Using Yield Spreads to Estimate Expected Returns on Debt and Equity

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Abstract

This paper develops and tests a method of extracting expectations about default losses on corporate debt from yield spreads. It is based on calibrating the Merton (1974) model to yield spread, leverage and equity volatility. For rating classes, the approach generates forward-looking expected default loss estimates similar to historical losses, and is also applicable for individual bonds. The information content of the estimate is superior to linear ex ante functions of the variables it uses as inputs. We also find that estimates of equity risk premia consistent with historical default experiences range from 3.1% to 8.5% depending on rating.

I. Introduction

The expected loss on corporate debt is an important input to many financial decisions, including lending, bank regulation, portfolio selection, risk management, and valuation. Starting with Altman (1968), various methods of forecasting default losses using characteristics of individual firms or rating classes have been proposed. These include discriminant analysis, approaches based on rating transitions (Elton *et al.* (2001)), structural models of risky debt (Leland (2002)), and various proprietary models, of which the KMV model is probably the best known (Crouhy *et al.* (2001)). The extensive development of bond markets offers another opportunity, which we pursue in this paper: to extract the expected default loss on a corporate bond from its yield spread. We calibrate the Merton (1974) structural model of risky debt using observed bond spreads in conjunction with information on leverage, equity volatility, and equity risk premia to yield an estimate of expected future default losses incorporated in current market prices.

In contrast with commonly used estimation methods based on historical data, our forecast uses market prices and reflects current market expectations about default. Our estimates are based on an equilibrium model, and are consistent with current market yields. They provide neutral estimates of expected losses for anyone who does not believe that their forecasting ability is better than the bond market's. Expected returns on bonds are the difference between promised returns and expected default losses. If default loss forecasts are made independently of yields, the resulting expected return estimates can have undesirable properties. Any forecasting method that does not reflect current capital market data, such as methods based on rating transitions, will translate all short-term variation in yields into variation in expected returns. Structural models based on current capital market data, such as Leland (2002) or the KMV model (Crosbie and Bohn (2002)), will assign all variation in yields unexplained by the model to variation in expected returns. In contrast, our method produces estimates of expected returns that are neutral in the sense that, as yields vary, expected losses vary as an equilibrium fraction of the yield change. For this reason, we believe that default loss estimates produced by a procedure based on yields, such as ours, should have a central role in bank management and regulation, and the management of fixed income portfolios.

The proposed method is based on splitting the observed market spread into the part due to expected default and that due to other factors. This decomposition is achieved by first adjusting the observed spread to exclude non-default factors. The remaining spread is then calibrated to a structural model of risky debt and other capital market variables: market leverage, equity volatility and equity risk premia. Thus, the estimate of the expected default loss incorporates information contained in current bond yields, which have been shown to predict expected default.[1] Leverage, equity prices and volatility have also been shown to contain information about future default, and form the basis of models that are widely used in practice (Crosbie and Bohn (2002)). In these methods, the Merton model is calibrated to these three variables to derive a default measure which is then used in combination with historical default and recovery data to give a forecast of expected default losses. Although our approach is similar, we calibrate the Merton model to current yield spreads and do not use historical default data.[2]

The approach has several potential advantages over existing methods. The prediction depends on easily observable current capital market variables which should contain consensus market expectations about future default. Other estimates of future default losses are based on combinations of historical default and recovery rate data, accounting variables, and equity prices. Unlike such models, our approach does not require empirical calibration to past data or any assumptions of stability of default rates over time. It gives a direct estimate of the expected loss from default, rather than relying on separate estimation of the probability of default and the recovery rate. It is independent of accounting conventions, and thus can be used without adjustment in any country. Finally, unlike some methods, it can be applied to estimate expected default losses on individual bonds rather than on broad ratings categories. Altman and Rijken (2003) show that there is significant variation of expected default losses within ratings classes, which ratings-based approaches will fail to capture.

We examine empirical properties of the estimator and find it to be robust to model specification. We also show that it gives estimates of expected default that are broadly consistent with historical data for ratings categories. We test the ability of the estimator to predict ratings transitions and show that it appears to incorporate much of the information contained in spreads, leverage and volatility. The estimate of the expected default loss is relatively insensitive to the values of spread, leverage and equity premium used as inputs. However, it is sensitive to the forecast of volatility. Improving volatility estimates may be a fruitful way to improve the accuracy of the predictions.

Our procedure can also be used to obtain equity risk premia estimates. Existing estimates of equity premia are usually based on historical equity returns or variants of the dividend growth model.[3] Such methods generate large standard errors, so additional sources of estimates of equity premia can have high incremental value.[4] We obtain such estimates by equating, for ratings classes, the expected default losses recovered from yield spreads using our approach, with historical default experience. The former depend monotonically on expected equity

[1] Hand *et al.* (1992), for instance, show that the yield on a bond relative to the average yield of its rating class predicts ratings transitions.

[2] Delianedis and Geske (2001) mention the possibility of such calibration but do not implement it.

[3] See Welch (2000) for a survey of existing practices.

[4] Brealey and Myers (2003) report a standard error of the market risk premium based on historical data of 2.3%.

returns, so there is a unique equity premium that equates the two estimates of default losses. Such equity premia estimates utilize information contained in yield spreads, a forward-looking capital market variable hitherto unused for this purpose. We obtain asset risk premia estimates of about three percent, and equity risk premia between three and nine percent depending on the bond rating.

Existing methods of predicting default losses have different strengths and weaknesses. The most widely applicable approach, such as the z-score suggested by Altman (1968), employs the empirical relationship between observed defaults and accounting ratios and other variables. This approach can be used for individual firms without traded equity. However, it does not usually incorporate current capital market information. Moreover, the empirical functions relating default to fundamental variables can vary over time and between countries. Another widely used approach relies on historical data for different rating classes to estimate the expected future default loss. In this vein, Elton *et al.* (2001) study the frequency of past ratings migrations as a proxy for the future, and split the expected default loss spread out of the observed bond spread. Such an approach gives a direct estimate of default losses, but can be applied only to ratings categories and not to individual companies. Crucially, it assumes that the process governing rating transitions and default is constant over time and that ratings are sufficient statistics for expected default. Asquith *et al.* (1989) argue that the constant transition probability assumption is unlikely to be true, and Altman and Rijken (2003) show that ratings are not sufficient statistics. A third approach is to use a structural model of default risk. This is employed in practice in default risk predictions provided by the credit analysis company KMV, as described in Crosbie and Bohn (2002). In this implementation, a version of the Merton model is calibrated to the face value and maturity of debt and a time series of equity values. A 'distance to default' is then calculated and used in conjunction with KMV's proprietary default database to estimate the probability of default. This procedure requires knowledge of the function relating the distance to default and the default probability, which is not public, and, presumably, assumes that this function is stable over time.

All the above methods are usually used to predict the probability of default. To obtain the expected loss from default, the estimates of default probabilities are typically combined with historical average recovery rates. This approach assumes that recovery rates are stable over time. Acharya *et al.* (2003) find that recovery rates depend on industry conditions and are correlated with the probability of default. The instability of recovery rates means that forecasts of expected losses, the variable of most interest, suffer from this additional source of uncertainty. By contrast, our method yields a direct estimate of the expected loss without the necessity to forecast the recovery rate.

Similarly to KMV, our method employs the Merton (1974) model calibrated to capital market variables. The

Merton model is the simplest structural model of risky debt pricing that relates firm value and volatility, debt face value and maturity, and the riskless interest rate, to the yield on the firm's debt. Various authors, including Jones *et al.* (1984), Delianedis and Geske (2001), Huang and Huang (2003), and Eom *et al.* (2004) have shown that structural models perform poorly in explaining the observed magnitudes of spreads on risky debt. The Merton model in particular has been shown to consistently under-predict risky bond spreads, especially for high grade debt. Many papers, including Black and Cox (1976), Geske (1977), Leland (1994), Leland and Toft (1996), Longstaff and Schwartz (1995), Anderson and Sundaresan (1996), Mella-Barral and Peraudin (1997), and Collin-Dufresne and Goldstein (2001) have extended the basic Merton (1974) model to incorporate more realistic assumptions. These models improve the fit to the general level of yields, but none shows a good performance in explaining cross-sectional spread variations (Eom *et al.* (2004)). Therefore, doubts may be raised about the applicability of the Merton model for splitting the expected default loss from the observed yield spread as we propose.

However, there are several observations suggesting that the inaccuracy of predictions of the Merton model with regards of the absolute levels of spreads does not necessarily imply that it is inappropriate in this application. First, most default risk in debt portfolios occurs in low grade debt, where the Merton model performs relatively well. Second, we use the model to split the observed spread into its components, not to predict the absolute level of the spread. Moreover, we adjust the observed spread by subtracting the component unrelated to default; once this adjustment is made, the spread under-prediction of the Merton model is likely to become considerably less pronounced. Furthermore, we show that our results do not vary much when the specification of the structural model employed is perturbed, suggesting that the precise specification is not central in this application. This finding is similar to what Huang and Huang (2003) find in a related context: very different structural models predict similar spreads when calibrated to the same historical default frequencies and recovery rates. In this sense, the choice of the model structure appears less important when calibrated to fit a variable that measures expected default. These observations motivate our choice of the simplest equilibrium structural model.[5]

Our method relies on yield spread observations from a competitive debt market, and as such is only applicable to companies with traded bonds or credit derivatives. However, as these are usually the largest firms, their analysis is also central for most debt portfolios. The international growth of bond markets and credit derivatives results in rapid expansion of the set of companies with traded credit risk. Even for companies without traded

[5]Risky debt pricing can also be analyzed using the reduced-form approach, as in Duffie and Singleton (1999). There are two differences between this approach and ours. First, the analysis in such models is usually carried our under a risk-neutral probability measure, whereas we are concerned with expected losses under the true probability. Second, reduced-form models do not use such firm-specific variables as equity prices and volatility.

debt the procedure offers a way of improving estimates of other methods. Functions used to forecast expected default could be calibrated to estimates based on yield spreads for companies with traded debt, and then used for firms without traded debt.

The article is organized as follows: Section II describes the estimation method, and Section III the data. In Section IV we test the properties of the estimator. Section V uses the procedure to estimate equity risk premia. Section VI discusses applications and extensions, and Section VII concludes.

II. The estimation method

A spread on a risky bond consists of three parts: the expected loss due to default, the risk premium associated with the default, and components unrelated to default. The goal of this paper is to separate the first component, the expected default loss. Structural models make predictions about the sum of the first two components, which is the total spread due to default. Our approach of decomposing the observed spread therefore consists of two steps. First, we subtract the non-default component of the spread, which we proxy by the average matched AAA spread. Second, we calibrate the Merton model to the adjusted spread to estimate the expected default loss.

A. Spread adjustment

To calibrate a structural model to bond spreads, one should use only that part of the observed spread which is due to default (the expected default loss and default risk premium). We therefore adjust the observed spreads by subtracting the average spread on AAA-rated bonds, which we take to reflect non-default components of spread common to all bond rating classes. This adjustment is based on a developing literature that estimates the components of yield spreads. Research shows that the expected default component of AAA bond spreads is very low (Elton *et al.* (2001); Delianedis and Geske (2001); Huang and Huang (2003)). Thus, spreads on AAA bonds reflect almost entirely non-default factors. These could include tax, bond-market risk factors, and liquidity. Elton *et al.* (2001) argue that a part of the spread for U.S. corporate bonds is due to the state tax on corporate bond coupons which is not paid on government coupons. Their results suggest that this component is almost identical for all ratings. Collin-Dufresne, Goldstein and Martin (2001) demonstrate the presence of a systematic factor in credit spreads that appears to be unrelated to equity markets. They report that the factor loadings of different rating categories on this bond-market risk factor are similar. This suggests that any risk premium associated with this factor will be similar for different rating categories. Janosi *et al.* (2002) find that that bond liquidity is an important determinant of spreads. However, their results suggest that idiosyncratic liquidity controls do not radically improve upon models which control only for aggregate liquidity.

Taken together, this empirical evidence suggests that the spreads on AAA bonds reflect almost entirely non-default factors, and that these factors (possibly except liquidity) are similar across ratings categories. These results form a basis of our adjustment of spreads for non-default components: We subtract time-matched average AAA spreads from our studied lower grade bond spreads irrespective of their rating, and take the remainder to be to a first approximation entirely due to default.[6]

B. Merton model calibration

Once the observed spread is adjusted for non-default component, it is split into the expected default and associated risk premium using the Merton (1974) model of risky debt. The Merton model assumes that the value of the firm's assets follows a geometric Brownian motion:

$$\frac{dV}{V} = \mu dt + \sigma dW_t \tag{1}$$

where V is the value of the firm's assets, μ and σ are the constant asset drift and volatility, and $\{W_t\}$ is a standard Wiener process.[7] The model further assumes that the firm has a single class of zero-coupon risky debt of maturity T, with a very simple default and bankruptcy procedure.

Because of omitted factors, including coupons, default before maturity, strategic actions, and complex capital structures, the Merton model is too simple to reflect reality. Firms with a single zero-coupon bond outstanding are almost non-existent. Consequently, the choice of bond maturity when implementing the Merton model is difficult and often arbitrary. For instance, in their implementations Huang and Huang (2003) use actual maturity, Delianedis and Geske (2001) use duration, and KMV use a procedure that mainly depends on liabilities due within one year (see Crosbie and Bohn (2002)). To avoid an arbitrary exogenous choice of T and give the model enough flexibility to fit actual yield spreads, we simply *endogenize* T and solve for the value of maturity which makes the model consistent with observed spreads adjusted for non-default factors. Thus found, T reflects not only the actual maturity of the debt, but also spread-relevant factors ignored in the Merton model. We later test the robustness of the procedure to this assumption by using a different model specification that allows us

[6] Jarrow *et al.* (2003) also use a AAA adjustment for the same purpose in a different application.
[7] The drift must be adjusted for cash distributions.

to match the actual maturity of the debt.

Merton's formula can be written in a form that gives a relationship between the firm's leverage w, the maturity of the debt T, the volatility of the assets of the firm σ, and the promised yield spread s (see Appendix):

$$N(-d_1)/w + e^{sT}N(d_2) = 1 \tag{2}$$

where $N(\cdot)$ is the cumulative normal distribution function and

$$d_1 = [-\ln w - (s - \sigma^2/2)T]/\sigma\sqrt{T} \tag{3}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{4}$$

Another implication of the model, which follows from Itô's lemma, is that the equity volatility σ_E satisfies:[8]

$$\sigma_E = \sigma N(d_1)/(1-w) \tag{5}$$

We now have five variables: w, s, σ_E (all observed), σ and T (both unknown), and two equations.[9] We solve equations (2) and (5) simultaneously to find values of σ and T which are consistent with the observed values of w, s and σ_E.[10]

Once the model is calibrated, the expected return on assets, equity and debt are related as follows. Since equity is a call option on the assets and therefore has the same underlying source of risk, the risk premia on assets $\pi \equiv \mu - r$ and equity π_E are related as:

$$\pi = \pi_E\sigma/\sigma_E \tag{6}$$

Now the spread which is due to expected default, which we call δ, can be calculated by taking expectations

[8] In contrast to the asset volatility, the short-term equity volatility is easily observable from either option-implied volatilities or historical returns data.

[9] Note that, although equation (5) is often used to find σ, in our equation system T is not a known input.

[10] The system of equations is well-behaved, and we generally had no difficulties solving it applying standard numerical methods. To assure a starting point for which standard algorithms quickly yield a solution, one can solve equations (2) and (5) separately for σ for a few fixed values of T (or vice versa). This procedure always converged for any reasonable starting points. The intersection of the solution curves $\sigma(T)$ from equations (2) and (5) can then be used as a starting point for the system of these equations.

under the real probability measure (see Appendix), and is given by:[11]

$$\delta = -\frac{1}{T}\ln\left[e^{(\pi - s)T}\, N(-d_1 - \pi\sqrt{T}/\sigma)\,/w + N(d_2 + \pi\sqrt{T}/\sigma)\right] \tag{7}$$

Note that if the expected default loss on debt δ is known, then the procedure can be reversed to yield the expected equity premium π_E.

The default risk premium on debt over the bond's life is equal to $s - \delta$, the part of the spread which is not the expected default loss. Conditional on the spread, this risk premium falls when δ increases. However, within our sample described below, the two are strongly positively correlated, because both tend to increase when spreads rise.

III. Data

To test the properties of the estimator for individual bonds we use bond trade data supplied by the National Association of Insurance Commissioners (NAIC). These include all transactions in fixed-income securities by insurance companies in the US in the period 1994–1999. We augment this with information on bond details from the Fixed Income Securities Database (FISD), and on ratings transitions from Moody's ratings database. To benchmark the estimates using aggregate data for ratings we use information in Huang and Huang (2003).

The NAIC dataset includes trade prices for more than six hundred thousand transactions over the period 1994-1999. We exclude all bonds other than senior unsecured fixed-coupon straight US industrial corporate bonds without call/put/sinking fund provisions and other optionalities, bonds for which we are unable to unambiguously identify the promised cash flow stream, or Moody's rating at the date of trade. Also excluded are bonds with missing issuing company's accounting data in Compustat for the fiscal year immediately preceding the date of trade, or a 2-year history of its stock prices in CRSP. We use only senior unsecured debt, as this is the type of debt on which Moody's company ratings are based. To improve the matching of the inputs by maturity, we retain in the sample only bonds with remaining maturity between 7.5 and 10 years. We use a relatively long maturity because we are interested in expected returns for relatively long horizons. We use the subsample of trades shortly after the fiscal end (within three months) to better match the accounting information to the trade data. Thus constructed, the final sample includes 2632 trades on 553 bonds of 292 issuers.

[11]Note that, unlike the return on assets and equity, the calculated return on debt is an annualized compounded return rather than an instantaneous return.

We estimate spreads on these bonds using data on U.S. Treasury STRIPS (risk-free zero-coupon securities) using the procedure suggested in Davydenko and Strebulaev (2003). We first compute the yield for each bond trade from the transaction price recorded by NAIC. We then calculate the yield on a risk-free bond with the same promised cash flows using Treasury STRIPS prices as of the date of trade.[12] We subtract the estimated cash-flow matched risk-free rate from the yield on the bond to obtain the yield spread for the trade.

We measure the leverage as the ratio of the Compustat-recorded book value of debt to the sum of the book value of debt and total market value of equity obtained from CRSP for the last business day before the trade. We measure total debt by the book value of short term and long term debt. Some other authors do not use observed leverage in structural debt models because the book value of debt may not proxy well for its market value. An alternative is to use the book value of debt to proxy for the face value of debt (Crosbie and Bohn (2002); Delianedis and Geske (2001)). This approach is also subject to criticism unless the structural model used is one that explicitly deals with the coupon flows on the bonds. We use leverage based on the book value of debt, but later find that our results are relatively insensitive to the precise measurement of leverage. We estimate equity volatility as the volatility of daily equity returns as recorded in CRSP over two years prior to the bond trade. We use equity risk premium estimates for different ratings classes from Huang and Huang (2003). These are based on the empirical relationship between leverage and equity returns in Bhandari (1988). We adjust for the AAA spread in each year matched to the maturity of the bond.

Table 1 shows summary statistics for spreads and other fundamental variables for our NAIC sample. The variation of all the variables with rating conforms to expectations, with spread, equity volatility, and leverage increasing on average as the rating deteriorates. There is, however, significant variation of these variables within ratings classes. The table also reports maturity and duration, which are similar across ratings classes for the subsample. Finally, it gives the asset volatility for firms in our sample calculated using the KMV method as described in Crosbie and Bohn (2002), which we later use to benchmark our own estimates of asset volatility. One interesting feature of this variable is that its average value is relatively constant across ratings categories, apart from the B category.

INSERT TABLE 1 HERE

[12] For the majority of trades there are 4 annual STRIPS returns available. We use a linear approximation of the STRIPS yield curve to discount the corporate bond coupon payment which occurs between maturity dates on two STRIPS.

IV. Properties of the estimator

The purpose of the estimator is to measure the long-term expected default loss from bonds. We do not have a long enough history of default losses on bonds in our sample, which begins in 1994, to conduct a meaningful direct test. We therefore use three indirect tests to investigate the properties of the estimator. The first test compares the estimates of expected default for ratings categories to those based on historical data. The second examines the robustness of the estimates to model specification and its sensitivity to input parameters. Finally, the information content of the estimator is tested by studying its ability to predict ratings transitions.

A. Expected default losses for ratings categories

To test the properties of the estimator for ratings categories, we use the data for ratings from Huang and Huang (2003). Table 2 shows in columns (1) to (3) the values of spreads, leverage and equity expected return given by Huang and Huang for six ratings groups for bonds of ten years maturity, which in this test are used as inputs to our procedure. As these are drawn by them from a variety of sources and do not necessarily correspond to the same period of time, we use these data only to evaluate general properties of the calibration procedure. We also need an estimate of equity volatility, which Huang and Huang do not use. For this purpose we use the median volatility for each rating class from our dataset of bond trades. This is given in column (4).[13]

To benchmark our procedure against ratings class data, we calculate default loss estimates based on historical default experience. Elton *et al.* (2001) provide such estimates over different maturities conditional on starting from a particular rating class. We use these as one benchmark. However, the usefulness of these estimates for our purposes is limited. They assume that recovery is a function of ratings class, whereas Altman and Kishore (1996) document that recovery rates are highly dependent on industry and bond seniority, but not on initial rating after controlling for these variables. Moreover, Elton *et al.* also assume that annual ratings transitions are Markovian, and use these to estimate cumulative default probabilities for different horizons. Instead, we produce our own estimates of the yield equivalent of expected default using Moody's historical default frequencies reported in Keenan *et al.* (1999), also used by Huang and Huang (2003). These are direct estimates of cumulative default probabilities over different time horizons, conditional on starting from a particular rating. We assume a recovery rate for senior unsecured bonds of all ratings equal to 48.2% reported by Altman and Kishore (1996). This recovery rate is similar to the 51.3% from Moody's used by Huang and Huang. We combine default probabilities

[13]Note that the medians are slightly different from those reported in Table 1, because to increase the quality of the statistics here we select all trades rather than only those executed within three months after fiscal year end.

and recoveries to obtain an estimate of expected default loss over the life of the bond in a way similar to that of Elton *et al.* Namely, the historical default spread is the excess over the risk-free rate of the coupon with which the bond would trade at par in a risk-neutral world, assuming that cumulative default probabilities for each year until maturity are equal to the historical frequencies, and that upon default the recovery rate is equal to the historical average. This coupon, C, is defined implicitly by the relationship:

$$\sum \frac{(P_t^c - P_{t-1}^c)R + (1 - P_t^c)C}{(1+r)^t} + \frac{1 - P_T^c}{(1+r)^T} = 1$$

where R is the recovery rate and P_t^c is the cumulative probability of defaulting over t years. The spread due to expected default risk is $C - r$. Our estimates of the absolute and relative historical default loss spreads are reported in columns (10)–(11) of Table 2, and the estimates of default losses estimated by Elton *et al.* for AA-BBB rated bonds are reported for comparison in column (12).

Columns (5)–(9) of Table 2 present estimation results. For each rating, we calibrate the model (Equations (1)–(7)) when the unadjusted observed spread is used as an input, and also (except AAA) when the spread is adjusted for non-default factors by subtracting the average AAA spread of 63 basis points. The calibrated model parameters T, σ, and π are given in columns (5) to (7). For AAA-adjusted estimates, the asset risk premium π is generally about 4.5% and constant across ratings groups. This suggests that our procedure is not generating any systematic bias in the relationship between equity and asset risk. The calibrated values of asset volatility, σ, also appear reasonable. Although they should not necessarily be equal across ratings classes, they are sufficiently similar to suggest that most of the variation in equity volatility reported in Table 1 is coming from differences in leverage between ratings classes rather than differences in the nature of the assets.

The implied maturity parameter T is given in column (5). This reflects not only the actual ten year maturity of the debt, but also any other factors ignored in the Merton model but reflected in the spread s. The implied values of T are typically higher than the true debt maturity, which is consistent with the fact that the under-prediction of spreads by the Merton model is less pronounced for longer maturities.

INSERT TABLE 2 HERE

The estimated values of the default loss spread are given in column (8) of Table 2, and column (9) expresses them as a proportion of the full observed spread. Interestingly, in absolute terms the estimated spread due to default is not highly sensitive to the deduction of the AAA spread. However, we believe that the reasons for making this adjustment are so compelling that we use it throughout the rest of the paper.

The estimated spreads due to default for AAA (unadjusted), AA, A, BBB, BB and B ratings categories are 5, 4, 9, 21, 78, and 237 basis points out of total spreads of 63, 91, 123, 194, 320, and 470 b.p., respectively. The corresponding estimates based on historical data, reported in column (11), are 4, 5, 8, 24, 132, and 353 b.p. For investment grade bonds, our loss estimates are consistent with those obtained from historical default and recovery data. These ratings categories are where the Merton model performs most poorly in tests of its absolute pricing estimates. Thus, the results suggest that its performance in the current application is much better. For the junk grades, our estimates are lower than those based on historical data. However, uncertainties about the estimates based on historical data are quite large, so the correspondence between the fitted and historical default risk components appears reasonable. Indeed, it is unlikely that the B spread of 470 basis points can be consistent with the expected default spread of 353 basis points computed on the basis of historical data. The historical estimate would leave only 117 basis points for liquidity, tax, bond-specific risk premia and the default risk premium. This is significantly lower than the corresponding 188 basis points for the BBB spread, which is difficult to justify. In contrast, our calibration-based estimates are 242 bp for BB and 233 bp for B. Thus, our estimates appear more reasonable when they differ from those based on historical data.

Our estimates of the proportion of the spread due to expected default reported in column (8) share one important property with the historical estimates in column (10): the proportion is increasing as the debt quality deteriorates. This demonstrates that using either a constant value for the default risk spread within a ratings category or even a constant proportion of the spread is unlikely to be correct, and a procedure such as ours is necessary to estimate the default spread accurately, even within a rating category.

As well as the spread due to default risk, which reflects the probability of default and the recovery rate, we estimated the model-implied probabilities of default, and found that these differed markedly from the historical default frequencies. Even though our procedure matches the expected *spread* due to default well, it gives a generally higher *probability* of default than the historical data. This is not surprising given the fact that continuous models of the Merton type tend to have a high probability of small losses in default; it is difficult to have a high loss rate in conjunction with a low probability of default in such models.

B. Robustness

We study the sensitivity of the model to the values of input parameters, and also test its robustness with respect to the precise model specification by introducing bankruptcy costs and strategic default into the basic Merton setup. Finally, we examine whether cash distributions in the form of dividends can change the model's predictions significantly.

1. Sensitivity to parameters

Table 3 presents sensitivity analysis for our procedure. We use AA and BB ratings categories and vary input parameter values. These are given in columns (1) to (5). The parameters are each varied individually up or down by 10 percent of their base value. The results are presented in columns (6) to (10).

INSERT TABLE 3 HERE

For both ratings categories, the estimated values of asset volatility and asset risk premia are quite robust with respect to variation in the inputs and the structure of the model. Even when equity volatility is varied, the asset volatility estimates remain stable. The expected default spread, δ, is also not very sensitive to individual parameter values. Table 2 demonstrated that it is not very sensitive to the subtraction of the AAA spread. Equation (7) shows that it does not depend at all on the risk-free interest rate. Table 3 also shows that it is insensitive to leverage. Thus, the relatively crude measure of leverage that we use is unlikely to be an issue. On the other hand, δ is somewhat sensitive to the estimate of the equity risk premium. We use this sensitivity below when we invert the procedure to estimate equity premia when expected default loss δ is given. The one variable to which the expected default spread shows high elasticity is equity volatility, σ_E. Second moments such as σ_E can be estimated quite accurately for equity returns. Thus, the procedure has the merit of giving a result that is sensitive only to a parameter that can be observed relatively accurately.

2. Sensitivity to model specification

To test robustness to model specification, we also use a simple variation of the Merton model which allows for liquidation costs and strategic debt service of the Anderson and Sundaresan (1996) type, as suggested by Davydenko and Strebulaev (2003). The model is described in the Appendix. It requires another parameter θ, which can be thought of as the proportional deadweight loss in bankruptcy. When bankruptcy costs and strategic debt service are introduced into the model, the implied value of maturity T inversely depends on the assumed bankruptcy cost θ. In particular, we can solve for the level of θ which makes the implied value of T equal to the actual ten year maturity of the debt.

Columns (2) and (3) of Table 4 give the results of these estimates, first using bankruptcy cost of 5% of the debt face value suggested by Anderson and Sundaresan, and then solving for θ using the actual 10 year maturity for T. Thus adjusted, the model produces higher values of the expected loss, but the increase is not substantial. For the BB bond it is 30 basis points of of the total spread of 320 basis points, and it is much smaller for the AA bond. These are small proportions of the total spread. The results therefore do not appear highly sensitive to model specification.

INSERT TABLE 4 HERE

The values of bankruptcy costs which make the Merton model consistent with the AAA-adjusted observed spread are 36% of the face value for the AA bond, and 12% for the BB bond. The latter is within the 10-20% range for bankruptcy costs estimated by Andrade and Kaplan (1998), which is consistent with the fact that the Merton model predicts spreads for low-grade bonds reasonably well. The former is higher than bankruptcy costs estimates of Adrade and Kaplan. However, for the AA bond the estimated expected loss δ is invariably very small regardless of the assumptions of the model. For both bonds, the estimate of δ is not highly sensitive to our choice of the calibration method for the Merton model, in which T is a free parameter.

3. Sensitivity to dividends

The version of the Merton model that we use does not include distributions in the form of dividends or coupons on debt. We deal with the debt structure by allowing the maturity of debt to be endogenous. To test for sensitivity to dividends, we amend the standard Merton model by assuming that the firm pays continuous dividends that are a constant proportion γ of the value of the firm V, as described in the Appendix.

Columns (4)–(6) of Table 4 report the results of model calibration for different values of the instantaneous equity dividend yield $g = \gamma/(1-w)$. For the AA bond, the expected default loss estimate changes by less than 1 basis point when the dividend yield rises from zero to 2% of the equity value. For the BB debt, the corresponding change in δ is less than 19 basis points, which is almost a quarter of the base case prediction, but still less than 6 per cent of the total observed spread. Thus, substantial variation in the dividend yield has little impact on the proportion of the spread that is due to expected default. The dividend yield does, however, have a major impact on the implied maturity of the debt, T. It brings this down from the high values shown in Table 2 to levels considerably closer to the actual ten years of maturity.

4. Summary of robustness

We find that the estimate of the expected default loss generated by our procedure is not very sensitive to the values of the input parameters other than equity volatility. Although different model specifications or assumptions about cash distributions result in a wide range of values for calibrated model parameters, the resulting default loss estimate does not vary nearly as much. Across all specifications and input values reported, for AA bonds the expected default spread δ is invariably less than 7 per cent of the total observed spread. Thus, it is safe to conclude that the expected default spread is a very small proportion of the observed high-quality bond spread. For BB debt, the expected default component of the spread is between 16 and 32 percent of the total spread. Although this is a substantial variation, it reflects a very wide range of parameter values and model structures. We conclude that the split of the spread between expected default and other components is robust to model specification and the choice of the parameter values.

C. Expected default losses for individual bonds

Table 5 shows the estimates of the expected default loss for individual bonds in our sample. The calibration produces well-behaved estimates of asset volatility and risk premia. In particular, like the KMV estimates shown in Table 1, the asset volatility estimates are similar across ratings classes. The main difference is that they do not exhibit the high estimate for the B class that is produced by the KMV procedure.

INSERT TABLE 5 HERE

The estimates of δ are on average consistent with those based on ratings class data examined earlier. However, there is large variation within ratings classes. The coefficients of variation are greater than one for all but the B class, for which the cross-sectional standard deviation is large in absolute magnitude (124 b.p.) but lower than the mean spread (196 b.p.). These results indicate that using estimates of expected default averaged across a ratings group may be misleading if applied to individual bonds in the group. In particular, because of the large variation within each ratings category, methods which largely rely on ratings to estimate the expected default for individual bonds may be inaccurate.

One could argue that, although there is variation in values of δ within ratings classes, they may be accompanied by roughly proportional changes in the spread s, and therefore one could assume a constant default loss proportion δ/s for ratings classes. Table 5 demonstrates that, although this ratio is indeed slightly less variable within ratings categories than the absolute value of δ, it still exhibits significant variation. Therefore, the use of our estimation procedure appears preferable if estimates of losses for individual bonds are required.

D. Prediction of ratings transitions

The most direct test of the empirical validity of our estimator of the expected loss would be to compare actual realized losses with those estimated ex ante using the model. However, our data for individual bonds are for the period 1994–1999, whereas the predicted loss is for the actual bond maturity period of 7.5-10 years. We therefore cannot apply the direct test. Instead we test the information content of δ by relating it to future rating transitions for individual bonds. Since rating transitions precede default, any variable that predicts ratings transitions is likely to contain information about expected default. We regress three-year rating transitions in notches on the beginning of the period expected default loss estimate δ.[14] For homogeneity, we use only BBB bonds, because higher grade bonds have much lower expected losses, and lower grade bonds are much less frequent. We compare the predictive ability of δ with regards to the rating transition over the next three years with a linear regression on the three input variables: spread, leverage and volatility. Table 6 presents the result of this test.

INSERT TABLE 6 HERE

In specification (1), for each year's subsample of trades we estimate the following equation:

$$(rating\ change)^i = const + \beta_1 s^i + \beta_2 w^i + \beta_3 \sigma_E^i + \epsilon^i$$

This regression appears to suffer from overfitting in the sense that the coefficient estimates change a lot from year to year, and the variables with the highest predictive power also varies. In regression (2) we use a linear combination of the variables, using the weights from the prior year's regression. These are the weights that could be used in practice to estimate expected default, because they are known ex ante. The final regression (3) uses only the expected loss δ as the independent variable.

For each year other than 1994 the raw variables have significant predictive power for three-year ratings

[14] We use a regression rather than an ordinal procedure, such as probit or logit, because ratings notches are proxies for the cardinal variable expected loss, rather than just categories.

transitions (see specification (1)). The expected default variable, δ, is also significant in all years other than 1996 (specification (3)), although the R^2 in these univariate regressions is lower in all years except 1994. This suggests that the individual input variables together contain more information than the derived scalar loss predictor δ. However, year-by-year regression coefficients for the three input variables are highly unstable. The ex ante choice of weights for these variables for the linear combination which best predicts rating transitions for the future is therefore problematic. In practice, one could use the previous year's coefficients together with the current year's observations of the inputs to form an ex ante predictor. Specification (2) reports the results of regressing actual three-year transitions on this predictor.[15] The results for this variable are much worse than for the expected default variable in all years other than 1999. In most years it contains very little information. Thus, although ex post the spread, leverage and volatility appear to be informative with regards to ratings transitions, it is difficult to decide what combination of them should be used to form the prediction. By contrast, the estimated default loss δ is a theory-based non-linear function of the three inputs, which is known ex ante. In summary, the expected default variable is a significant predictor of ratings transitions and performs at least as well as a linear combination of its constituent variables that can be specified ex ante.

V. Equity risk premia estimates

Our approach can also be used to estimate equity risk premia from debt yields if expected bond losses are known from an independent source. The equity risk premium is one of the most important parameters in corporate finance and valuation, and its value is the subject of great controversy (Welch, 2000). Even small differences in estimates can have a major effect on valuations, and estimates ranging from 0% to more than 12% have been advocated. The reason for the disagreement is that all estimates are potentially subject to large standard errors. The equity risk premium is such an important and controversial parameter that any extra information that assists in its estimation is potentially very valuable. The advantage of using our approach for this purpose is that it relies on debt spreads and other observable capital market variables which aggregate agents' expectations about future returns. It avoids the measurement problems of other expectational variables, such as the analysts' forecasts used by Harris and Marston (1992).

To estimate equity risk premia, we equate the expected loss computed using our procedure to historical bond default losses by varying the equity risk premium used as an input, as follows. First, for each bond in the

[15] This variable still contains some ex post information, as the coefficients on which it is based come from three-year ratings transitions.

sample, we use cumulative default probabilities documented in Keenan *et al.* (1999) in conjunction with the historical average recovery rate on senior unsecured bonds of 48.2% reported in Altman and Kishore (1996), to calculate the historical default loss δ_h for the maturity of the bond. Second, we find asset and equity premia, π and π_E, which make equations (7) and (6) hold when $\delta = \delta_h$. Table 7 presents our results.

Across our sample of firms, the mean equity premium is 4.8%, and the asset premium 3.3%. These estimates are lower than those usually obtained from unadjusted historical averages. For instance, Brealey and Myers (2003) report an average premium for equities relative to treasury bills of 9.1% based on the period 1926–2000. Our estimates are closer to those of Dimson *et al.* (2001), who use a different historical period and make various adjustments to the raw historical averages. For ratings classes, the equity premia estimates range from 3.1% for AA companies to 8.5% for B companies, reflecting the different leverage in the different ratings classes. The asset risk premia exhibit less variability and no clear pattern across ratings.

INSERT TABLE 7 HERE

Apart from the robustness of our calibration approach, the validity of these estimates depends on the usability of the historical default data for ratings groups as predictions of future default probabilities for individual bonds in the sample. As the procedure is applied to individual bonds, the heterogeneity of expected default probability within rating groups and in time is likely to be an issue. Nevertheless, we believe that the reported equity premia estimates are at least suggestive, and can be used as cross-checks for other estimates reported in the literature.

VI. Applications and extensions

A. Applications

The expected return on debt plays a central role in many applications. Here we discuss three: in lending, portfolio management, and corporate finance.

The expected default loss is an important input to lending decisions and assessment of lending risk and performance. The expected return on a debt portfolio is the promised return net of the expected loss. Existing default loss estimation methods which do not use market yields may produce signals inconsistent with current yields. For instance, if expected loss is based on the ratings class, the highest yield bonds in the class will appear to have the highest expected return, even if the high yield is really due to higher expected loss. Our procedure, on the other hand, is calibrated to market yield spreads, and will not produce speculative forecasts of default. It can therefore be used as a benchmark against which to judge other default forecasts and risk models, as it allows to estimate what part of a credit forecast is based on beliefs that are speculative relative to the those implicit in current market prices.

A similar issue of using market consensus beliefs as a neutral expectation arises in portfolio management. In deciding how much risky debt to hold in a portfolio, the expected return plays a key role. Our method enables one to extract the market consensus expected return, which should assist in determining the neutral holding of each bond. Holdings based on speculative views will involve deviations from this neutral holding, and should be based on the difference between the speculative view and the market consensus view.

An important corporate finance application of the method is accounting for expected default in calculations of the cost of debt for use in the cost of capital. Standard methods of cost of debt estimation assume that the cost of debt is equal to either the promised yield on newly-issued debt of the firm or the risk-free rate. Both approaches fail to make a proper adjustment for the possibility of default. Neither is correct when only a part of the yield spread is due to expected default. The errors are most significant when the debt is risky. As Brealey and Myers (2003) say: 'This is the bad news: There is no easy or tractable way of estimating the rate of return on most junk debt issues' (p. 530). Our method helps to overcome this problem.

B. Extensions

The method proposed in this paper can be varied, extended and applied in many ways. For instance, we calibrate to the yield spread assuming that leverage is observable but debt maturity in the model is not. We could, alternatively, calibrate to the yield spread using the procedure of Delianedis and Geske (2001), which assumes that the market value of debt is unobservable and generates an implied firm value. Another extension would be to use different structural models to split the observed spread. Although we have performed a number of robustness tests, alternative specifications and models could be examined. In particular, the modelling of volatility, which is by far the most influential input to our procedure, may be extended. Also, spread adjustment for non-default factors may warrant research effort; in particular, a more complex model of liquidity could be used to address cross-sectional variation in this component. Finally, the rapidly emerging market for credit swaps is likely to provide an alternative source of information on default risk expectations.[16]

[16] Longstaff *et al.* (2003) provide evidence on relative pricing of corporate bonds and credit default swaps.

VII. Summary

This paper derives and tests a method of extracting the expected default loss on a corporate bond from its yield spread. The estimate also incorporates information from leverage, equity volatility and equity risk premia. The spread is adjusted for factors other than default risk by subtracting the AAA spread. The remainder is then split into expected default loss and risk premium using the Merton (1974) model of risky debt pricing. The idea of the method is to extract current forward-looking market expectations about future default losses incorporated in observed debt and equity prices. The method does not rely on historical data, can be applied to individual bonds, and does not produce signals that would be speculative relative to current market yields.

We test robustness of the method by varying the structure of the model used to split the spread, and its parametrization. The procedure, though based on the simplest contingent-claims model of risky debt, is found to be robust in estimating the default loss component of the spread. We believe that this robustness comes from the fact that all models of risky debt must preserve the basic structure of debt and equity: that debt is senior to equity. This makes the choice of the particular structural model secondary when the goal is splitting the observed market spread into default and non-default components. We find that predicted default losses are consistent with historic experience for different rating classes. We test the ability of the estimator to predict ratings transitions and show that it appears to incorporate much of the information contained in spreads, leverage and volatility. It predicts three-year rating transitions with an R^2 of about 10 percent. However, an important aspect of the estimator is that it is sensitive to the forecast of volatility; this is an aspect of the estimation procedure that could be extended to possibly improve the estimator.

The method has many possible applications in lending decisions, bank regulation, portfolio building, risk management, performance evaluation and cost of capital analysis. We use it to provide an entirely new set of equity risk premium estimates, based on data hitherto unused for this purpose. We obtain asset risk premia estimates of about three percent, while equity risk premia vary from three to nine percent depending on the firm's rating.

Appendix

In its standard form, the Merton model states that:

$$B = VN(-d_1) + Fe^{-rT}N(d_2) \tag{A.1}$$

where V is the value of the assets of the firm, B is the value of the debt, F is the promised debt payment (the face value of the debt for a zero-coupon bond), and:

$$d_1 = [\ln[V/F] + (r + \sigma^2/2)T]/\sigma\sqrt{T} \tag{A.2}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{A.3}$$

The promised debt yield spread over Treasury, and the financial leverage are given by:

$$s = \frac{1}{T}\ln\frac{F}{B} - r \tag{A.4}$$

$$w = B/V \tag{A.5}$$

Substitution of (A.4)-(A.5) into (A.1)-(A.3) yields equations (2)-(4) in the main text.

From the dynamics of the firm's assets given by (1) it follows that the value of assets at debt maturity V_T is:

$$V_T = Ve^{(r+\pi-\frac{\sigma^2}{2})T+\sigma\sqrt{T}Z} \tag{A.6}$$

where Z is a standard normal variable, and the asset risk premium $\pi = \mu - r$. Then, the yield spread which is due to the expected default loss over the maturity period is found from:

$$Be^{(r+s-\delta)T} = \int_{Z:\,V_T<F} V_T\,dN(Z) + \int_{Z:\,V_T\geq F} F\,dN(Z) \tag{A.7}$$

Evaluating the integral yields equation (7) of the main text.

The basic Merton model can be perturbed to account for bankruptcy costs and strategic default similar to that of Anderson-Sundaresan (1996), as suggested in Davydenko and Strebulaev (2003). In this model the transfer of the firm's assets to bondholders in bankruptcy involves a fixed cost of H. Moreover, the debt contract can be renegotiated, and bankruptcy does not automatically occur when equityholders fail to repay F to bondholders at maturity. In equilibrium, equityholders make opportunistic take-it-or-leave-it offers to bondholders regarding the level of debt repayment, which may be lower than the contracted amount F but high enough to persuade bondholders to renegotiate the debt rather than demand costly bankruptcy. The equilibrium payoff to debt at maturity is:

$$B_T = \min\{F, \max\{V_T - H, 0\}\}$$

The value of the bond is:

$$\begin{aligned} B &= Call(H) - Call(F+H) = \\ &= V\left[N(d_1^H) - N(d_1^{F+H})\right] + Fe^{-rT}\left[(1+\theta)N(d_2^{F+H}) - \theta N(d_2^H)\right] \end{aligned}$$

where $\theta = H/F$ is the bankruptcy cost expressed as a fraction of the debt par value, and:

$$\begin{aligned} d_1^H &= \left[-\ln w - (s - \sigma^2/2)T\right]/\sigma\sqrt{T} - \ln\theta/\sigma\sqrt{T} \\ d_1^{F+H} &= \left[-\ln w - (s - \sigma^2/2)T\right]/\sigma\sqrt{T} - \ln(1+\theta)/\sigma\sqrt{T} \\ d_2^i &= d_1^i - \sigma\sqrt{T}, \qquad i = H, F+H \end{aligned}$$

Dividing by B yields:

$$1 = \left[N(d_1^H) - N(d_1^{F+H})\right]/w + e^{sT}\left[(1+\theta)N(d_2^{F+H}) - \theta N(d_2^H)\right] \tag{A.8}$$

Itô's lemma also implies that:

$$\sigma_E/\sigma = \frac{\partial E}{\partial V}V/E = \left[1 - N(d_1^H) + N(d_1^{F+H})\right]/(1-w) \tag{A.9}$$

The system of equations (A.8)-(A.9) is analogous to system (2)-(5) in the basic specification of the model. For a given value of θ we can solve the system to determine T and σ which are consistent with the observed firm's characteristics w, σ_E, and s. Alternatively, assuming that T is known, θ can be treated as an unknown parameter which makes the model consistent with the observed spread. In this case, the system can be solved for θ and σ instead. Once this is done, the expected loss over the maturity period is:

$$\delta = -\frac{1}{T}\ln\left[e^{(\pi-s)T}\frac{N(K_1^H) - N(K_1^{F+H})}{w} + (1+\theta)N(K_2^{F+H}) - \theta N(K_2^H)\right] \tag{A.10}$$

$$K_j^i = d_j^i - \pi\sqrt{T}/\sigma, \qquad i = H, F+H, \quad j = 1, 2$$

which is the analog of formula (7) for this case.

Another robustness check of the model we perform is a test of its sensitivity to cash distributions. To this end, we assume in the basic model that the firm pays continuous dividends that are a constant proportion γ of the value of the firm V. The instantaneous equity dividend yield is then $g = \gamma/(1-w)$.

Repeating the analysis under this assumption, equations (2)–(7) become:

$$e^{-\gamma T} N(-d_1)/w + e^{sT} N(d_2) = 1 \tag{A.11}$$

where

$$d_1 = [-\ln w - (s + \gamma - \sigma^2/2)T]/\sigma\sqrt{T} \tag{A.12}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{A.13}$$

and:

$$(1 - w)\sigma_E = \sigma[1 - e^{-\gamma T} N(-d_1)] \tag{A.14}$$

$$\delta = -\frac{1}{T} \ln \left[e^{(\pi - \gamma - s)T} N \left(-d_1 - (\pi - \gamma)\sqrt{T}/\sigma \right) /w + N \left(d_2 + (\pi - \gamma)\sqrt{T}/\sigma \right) \right] \tag{A.15}$$

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Table 1
Summary Statistics on Credit Risk Variables

		AAA	AA	A	BBB	BB	B	All
Spread, b.p.	Mean	28	45	69	107	208	396	101
	Median	28	47	66	95	182	369	81
	Std. Dev.	10	21	39	50	111	119	80
Leverage	Mean	0.06	0.13	0.25	0.35	0.49	0.63	0.31
	Median	0.06	0.12	0.24	0.35	0.44	0.61	0.29
	Std. Dev.	0.03	0.07	0.14	0.14	0.20	0.15	0.17
Equity volatility	Mean	0.33	0.30	0.33	0.33	0.39	0.62	0.34
	Median	0.33	0.28	0.29	0.30	0.38	0.62	0.30
	Std. Dev.	0.17	0.10	0.12	0.11	0.12	0.18	0.12
Maturity	Mean	8.53	8.81	9.00	8.86	8.91	8.87	8.92
	Median	8.53	8.81	9.12	8.88	9.15	9.01	8.99
	Std. Dev.	0.21	0.75	0.75	0.74	0.69	0.87	0.74
Duration	Mean	6.56	6.69	6.76	6.57	6.47	6.14	6.64
	Median	6.56	6.71	6.79	6.58	6.48	5.99	6.65
	Std. Dev.	0.16	0.48	0.52	0.47	0.56	0.54	0.52
KMV asset	Mean	0.24	0.25	0.25	0.25	0.26	0.49	0.25
volatility	Median	0.24	0.25	0.22	0.23	0.25	0.39	0.23
	Std. Dev.	0.07	0.06	0.09	0.10	0.10	0.30	0.10
	N	2	231	1088	1003	266	42	2632

This table reports summary statistics for the final sample, which includes trades on non-callable senior unsecured bonds between 7.5 and 10 years to maturity, executed within 3 calendar months after the last fiscal year end. Yield spreads are calculated relative to a matched portfolio of STRIPS, and given in basis points. Leverage is the ratio of the book value of debt to the book value of debt plus the market value of equity on the last business day before the trade date. Equity volatility is the annualized volatility of daily share price returns over 2 years before the trade date. KMV asset volatility is the annualized volatility of asset returns implied by the Merton (1974) model estimated using the KMV procedure described in Crosbie and Bohn (2002).

Table 2
Estimated expected default losses

Rating	Spread adjust-ment	Model inputs				Model parameters			Default loss: Model		Default loss: Historical		Default loss: EG
		s b.p. (1)	w (2)	π_E % (3)	σ_E (4)	T yrs. (5)	σ (6)	π % (7)	δ b.p. (8)	δ/s (9)	δ_h b.p. (10)	δ_h/s (11)	δ_{EG} b.p. (12)
AAA	None	63	0.13	5.38	0.27	51.08	0.24	4.83	5.36	0.09	3.95	0.06	
AA	None	91	0.21	5.60	0.28	51.97	0.23	4.74	9.45	0.10	5.41	0.06	4.80
	AAA	28				19.60	0.22	4.51	3.87	0.04			
A	None	123	0.32	5.99	0.29	49.86	0.23	4.68	15.58	0.13	8.33	0.07	14.00
	AAA	60				22.97	0.21	4.37	9.46	0.08			
BBB	None	194	0.43	6.55	0.31	65.38	0.23	4.91	26.85	0.14	24.40	0.13	40.90
	AAA	131				35.22	0.21	4.51	21.28	0.11			
BB	None	320	0.54	7.30	0.38	43.05	0.27	5.07	93.02	0.29	132.24	0.41	
	AAA	257				29.25	0.25	4.73	78.15	0.24			
B	None	470	0.66	8.76	0.57	9.87	0.30	4.54	271.34	0.58	352.87	0.75	
	AAA	407				8.27	0.28	4.33	236.70	0.50			

The table gives model-predicted expected default losses and probabilities for generic bonds in 6 rating groups. The second column indicates whether the observed spread was adjusted for non-default factors by subtracting the average spread on AAA bonds. The inputs are mean values in each rating class of the promised spread on debt s, leverage w, and assumed equity risk premium, π_E, as used in Huang and Huang (2003); and the median volatility of equity σ_E from our studied sample. T, σ and π are model-implied maturity, volatility of assets and asset risk premium. The outputs is the predicted expected default loss on debt δ. δ_h is the excess over the risk-free rate of the coupon rate on a 10-year bond with default probabilities in each year 1–10 equal to those reported by Moody's in Keenan *et al.* (1999), and a recovery rate of 48.2%, which makes its risk-neutral value equal to par. δ_{EG} is the default loss for a 10-year bond estimated in Elton *et al.* (2001).

Table 3
Sensitivity to Parameter Values

Model inputs					Parameter estimates				
s b.p. (1)	s adj. b.p. (2)	w (3)	π_E % (4)	σ_E (5)	T (6)	σ (7)	π % (8)	δ b.p. (9)	δ/s (10)
Panel A: Typical AA-rated bonds									
91	28	0.21	5.60	0.28	19.60	0.22	4.51	3.87	0.043
82	19				15.80	0.22	4.48	2.77	0.034
100	37				23.44	0.22	4.55	4.87	0.049
		0.19			20.88	0.23	4.62	3.63	0.040
		0.23			18.51	0.22	4.40	4.09	0.045
			5.04		19.60	0.22	4.06	4.85	0.053
			6.16		19.60	0.22	4.96	3.06	0.034
				0.25	27.61	0.20	4.54	2.09	0.023
				0.30	14.53	0.24	4.49	5.83	0.064
Panel B: Typical BB-rated bonds									
320	257	0.54	7.30	0.38	29.25	0.25	4.73	78.15	0.244
288	225				24.03	0.24	4.56	70.10	0.243
352	289				35.56	0.26	4.90	85.86	0.240
		0.48			30.23	0.26	5.01	75.96	0.237
		0.59			28.71	0.23	4.44	80.10	0.25.0
			6.57		29.25	0.25	4.26	90.00	0.281
			8.03		29.25	0.25	5.20	67.47	0.211
				0.34	52.26	0.24	5.06	51.14	0.160
				0.42	18.35	0.26	4.49	101.86	0.318

For the generic AA and BB bonds from Table 2, this table reports the sensitivity of the predicted expected default loss to model inputs, obtained by decreasing and increasing the base values of individual parameters by 10%. The inputs are the promised spread on debt s adjusted for non-default factors by subtracting the average AAA spread (s adj. is the adjusted spread value), leverage w, equity risk premium, π_E, and equity volatility, σ_E. The outputs are model-implied maturity T, volatility of assets σ, asset risk premium π, and the predicted expected default loss on debt, δ.

Table 4
Robustness To Model Specification and Dividend Yield

	Base case	Strategic default		Dividends		
	$\theta = 0$	$\theta = 5\%$	$T = 10$	$g = 1\%$	$g = 2\%$	$g = 3\%$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Typical AA-rated bond						
s=91 b.p., s adj. =28 b.p., $w = 0.21$, $\pi_E = 5.60\%$, $\sigma_E = 0.28$						
T	19.6	17.6	10	16.3	14.0	12.4
σ	0.22	0.22	0.22	0.22	0.22	0.22
π, %	4.51	4.51	4.49	4.51	4.50	4.50
θ, %	–	5	36	–	–	–
δ, b.p.	3.87	4.16	5.99	4.08	3.02	0.42
δ/s, %	0.043	0.046	0.066	0.045	0.033	0.005
Panel B: Typical BB-rated bond						
s=320 b.p., s adj.=257 b.p., $w = 0.54$, $\pi_E = 7.30\%$, $\sigma_E = 0.38$						
T	29.3	16.9	10	19.4	14.9	12.3
σ	0.25	0.24	0.23	0.24	0.24	0.23
π, %	4.73	4.60	4.45	4.60	4.51	4.45
θ, %	–	5	12	–	–	–
δ, b.p.	78.2	92.7	108.3	90.4	96.7	99.8
δ/s, %	0.244	0.290	0.339	0.283	0.302	0.312

For the generic AA and BB bonds from Table 2, this table reports the sensitivity of the predicted expected default loss to model assumptions and cash distributions. Column (1) reports base-case results for the standard model. Columns (2) and (3) report results of the modified model with proportional bankruptcy costs θ and strategic default. Columns (4) to (6) report results of a modified model that allows cash dividend distributions which are a constant fraction of the firm's value, for different levels of the instantaneous dividend yield as a proportion of equity value, g. The inputs are the promised spread on debt s adjusted for non-default factors by subtracting the average AAA spread (s adj. is the adjusted spread value), leverage w, equity risk premium, π_E, and equity volatility σ_E. The outputs are model-implied maturity T, volatility of assets σ, asset risk premium π, and the predicted expected default loss on debt, δ. The details of the model modifications are described in the Appendix.

Table 5

Expected losses for individual bonds in the sample

		Model inputs					Parameter estimates				
		s b.p. (1)	s adj. b.p. (2)	w (3)	π_E % (4)	σ_E (5)	T (6)	σ (7)	π (8)	δ b.p. (9)	δ/s (10)
AA	Mean	57.06	11.08	0.17	5.60	0.28	19.67	0.24	4.71	1.78	0.027
(N=90)	Median	53.24	7.90	0.17	5.60	0.27	14.24	0.22	4.68	0.54	0.012
	Std. Dev.	12.08	9.99	0.08	0.00	0.09	16.87	0.08	0.41	2.98	0.040
A	Mean	78.06	27.63	0.27	5.99	0.31	19.87	0.23	4.49	6.19	0.064
(N=825)	Median	70.40	21.79	0.26	5.99	0.28	14.10	0.21	4.52	2.31	0.034
	Std. Dev.	29.36	25.06	0.14	0.00	0.11	18.81	0.10	0.79	10.39	0.075
BBB	Mean	110.13	58.56	0.36	6.55	0.33	28.22	0.23	4.55	13.83	0.107
(N=949)	Median	96.14	47.14	0.35	6.55	0.30	15.03	0.21	4.58	7.03	0.076
	Std. Dev.	45.63	43.48	0.14	0.00	0.10	68.19	0.09	0.76	20.79	0.102
BB	Mean	208.13	155.07	0.49	7.30	0.39	28.57	0.23	4.49	55.58	0.220
(N=255)	Median	182.16	130.42	0.45	7.30	0.37	19.01	0.21	4.85	31.75	0.200
	Std. Dev.	110.75	109.85	0.19	0.00	0.12	33.26	0.08	1.20	69.17	0.162
B	Mean	395.65	335.46	0.63	8.76	0.62	16.33	0.29	4.35	195.74	0.473
(N=42)	Median	368.59	315.65	0.61	8.76	0.62	4.44	0.29	4.10	157.15	0.489
	Std. Dev.	119.35	121.24	0.15	0.00	0.18	23.64	0.09	1.37	124.44	0.184
All	Mean	112.79	61.55	0.34	6.43	0.33	24.49	0.23	4.52	18.88	0.108
(N=2161)	Median	88.25	38.00	0.32	6.55	0.30	14.67	0.21	4.58	5.67	0.064
	Std. Dev.	78.63	76.24	0.17	0.55	0.12	48.44	0.09	0.84	44.04	0.125

The table gives model-predicted expected default losses for non-callable senior unsecured bonds with maturity between 7.5 and 10 years to maturity. The inputs are the annualized promised debt spread s relative to a matched portfolio of STRIPS, adjusted for non-default factors by subtracting the average AAA spread for the year of trade (s adj. is the adjusted spread value); leverage w calculated as the ratio of the book value of debt to the sum of the book value of debt and market value of equity; equity risk premium π_E for the rating class used in Huang and Huang (2003), and equity volatility σ_E, calculated as the annualized volatility of daily share price returns over 2 years before the trade date. The outputs are model-implied maturity T, volatility of assets σ, asset risk premium π, and the predicted expected default loss on debt, δ.

Table 6
Predicting rating transitions

Year		*const*	s	w	σ_E	lagged	δ	R^2
1994	(1)	0.95(1.16)	-0.08 (-0.18)	-1.44 (-1.42)	-0.91 (-0.52)			3.8%
	(2)	N/A				N/A		N/A
	(3)	0.27 (1.37)					-0.026 (-1.85)	4.5%
1995	(1)	3.05 (6.86)	-0.55 (-2.40)	-2.43 (-3.49)	-3.91 (-3.59)			24.0%
	(2)	0.56 (1.01)				0.37 (0.56)		0.2%
	(3)	0.63 (5.52)					-0.029 (-5.44)	16.8%
1996	(1)	-1.07 (-2.07)	0.01 (0.05)	1.90 (2.85)	2.33 (1.68)			5.2%
	(2)	-0.13 (-0.27)				-0.15 (-0.86)		0.4%
	(3)	0.17 (1.64)					0.011 (1.66)	1.5%
1997	(1)	2.18 (3.27)	-1.43 (-2.90)	2.79 (2.61)	-8.16 (-6.61)			35.1%
	(2)	-1.51 (-2.56)				0.55 (1.53)		1.2%
	(3)	0.27 (1.93)					-0.121 (-9.58)	32.9%
1998	(1)	3.45 (3.54)	-1.70 (-4.23)	-0.97 (-0.52)	-5.96 (-3.37)			17.2%
	(2)	-2.21 (-3.89)				-0.23 (-2.22)		2.4%
	(3)	-0.38 (-1.72)					-0.035 (-5.60)	13.7%
1999	(1)	10.31 (8.71)	0.39 (0.89)	-10.66 (-7.26)	-18.65 (-9.06)			42.6%
	(2)	-6.68 (-7.29)				-0.31 (-6.83)		24.1%
	(3)	0.49 (1.35)					-0.048 (-4.50)	12.1%

The table reports the results of regression analysis of rating predictions by year of trade. The dependent variable is the rating transition in notches in 3 years subsequent to the date of trade for each trade in the dataset, consisting of bonds with maturity between 7.5 and 10 years. Independent variables in specification (1) are the spread (s), leverage (w), and equity volatility (σ_E) for the trade. Regression (2) in each year between 1995 and 1999 uses the regression coefficients for the variables s, w and σ_E estimated in regression (1) for the previous year to form a linear combination of these variables. This linear combination is then used as a regressor. In regression specification (3) the independent variable is δ, the expected default spread estimated for the trade using the procedure. t-statistics are reported in parentheses.

Table 7
Estimated cost of equity for individual bonds in the sample

		Model inputs					Model parameters			Model estimate
		s b.p. (1)	s adj. b.p. (2)	w (3)	σ_E (4)	δ b.p. (5)	T (6)	σ (7)	π % (8)	π_E, % (9)
AA	Mean	61.13	15.84	0.18	0.28	5.45	22.80	0.24	2.51	3.06
(N=58)	Median	57.98	13.02	0.20	0.27	5.46	15.54	0.22	2.09	2.68
	Std. Dev.	11.96	9.46	0.08	0.09	0.07	18.51	0.08	2.28	2.95
A	Mean	82.58	32.01	0.28	0.31	7.74	21.68	0.23	3.78	5.30
(N=696)	Median	74.14	25.30	0.28	0.28	7.78	15.32	0.20	2.61	3.42
	Std. Dev.	29.51	24.92	0.14	0.10	0.43	19.64	0.09	3.88	5.51
BBB	Mean	116.68	65.53	0.37	0.33	23.52	31.04	0.23	3.02	4.49
(N=815)	Median	103.32	52.13	0.37	0.30	23.58	16.59	0.20	2.03	2.98
	Std. Dev.	45.83	43.03	0.14	0.10	0.80	73.08	0.08	3.22	4.87
BB	Mean	280.53	226.46	0.55	0.42	134.93	35.60	0.24	2.31	4.30
(N=119)	Median	244.47	185.09	0.50	0.41	134.48	19.22	0.23	1.38	2.44
	Std. Dev.	125.31	125.20	0.21	0.11	1.40	43.71	0.09	2.72	4.31
B	Mean	534.86	475.14	0.61	0.73	367.05	14.91	0.35	3.83	8.53
(N=14)	Median	496.50	438.34	0.60	0.82	368.47	2.35	0.37	2.91	6.36
	Std. Dev.	96.30	90.08	0.14	0.22	4.50	21.72	0.08	3.47	8.34
All	Mean	115.74	64.75	0.34	0.33	27.07	27.12	0.23	3.27	4.79
(N=1702)	Median	91.45	41.40	0.32	0.30	22.38	16.38	0.21	2.20	3.18
	Std. Dev.	80.15	77.64	0.17	0.11	44.05	53.73	0.09	3.48	5.12

The table reports the cost of equity values consistent with historical default probabilities and recovery rates. The sample consists of senior unsecured bonds with maturity between 7.5 and 10 years. The inputs are the annualized promised debt spread s relative to a matched portfolio of STRIPS, adjusted for non-default factors by subtracting the average AAA spread for the year of trade (s adj. is the adjusted spread value); leverage w calculated as the ratio of the book value of debt to the sum of book value of debt and market value of equity; equity volatility σ_E, calculated as the annualized volatility of daily share price returns over 2 years before the trade date; and the expected default loss for the bond δ, estimated as the excess over the risk-free rate of the coupon rate which would make the risk-neutral bond value equal to par, assuming default probabilities in each year until maturity equal to those reported by Moody's in Keenan *et al.* (1999), and a recovery rate of 48.2%. The outputs are model-implied maturity T, volatility of assets σ, asset risk premium π, and the imputed expected equity premium π_E.