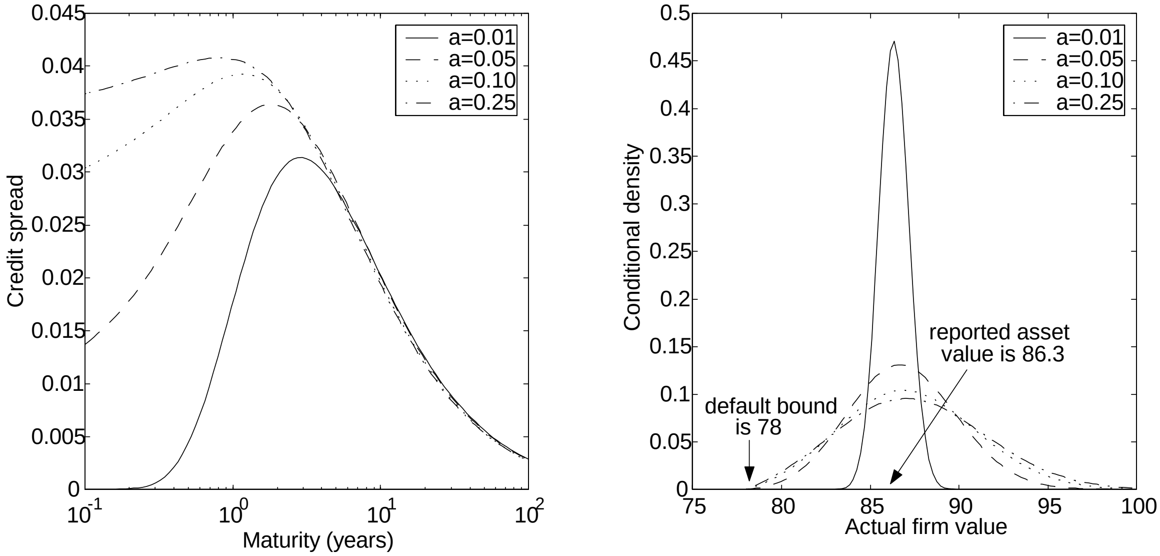

Figure 1: **Term structures of credit spreads and conditional distributions of firm value with different accounting precisions.**

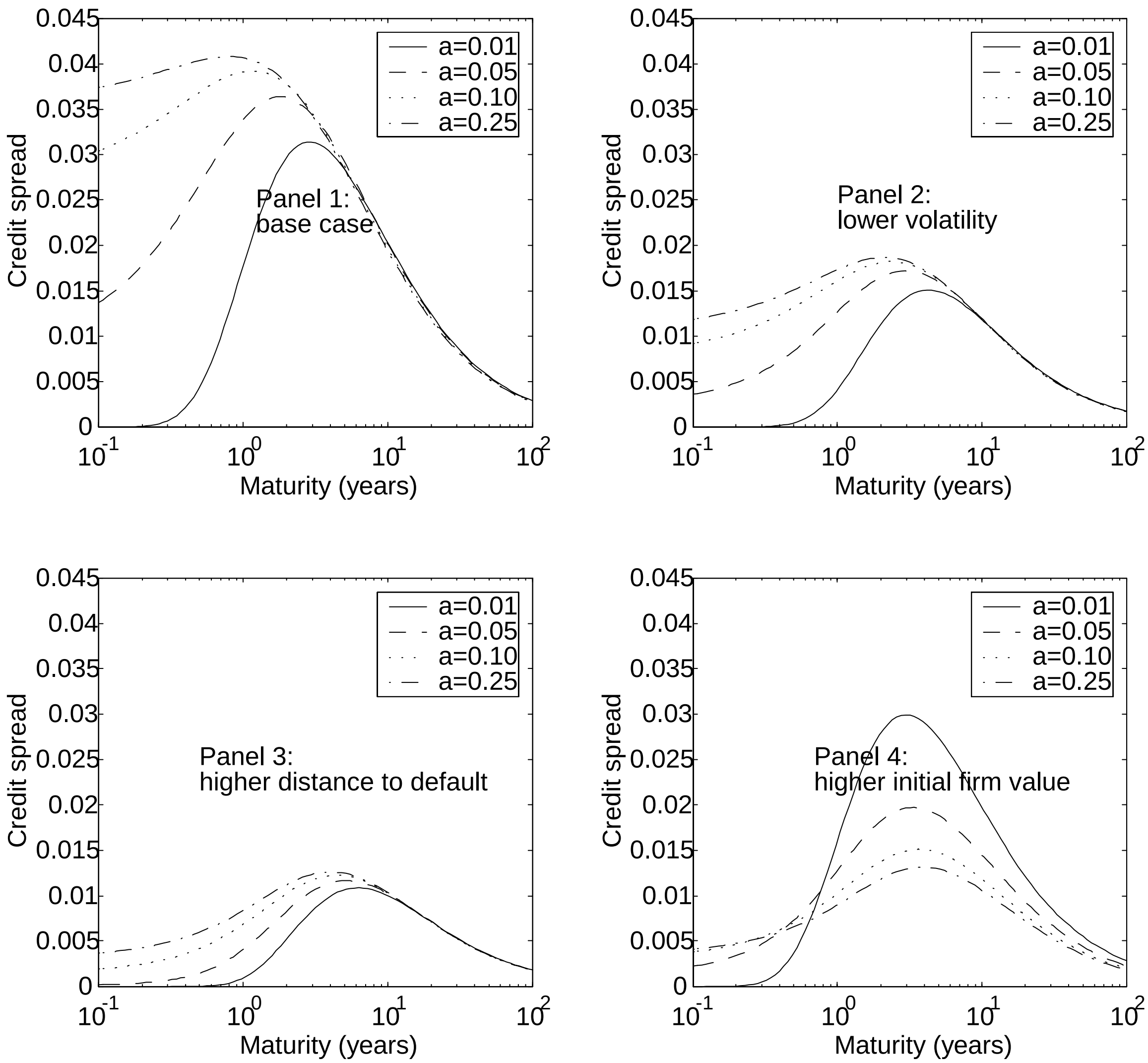

Figure 2: **Term structures of credit spreads with varying accounting precision, asset volatility, and initial and reported firm value.**

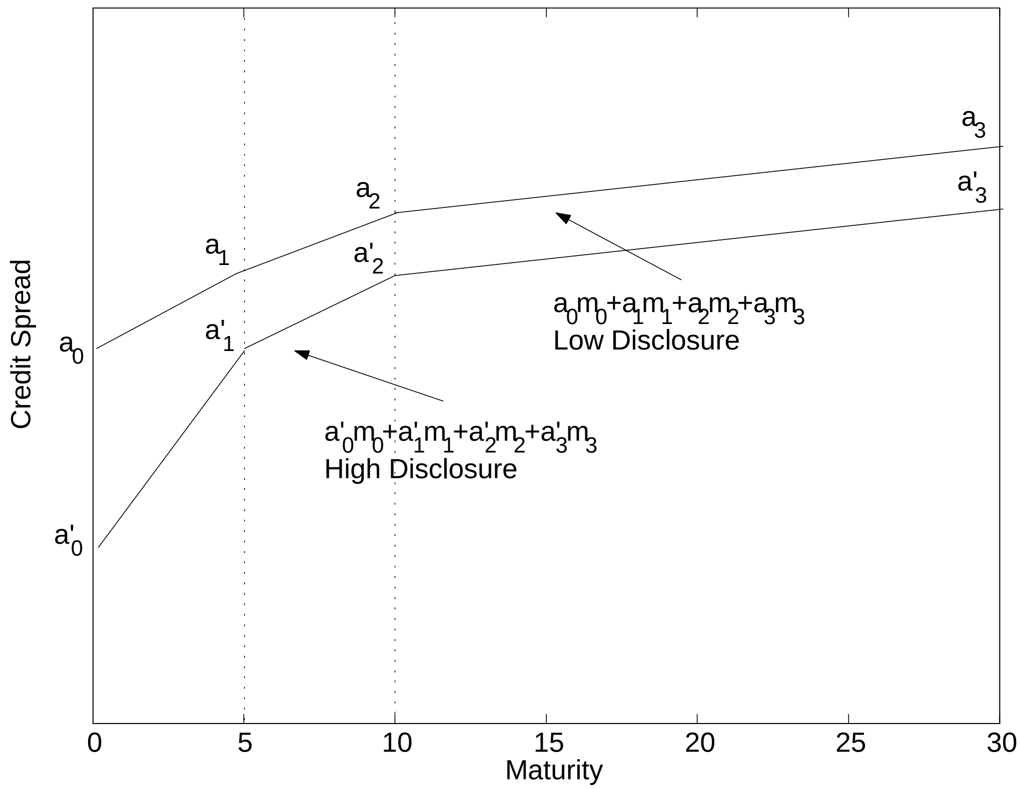

Figure 3: **High and low transparency credit spread curves.** Given are the term structures of credit spreads for high and low transparency issuers that are otherwise identical. The coefficient a_i represents the level of the term structure at different maturities. The difference between a_i and a_i' represents the "transparency spread."

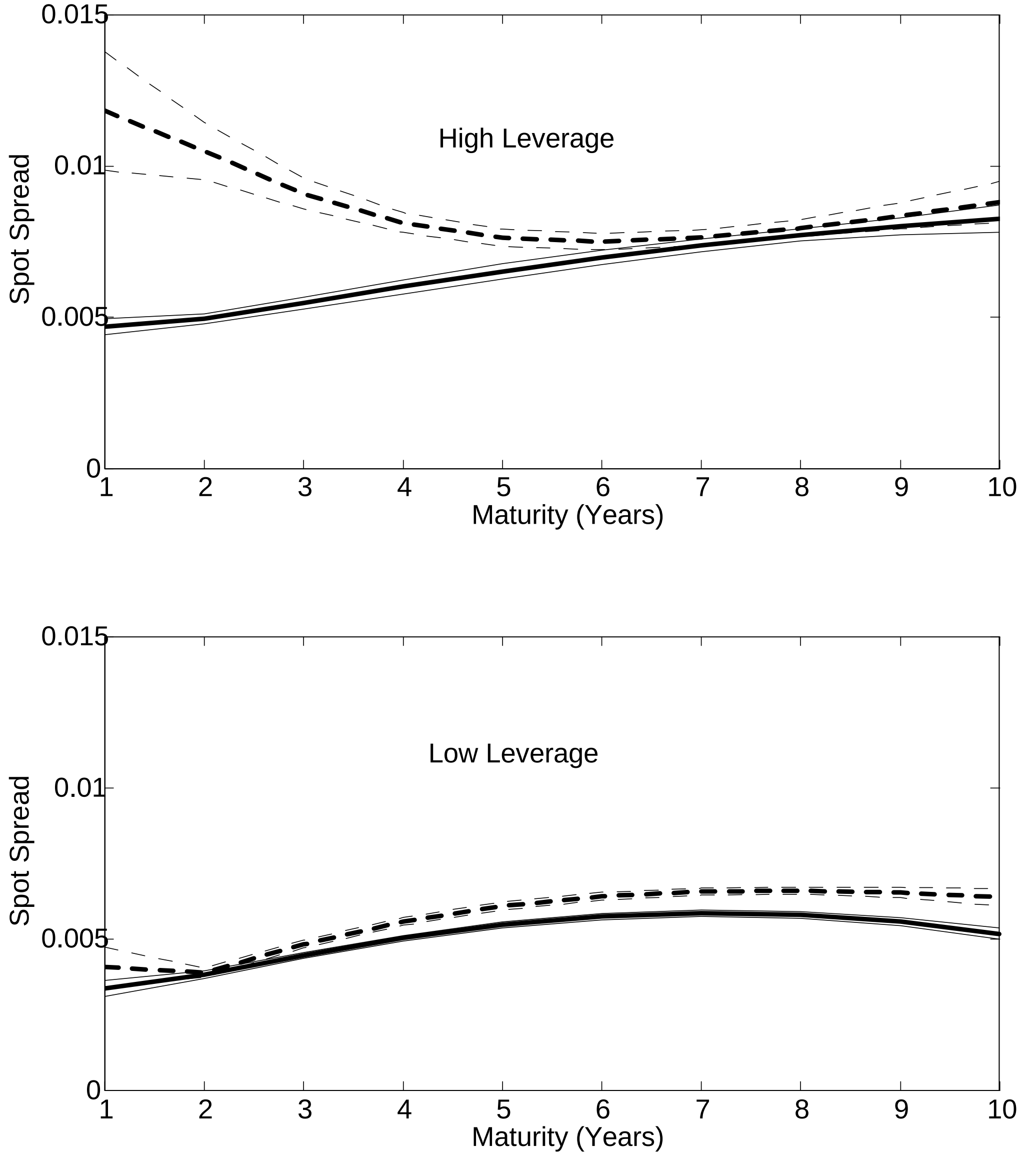

Figure 4: **Term structures of credit spreads by leverage groups.** The solid (dashed) line corresponds to firms with above-median (below-median) disclosure scores. The average across 36 monthly spread curves is presented. The thinner lines represent one standard deviation above or below the average spread curve.

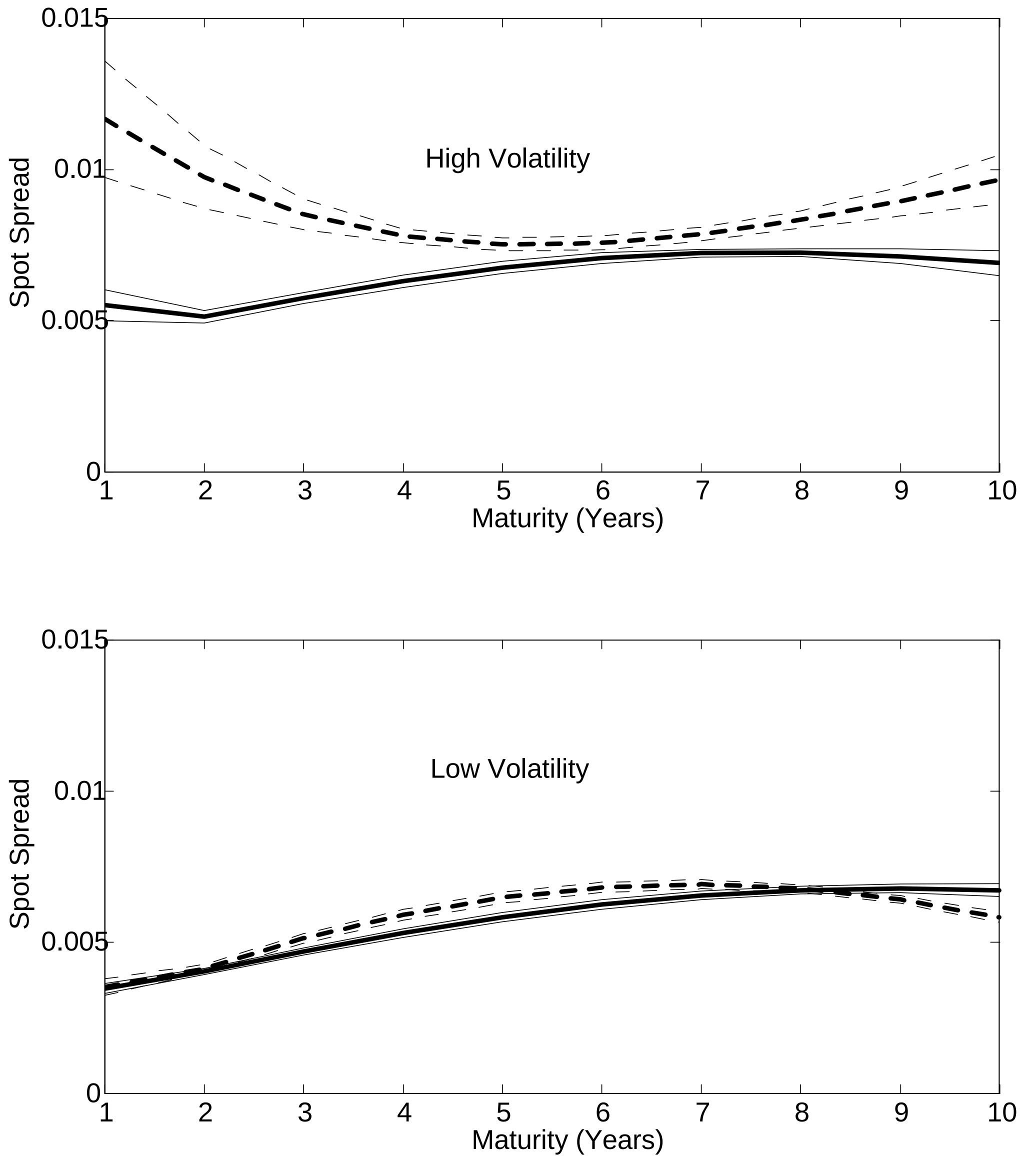

Figure 5: **Term structures of credit spreads by volatility groups.** The solid (dashed) line corresponds to firms with above-median (below-median) disclosure scores. The average across 36 monthly spread curves is presented. The thinner lines represent one standard deviation above or below the average spread curve.

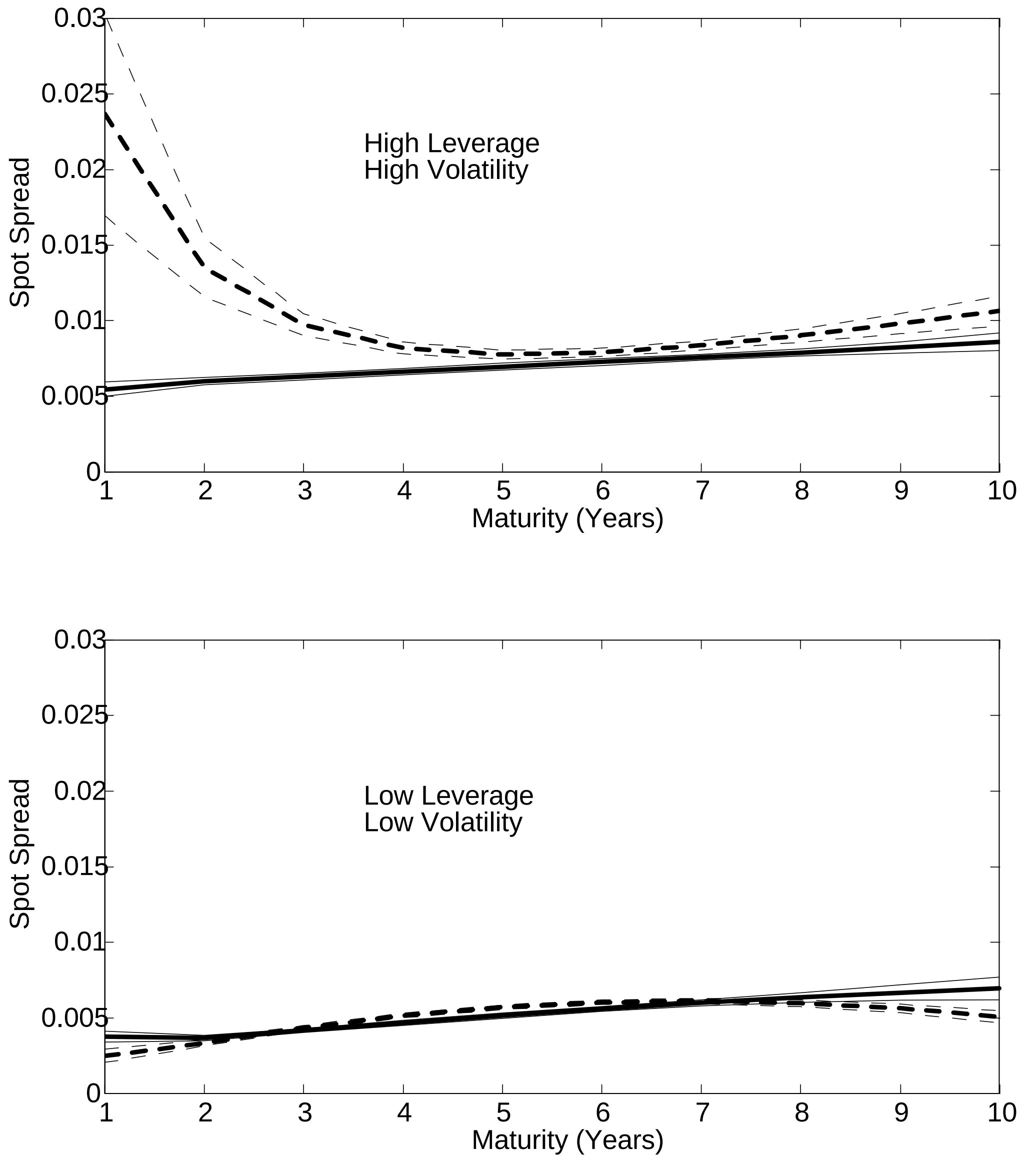

Figure 6: **Term structures of credit spreads by volatility and leverage groups**. The solid (dashed) line corresponds to firms with above-median (below-median) disclosure scores. The average across 36 monthly spread curves is presented. The thinner lines represent one standard deviation above or below the average spread curve.

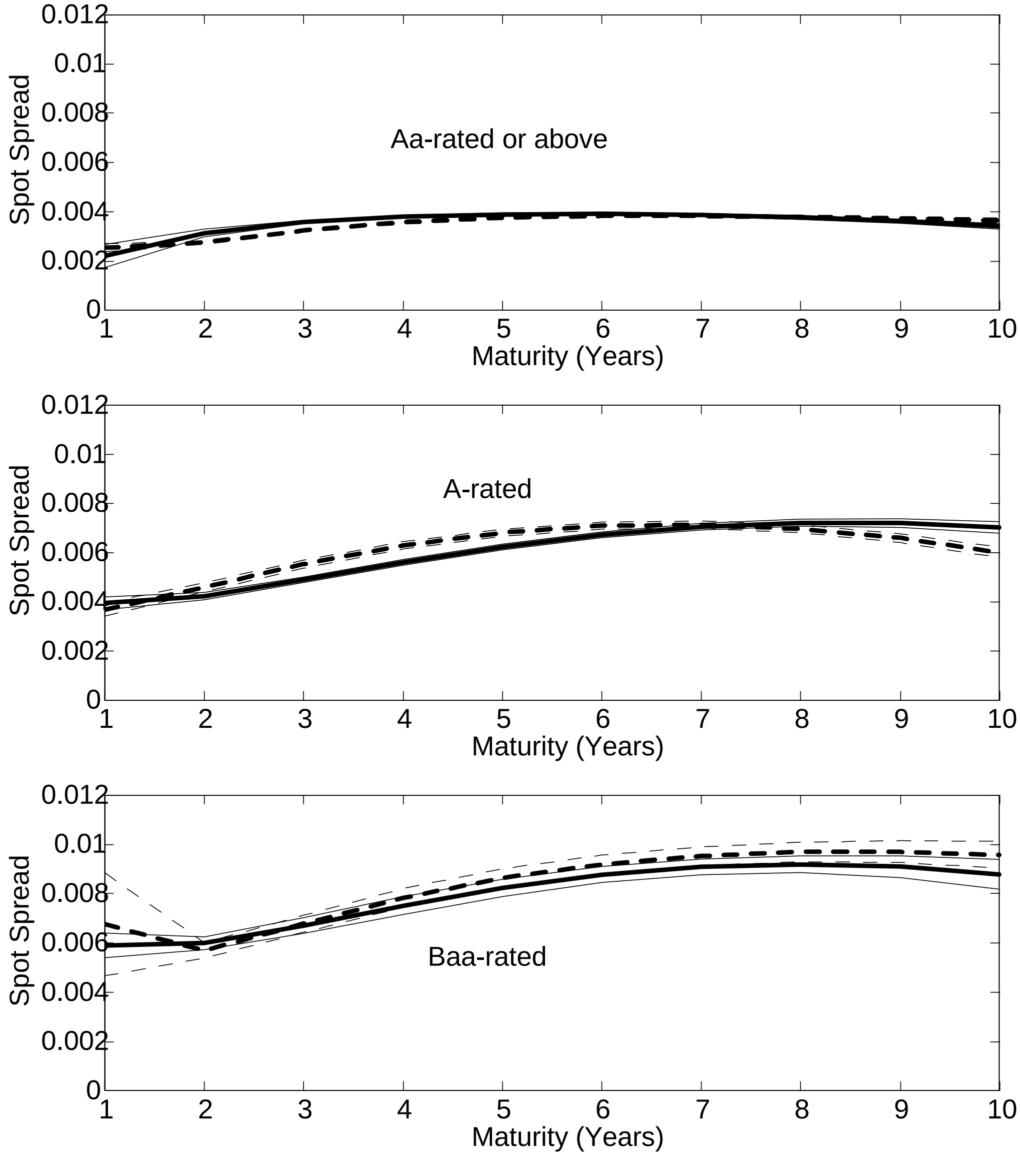

Figure 7: **Term structures of credit spreads by credit rating.** The solid (dashed) line corresponds to firms with above-median (below-median) disclosure scores. The average across 36 monthly spread curves is presented. The thinner lines represent one standard deviation above or below the average spread curve.