Absolute or Relative?
Which Standard do Credit Rating Agencies Follow? [1]

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Summary

In this paper we compare objective measures of the likelihood of firm default with the subjective ratings assigned to corporate debt issuers by one of the major credit rating agencies. By doing so we seek to determine whether the rating agencies use objective time invariant standards to assign credit ratings or whether the ratings can only be interpreted as relative ranking of credit quality conditional on the distribution of credit quality among issuers at a given point in time. We further seek to determine the nature of these time varying standards for different rating categories. Using a quarterly panel data set from 1986 – 2000, we first estimate an objective probability of default using a variant of Merton's market model of credit risk for all publicly traded companies in the Compustat database for which Standard and Poor's has assigned a credit rating. Then we estimate an ordered probit model of credit rating standards over the same time period to determine the standards employed by the rating agency for the period of our data. Finally, we demonstrate that the estimated thresholds from the ordered probit models are directly related to the probability of default for an average firm consistent with the hypothesis that ratings can only be interpreted as relative ranking of credit quality and that the rating standards are indeed time varying.

Introduction

It is difficult to understate the importance credit ratings play in modern global economies. Certainly almost all financial institutions use credit ratings to guide both their investing decisions and the manner in which they design securities. Likewise the capital structure decisions of almost all major corporations are, at least in part based upon the opinions of the rating agencies. Even governments have promulgated regulations that use the opinions of rating agencies for a variety of purposes (e.g., the credit risk charges in the Basel II banking regulations or SEC restrictions placing limits on the credit quality of bonds that various types of U.S. financial institutions are allowed to invest in).

Although a vast literature exists investigating various aspects of credit ratings, the standards used by the agencies to assign a discrete letter grade to an individual borrower and the manner by which those standards are implemented have, until recently, received little attention from academics.[3] However, a series of recent papers have begun to investigate the development of the standards used by the agencies and the results suggest a richness to the problem that deserves further study.

The recent literature investigating standards can roughly be divided into two areas of inquiry. The first branch focuses on changes in standards over long periods of time. The literature can be traced to a series of papers in which various authors suggested the credit quality of debt issued by U.S. corporations has been declining over time (for an early and prominent example, see Lucas and Lonski 1992). Although market participants expressed widespread belief in this view, Blume, Lim and MacKinlay (1998) published an influential paper suggesting that it was not the credit quality of corporate debt that has been declining but instead the standards used by the major rating agencies had become more stringent over the time period of their study (late 1970's through the mid 1990's). Doherty and Phillips (2002) conduct a similar investigation and also report that standards used by the A.M. Best Company to assign financial strength ratings to U.S. insurers also became more stringent during the late 1980's through the end of the twentieth century.[4]

The second branch of this literature is not focused on long term changes in standards but instead focuses on the short term "exceptions" that agencies admit they make to the own rules to avoid excessive volatility in the rating they assign. Known as "rating-through-the-cycle", all of the major debt rating agencies state they voluntarily avoid changing a rating standard even if the creditworthiness of the underlying firm has changed. They do so in order to balance the trade-

[3] Other areas of inquiry that appear in the literature are papers justifying the formation of the rating agencies themselves (e.g., Millon and Thakor 1985; Lizerri 1999), the informational content of the ratings (e.g., Hand, Holthausen and Leftwich 1992; Kliger and Sarig 2000), the determinants of ratings (e.g., Kaplan and Urwitz 1979), the performance of the ratings (e.g., Altman and Kao 1992, Lando and Skodeberg 2002) and the difference in opinions across rating agencies (e.g., Cantor and Packer 1997; Pottier and Sommer 1999).
[4] The A.M. Best Company is the oldest and arguably the most influential agency assigning rating opinions of both life-health and insurance companies.

off between the need for investors to have an accurate view of the borrower's ability to repay its obligations versus the desire for the rating to be somewhat stable over time such that only permanent changes in the creditworthiness of the borrower are reflected in the current rating. For example, Standard & Poor's suggest "the value of its rating products is greatest when it's rating does not fluctuate with near term performance. Ratings should never be a mere snapshot of the present situation." (Standard and Poor's, 2006). Thus, the through-the-cycle methodology compromises the need for the rating to reflect all current information versus the desire for the rating to be somewhat stable such that only permanent changes in creditworthiness cause changes in the current rating.

A small but growing literature has begun to investigate the through-the-cycle methodology employed by the rating agencies. Altman and Rijken (2004) empirically compare the dynamics of ratings assigned by one of the dominant ratings agencies with a point-in-time credit scoring model to demonstrate the differences in time series behavior of ratings assigned using the two methods. Loffler (2004a) develops a model to simulate a through-the-cycle methodology and demonstrates that many, but not all, of the empirical irregularities reported in the literature are consistent with agencies employing this method. Finally, in a related work, Loffler (2002, 2005) looks at another methodology agencies suggest they use to achieve stable ratings whereby the agency chooses to downgrade/upgrade a borrower's rating only when it is unlikely to be reversed within a short amount of time. Although similar to the through-the-cycle, the "avoiding the ratings bounce" strategy is implemented in a slightly different way as the agency chooses to violate its own rating standards regarding where the boundary lies for the assignment of a rating if there is some concern that the borrower's condition is likely to improve/deteriorate in the near term.

Although the agencies suggest they employ the through-the-cycle and rating bounce avoidance methodologies, none of these methods has been shown to be derived from a theoretical model based upon first principles. In particular, Lizzeri (1999) and Strausz (2005) suggest the standards rating agencies employ may change in the short term for reasons other than rating through the cycle. The intuition in these papers point more towards role of rater as an information intermediary above and beyond that of the desire of investors to avoid rating reversals, hence rating stability and rating through the cycle.

In this paper we draw upon Lizzeri (1999) and Strausz (2005) to test if the long term ratings perspective of rating agencies gets affected by current conditions of a "point in time" perspective as well, provided the "point in time" corresponds to the long term period associated with such long term ratings (see Altman and Rijken, 2004). With this objective in mind we adopt an empirical framework which is well established in the ratings literature i.e., the ordered probit model. Our findings indicate that stability of ratings noted in the literature may also be getting affected by factors other than the investors desire to "avoid rating bounce", "through the cycle methodology" (and by this we mean "notching" and "partial adjustment" (Altman and Rijken, 2004) of ratings), and the "long term trend" of default risk minus the "cyclical" component.

The finding suggests the rating standards are conditioned upon the entire distribution of the credit quality, while controlling for the momentum and business cycle effects (Amato and Furfine, 2004). The basis for segregating default risk from business cycles can be found in Koopman and Lucas (2005). Over the period considered in the paper, we find also find evidence corroborating the BLM finding that rating standards exhibit a tightening over time. The implication of this finding is that long term ratings reflect only a conditional probability of default and not an unconditional likelihood of default. The evidence calls into question the stated sharp dichotomy between banks internal rating models and those of Nationally Recognized Statistical Rating Organization (NRSRO) ratings being based upon "point in time" vs. "through the cycle" methodology.

The organization of the paper is as follows. In Section I, we review the nature of literature on ratings in general and specific to this study. In Section II, we develop the main hypothesis for this paper. Section III, contains the description of data, sample, and methodology. In section IV, we discuss the results. Section V concludes.

Section I

Literature Review

Beginning with Carey and Hrycay (2001), several papers have tried to analyze the rating stability and "rating through the cycle" methodology of rating agencies. Loffler (2004), Altman and Rijken (2005), present models wherein long term ratings are affected by permanent components of the default risk shocks and internal rating methods of agencies respectively. The thrust of these papers has been to study the long term nature of ratings as opposed to the market's "point in time" perspective in models which are consistent with ratings drift well established in the literature.

An aspect of ratings is providing information to the market in an asymmetric environment. Theoretical papers like Ramakrishnan and Thakor (1984) and Millon and Thakor (1985) focus on this aspect. Empirical papers find that the "timeliness" of ratings may not be optimal owing to their desire to achieve rating stability, thus making them informationally inefficient (see Loffler (2004)).

Boot *et al* (2006) focus on monitoring role of credit rating agencies. In their paper credit rating agencies not only act as information providers but also act as watchdogs over credit quality of borrowers. The authors argue that if there is a positive fraction of investors who believe in the ratings and bases its investment decisions on these ratings, then borrowers will not engage in asset substitution (Jensen and Meckling (1976)) and will choose projects commensurate with the riskiness associated with their ratings. Therefore, the rating agency in this paper acts as a coordination mechanism between investors and borrowers to remove bad equilibria associated with moral hazard problems.

Lizzeri (1999) and Strausz (2005) focus on the role of rating agencies as certifiers, given that other theoretical papers have focused on the informational role of rating agencies about credit quality. These papers argue that a monopolistic rater can capture informational surplus without completely transferring it to the market. However, empirical papers show that the information released is still substantial for markets to react abnormally. For a review of this set of empirical papers, please refer to Jorion et al., 2004.

Our study draws upon Lizzeri (1999) and Strausz (2005) to study the dichotomy between "point in time" vs. " though the cycle" ratings. In particular we study the standards employed by rating agencies (in essence we study the behavior of the rating agencies themselves). To do this we combine a model for insolvency prediction with a model for predicting ratings. Our paper is also related to Blume, Lim and MacKinlay (1998); and Doherty and Phillips (2002).

Lucas and Lonski (1992) analyzed the credit quality of firms between 1970 -1990 and came to the conclusion that the credit quality of the firms had declined over this period. BLM (1998) on the contrary focused on if the rating agencies changed their standards over time and concluded that the rating standards have become more stringent.

However, several critiques of the BLM study have been put forth. Nayak (2001) argues the intercept term is only a noisy proxy for rating standards since it captures the effects of all variables omitted from the regression, while Zhou (2001) points out the BLM study rests on the assumption that the model is not misspecified. Two other critiques of the BLM study can also be noted. One, they control for firm level systematic and idiosyncratic risks using a market model of equity. Although these equity risk measures are theoretically related to the likelihood of default in a complex non-linear manner (see Merton (1974)), BLM add them only in a linear fashion not interacted with the firm leverage. Thus equity risk measures may not be good proxies for bankruptcy risk, the risk that ratings are supposed to capture. Moreover, the proxies used by BLM may not measure the same risk exposure consistently over time. For example, off balance sheet (OBS) transactions, including derivatives, were largely absent in 1978 yet were very prominent in the 1990s. Therefore, firms can effectively increase their overall effective leverage by engaging in OBS activities even though their on balance sheet financial leverage appears no different. A market model overcomes this criticism since, presumably, investors take these types of transactions into account when setting prices. Second, the BLM study fails to control for industry effects that almost all rating agencies profess to take into account.

We adopt the model of BLM (1998) while accounting for its stated shortfalls in order to study the question of the "point in time" vs. "through the cycle" methodology: thus taking into account the changing rating standards.

Section II

Hypothesis

Because we use issuer specific rating of S & P, we provide a brief overview of the institutional definition. S &P states:

> "Issuer Credit Rating (ICR) is a current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations. This opinion focuses on the obligor's *capacity and willingness* (italics ours) to meet its long-term financial commitments (those with maturities of more than one year) as they come due."

These ratings range from AAA (extremely strong capability of repaying interest and principal) to CC (high vulnerability to default). The categories C and D are restricted and generally apply to companies that have filed for bankruptcy or have defaulted.

The intuition for the study can be grasped from figure 1 (discussed in Doherty and Phillips (2004)). Given a particular distribution of default risk in the economy at T = 0, firms go to the rating agency to get rated. If the rating agency has absolute standards, then the standardized distribution of risk of default at any point in time is irrelevant for rating standards. However, if the distribution of default risk in the economy at a particular "point in time" matters, then rating thresholds for different letter rating categories are based on this distribution. So we ask the question, if at time T = 1 this distribution changes, what happens to these thresholds?

Consequently, the question we need to answer is whether it is economics that governs the rating agency to base its decision conditional upon the default risk in the economy (hence follow relative standards)? Since the expected payoffs to the rating agency depends on the increase in firm value due to its letter ratings (as in Lizzeri (1999) and Strauz (2005)) at any point in time, a profit maximizing rating agency will condition its thresholds for different rating categories on the underlying distribution of risk. So this yields our testable hypothesis:

Null Hypothesis: *Rating Standards are conditional upon the average level of credit quality in the economy at any given point in time.*

Alternative Hypothesis: *Rating standards are independent of the average level of credit quality at any point in time.*

Before we embark on testing this hypothesis, we would like to briefly mention our testing methodology. In this paper we relate an objective measure of default probability with subjective ratings. Therefore, in the first step of the tests we employ a model that yields an objective probability of default. Having done that, in the second step we employ an econometric model of ratings and link the subjective rating categories to the objective probabilities obtained in the first stage. At this stage we take into account the criticisms of the BLM (1998) study. Then in the final step, we carry out further econometric analysis on the thresholds obtained from the ordered probit model to test for the hypothesis above.

Section III

Sample, Data and Methodology

Econometric Methodology

We utilize the same model of subjective ratings as has been used in previous studies (Blume *et al* (1998), Doherty and Phillips (2002), Nickell *et al* (2000), Amatto *et al* (2003)), viz., ordered probit model. The dependent variable is the rating category, y_{it}, where i refers to the firm and t to the period. A numerical value of 1 is assigned to the highest rating class AAA and a value of 7 assigned to lowest rating class, which is CCC and below (see table 1). Clearly, the dependent variable is an ordinal variable that gives rankings of the probability of default. The rating measure we utilize in the study is the long term domestic issuer credit rating from Compustat Industrial Quarterly files (Compustat data item SPDRC).

In an ordered probit model, the discrete ordered variable, y_{it} is assumed to be linked through an underlying continuous variable y_{it}^* which is unobserved and has the following form:

$$y_{it}^* = \alpha_t + \beta X_{it} + \varepsilon_{it}, \text{ and } E(\varepsilon_{it}) = 0 \text{ ; } E(\varepsilon_{it}^2) = [\mathrm{Exp}(\gamma W_{it})]^2$$

(1)

The model assumes heteroskedastic errors similar to BLM and Doherty and Phillips (2002). Note that in an ordered probit model of ratings, different rating categories y_{it} are observed as per the following rule:

$y_{it} = y_0$ if $y_{it}^* \in (-\infty, \mu_0)$

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$y_{it} = y_n$ if $y_{it}^* \in [\mu_{n-1}, \infty)$ where $y_0 \ldots y_n$ are consecutive integer values corresponding to the rating categories

i.e., the rating categories are based on the thresholds μ_0 , …, μ_{n-1} . Previous studies have interpreted the intercept term α_t to capture rating standards at a particular point in time. However, the intercept term summarizes all omitted variable effects hence these studies are susceptible to the omitted variable bias critique noted earlier. In order to avoid this problem, we test our hypothesis based on the analysis of thresholds obtained from a period-by-period ordered probit regression. That is, we will estimate equation (1) separately for each quarter of data and then study how the estimated thresholds, $\mu_0, \ldots, \mu_{n-1}$ change over time.

We model heteroskedasticity[5] under the assumption that large firms have more information available to market participants (and hence also the rating agency) and there exists less noise in their financial statements. The other explanatory variables are defined next.

Variable Definitions and Hypothesized signs

The set of variables that we employ in the econometric model for rating determination have been derived from ratings literature and a review of S & P's stated methodology. We include interest coverage ratios, profitability ratios and a leverage ratio. We expect leverage[6] to

[5] I use square root of total assets (Data 44 from Compustat North American Industrial File) for variable W_{it}.
[6] Long Term Debt (data51)/Total Assets (data44)

play an important role in the ratings since higher leverage ratios imply higher bankruptcy risk for a firm, so we expect a high leverage firm to receive lower letter ratings. We include return on assets[7] (ROA) as a measure of profitability. The higher the ROA the higher the letter ratings that a company can expect to obtain. A firm's ability to cover its operational expenses is captured through operating income to sales[8] and operating income to debt ratios[9]. These ratios are expected to be positively related to the letter ratings, i.e., the higher these ratios the higher the rating. A firm's ability to meet its debt obligations is reflected in the interest coverage ratio[10]. Consistent with BLM, we model the relationship between ratings and interest coverage as piecewise-linear (see BLM (1998) for details). Consequently, we divide this ratio into four ranges $(-\infty, 5)$, $[5, 10)$, $[10, 20)$ and $[20, \infty)$ to account for this piecewise linear effect. The higher this ratio the higher the letter ratings assigned. To control for the size effect on ratings we use natural log of market capitalization. Finally, to control for the industry effects we employ one-digit SIC code dummies.

Apart from the balance sheet variables we include Risk Adjusted Probability of Default (RAPD) obtained from the market data in our regressions. The reason why we employ this variable is because the accounting variables may not fully capture all the information that goes into the determination of credit rating. We expect a market determined variable to capture these effects. Although previous studies like BLM (1998) have included proxies of these variables (the drawbacks of which have been noted earlier), we employ a more direct measure of default risk. Simultaneously, this measure also has the effect of linking an objective measure of default with a subjective one. We calculate the RAPD using the BSM model as has been recently suggested by

[7] Net Income + Interest Expense (data69+data22)/Total Assets (data44)
[8] Operating Income Before Depreciation (data21)/Net Sales(data2)
[9] Operating Income Before Depreciation (data21)/Long-Term Debt (data51)
[10] Operating Income Before Depreciation + Interest Expense(data21 + data22)/ Interest Expense (data22)

Hillegeist *et al* (2004), who advocate its usage over regression based models. This is the RAPD obtained by numerically solving the simultaneous equation Merton model for default and then making the risk adjustment for leverage. We expect this variable to be positive and significant.

In Merton's model, default occurs when the value of the company's assets falls below its outstanding debt (the default boundary is thus exogenous in Merton's model). Moreover, default can occur only at the time of maturity of the liability. This model assumes that the asset value of the firm at time t, V (t), follows a lognormal stochastic process of the form

$$dV(t) = \mu V(t)\, dt + \sigma\, V(t)\, dZ(t) \quad (2)$$

where μ and σ are constants and Z(t) is the standard Weiner process. The firm's liabilities have face value M maturing at date T. Since a firm's liabilities are like a zero coupon bond in this model, the Macauley duration equals the time to maturity for these liabilities. The stockholders of the firm have a call option on the firm's underlying assets. If the value of the firm exceeds the value of its liabilities at the time of maturity, the shareholders keep the difference. Otherwise, they hand over the firm to the debtors and receive a payoff of zero. The boundary condition at time T is thus given by S (T) = Max (V (T) – M, 0).

This call option on assets at time t can then be calculated using the Black-Scholes formula:

$$S(V(t), t) = V(t)\, N(d_1) - Me^{-r(T-t)}\, N(d_2) \quad (3)$$

where T: time to maturity
t: Current time
r: risk free rate of interest
$d_2 = [\ln (V(t)/M) + (r - 0.5\sigma^2)(T-t)]/\sigma(T-t)^{1/2}$
$d_1 = d_2 + \sigma\, (T-t)^{1/2}$
N(.): standard univariate normal distribution
S (V (t), t): Value of equity holders call option

Merton's risk neutral probability of default (RNPD hence forth), which is the probability that the equity holder's call option is out of the money at maturity, is given by

$$RNPD = 1 - N(d_2). \qquad (4)$$

We note that the formulation in equation (1) above has two unobservables: $V(t)$ – is the market value of the assets; and σ – the volatility of the asset process. Therefore we use another equation that links these unobservables to the observables. Using options theory I can link the volatility of option to the volatility of the underlying with the optimal hedge equation (see Ronn and Verma (1986)):

$$\sigma_s = N(d_1).\ \sigma.\ [V(t)/S(t)] \qquad (5)$$

Here σ_s is the volatility of the observed equity price process. This equation estimates the volatility of the underlying asset as a function of equity call option delta. Equations (3) and (5) can now be solved simultaneously to calculate the RNPD (equation (2)).

The risk neutral valuation of the structural model (Merton, 1974) leading up to a measure of default probability as $1 - N(d_2)$ yields a probability of default that is invariant to investors' expectations on the return on assets. In a dynamic analysis the probability of default might change not only because the short rate changes *ceteris paribus*, but also because investors' expectations may change. Consequently, the expected return on assets needs to be calculated to extract the risk adjusted probability of default (RAPD henceforth). The formula for RAPD is given by $1 - N(d_2')$, where

$$d_2' = [\ln(V(t)/M) + (\mu - 0.5\sigma^2)(T-t)]/\sigma(T-t)^{1/2} \qquad (5')$$

and $\mu = r + \beta_A [E(R_m) - r]$. Here $E(R_m)$ is the expected return on the market and β_A[11] is the asset beta of the firm.

In order to calculate asset betas we calculate the equity betas first. We employ the market model (Campbell *et al*, 1997) to estimate the same. However, since firm level betas lack precision, we use portfolio betas, where portfolios are based on Fama-French (1997) 48 industry classification. The methodology adopted is similar to the one employed by BLM (1998) with one modification. We employ the Dimson (1979) correction with two leads and two lags while BLM use only one lag and one lead. The rationale for this is based on Damodaran (2004), who suggests that higher the frequency of the data the more the number of lags and leads which should be employed in estimation of equity beta. The portfolio beta (equity) is then calculated as equally weighted sum of individual equity betas in the portfolio. The portfolio betas are calculated on a rolling twelve month basis using firms that have more than 200 days of trading data.[12] The expected daily market risk premium at the end of the month is the long run average of excess returns up to that date. It is then multiplied by 262 to yield an annualized estimate of expected market risk premium. The series of RAPDs thus calculated is 98% correlated to the RNPDs for the entire sample period. In all of the analyses, we use RAPDs.

After calculating RAPD we run the econometric model of ratings (equation (1)) on a quarter by quarter basis with RAPD (the objective measure of default), as one of explanatory variables in addition to the BLM variables. We also control for the industry specific effects through industry dummies. This yields a time series of thresholds for each of the rating category. We then run a test for our hypothesis using a regression equation of the form:

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[11] I calculate asset beta from equity beta. For each firm, $\beta_A = \beta_P / (1 + D/E)$, where leverage (D/E) is equated to Long-Term Debt /BV (Assets – Liabilities) = data51/ (data44 –data54). β_P is the beta of the portfolio to which the firm belongs.

[12] The series of market excess returns is obtained from the daily data files on Kenneth French's website.

$$\mu_{jt} = k + \alpha t + \beta Median\_RAPD_t + \gamma Dispersion\_RAPD_t + \partial flagcyc + \eta\mu_{jt-1} + \varepsilon_t \quad (6)$$

where j refers to the threshold obtained from ordered probit regression for rating category j, k is the intercept term, t is the time index that ranges from 1 to 60, $Median\_RAPD_t$ is a measure of the central tendency of the distribution of default of the median firm at time t (we use the median as opposed to the mean because there is skewness in RAPD in the sample of observations in our dataset with the frequency of observations decreasing as the probability of default rises). If the hypothesis is correct then we should find β to be positive and significant. If there is a time variation in the rating standards then coefficient α should be different in sign and magnitude for different thresholds. The term $Dispersion\_RAPD_t$ is designed to capture the spread of the distribution and is measured as the range of RAPD between the 99th and the 1st percentile at any time t. *flagcyc* is a variable used to capture the business cycle effect observed by Amato and Furfine (2004) while the threshold of the previous period accounts for the rating drift (momentum) effects of ratings. The distinction between *RAPD* and *flagcyc* is made along the lines of Koopman and Lucas (2005) who distinguish between business cycle and default cycles.

Data

The period of the study is the years between 1986 and 2005. The data necessary to calculate RAPD come from merging both the CRSP daily stock files and Compustat North American Industrial Quarterly files. The data for equity risk premiums to convert RNPDs to RAPDs comes from the daily data files of Kenneth French's website. We use CRSP files to calculate the volatility of the asset process and Compustat Quarterly Files to calculate the strike price and the financial ratios employed in the econometric model of ratings. The monthly risk free rate of interest is hand collected from the Wall Street Journal (we use Treasury STRIPS to proxy for the spot rates for different maturities). The ratings considered are long term domestic issuer credit ratings (Data 280 from the Compustat file). The data for business cycles is obtained from the NBER website. Since this data is available only upto June 2003, estimation of equation (6) is done using threshold data up to the end of the second quarter of 2003.

Sample

Observations with missing values and firms whose issuer credit ratings is equal to zero (this is the default entry in Compustat and means that the corresponding data is not available) are deleted. The industry pertaining to Government and Public bonds is also deleted from the sample. E.g., municipal bond ratings are also determined by demographic factors (Loviscek and Crowley (1990)). Some firms drop out of the sample because we use a 60 day moving average window for the calculation of the daily volatility. On a firm-quarter basis we have 49956 observations belonging to 2136 firms. Not all firms appear in each quarter. Consequently, we have an unbalanced panel of quarterly data.

Construction of RAPD

We first construct a quarterly time series of the probability of default. The strike price M is constructed according to the following:

M = Total Liabilities (Data 54) – 0.5 Current Liabilities (Data 49)[13]

This is analogous to the strike price used by KMV (= 0.5 Short Term Debt +Long Term Debt), and similar to the strike price considered by Delianades and Geske (1999).

The time to maturity of liabilities is calculated using the Macauley duration. While it equals 1 year for the KMV model, we prefer to duration because our focus is on long term domestic issuer credit ratings, which as per S & P reflects on the ability of the obligor to meet

[13] Liabilities Total (Data54) = Current Liabilities (Data49) + Liabilities (Other) (Data50) + Long-Term Debt (Data51) + Deferred Tax and Investment Tax Credits (data52) + Minority Interest (Data53). Therefore, Data54 -0.5Data49 = 0.5Data49 + Other Long Term Liabilities (assumed to have a Maturity of 10 years).

liabilities beyond one year. The current liabilities are assumed to have a maturity period of six months and long term liabilities are assumed to have a 10- year maturity period.

The daily volatility of stock prices is calculated using the 60-day moving average rolling window for log of the ratio of stock prices obtained from the CRSP files. It is annualized by multiplying it by square root of the number of trading days in a year.

Equations (3) and (5) are solved simultaneously to obtain the risk neutralized probability of default. Then the risk adjustment is made using equation (5') to get RAPDs. One issue that we face while merging the CRSP and Compustat quarterly files is that of timing. Compustat quarterly data are on fiscal year basis while the CRSP data are on calendar year basis. S & P uses an internal algorithm to allocate calendar years to fiscal years and this paper uses that allocation (BLM do the same).

Section IV

Empirical Results

Table 1 describes the rating categories considered for the study and the numerical values assigned to them. Note the sample includes the "non-investment grade" (NIG) firms, as well as "investment grade" (IG) firms. Previous studies (like Blume *et al* (1998), Nayak (2001), Delianades and Geske (1999)) investigate only "IG" firms.

Upon aggregating the quarterly observations by calendar year, we find that 63.24 % of the observations between the years 1986-2005 belong to the numerical rating categories 1- 4, which is referred to as the "investment grade" category. However, a vast majority (72.78 %) of the firms lie in the middle rating categories, ranging from A to BB. In addition, firms rated B or below compose only 14.84 % of the sample, with the number of observations falls drastically as the letter rating falls below B. Surprisingly, the numbers of defaults in the sample outnumber

CCC ranked issuers in the first three years of the study. The average letter rating in the sample over the period has been around the BBB category. The median rating in the sample over this period is BBB. The average Merton RAPD over the entire time period is approximately 10.53% while the median is 0.99% and the standard deviation is 0.1884, with the probabilities covering the entire spectrum ranging from 0 to 1. These statistics demonstrate a highly skewed distribution of default probability. Consequently, in multivariate regression analysis of the rating model, we employ median as a measure of central tendency.

We find that, expectedly, that volatility in the RAPD is higher at lower levels of letter rating. An analysis of the standard deviation of RAPD demonstrates a positive relationship between the volatility of probability of default and letter ratings, that is the lower the ratings the higher the dispersion in the default probability. When we analyze the means and medians for investment vs. non-investment grade, I find that the mean and median for IG firm is 4.47% and 0.11%, while it is 20.95% and 12.03% for NIG firms respectively.

Figure 2 shows the RAPD for the median firm in IG and NIG categories for the various quarters in our time series. The jump in the last quarter of 1987 corresponds to the stock market crash and is indicative of the market revising its expectations of the default risk in the economy. We also see a rising trend in the RAPD from last quarter of 1997 onwards on a quarterly basis. Figure 3 shows the frequency polygon for the median RAPD in different rating categories. The modes for the different rating categories follow an expected pattern. By and large, the chart shows that there is not much overlap between the top and lowest rated categories. Given that default probability using Merton's model is determined from market parameters independent of the S & P ratings, the frequency polygon is in line with the quality of signal provided by ratings . The frequency polygon of the medians does show that there is considerable overlap between the

RAPD ranges especially in the middle letter rating categories. For the most part, the modes of RAPD for median firm occur at higher levels of RAPD for lower rated categories. On the other hand, Figure 4 displays the frequency distribution of RAPDs in the sample. The plot demonstrates the evidence of skewness in the distribution of the probability of default.

An analysis of the mean and median RAPD across rating categories is given in Table 2. The last column gives the z-test scores of the differences in average RAPD of one category from the previous one. I see that mean RAPD of AAA is not significantly different from that of the immediately following category AA in our sample. The means across the other categories are significantly different from one another. Summary statistics on RAPD over time is presented in Table 3. We find that the mean, median and standard deviation has constantly risen from 1995 onwards.

Summary Statistics for the variables used in the regression are given in table 4 panels A and B. Note that RAPDs are rounded off to the nearest decimal place. The mean values of the variables do not show an appreciable time trend although the market capitalization appears to be rising over time.

In the first step of the econometric model for ratings, I incorporate the market determined firm level probability of default (RAPD) as opposed to BLM who use market betas and residual error term for idiosyncratic risk. Since the effect of leverage on default risk is non-linear (whereas BLM incorporate it linearly) we use a more direct measure of default, viz., the RAPD. The results of the ordered probit regression results for the full sample over the entire period 1986-2005 are shown in table 5. The plot of the intercepts from this regression is shown in Figure 5. It shows an upward trend, and the result is consistent with BLM.

Not all balance sheet variables are statistically significant. The leverage ratio plays an important role in the determination of ratings over and above the RAPD. Very high interest coverage ratios are not statistically significant. All significant balance sheet variables have the expected sign. As expected the sign on RAPD is both positive and significant at the 1 % level. This is consistent with the hypothesized sign. It is noteworthy that even though this objective measure can be determined based solely on market based values, but because it predicts the future default risk *a priori*, it should be highly negatively correlated with letter ratings which are a subjective measure of the likelihood of default by a firm on its debt obligations in the future. Our regression results confirm this intuitive correlation.

In order to do an analysis of thresholds, we run the rating model for each of the sixty quarters.[14] The balance sheet variables after controlling for size that are found to be consistently significant in the quarter by quarter ordered probit regressions are leverage and interest coverage variables. As expected, very high interest coverage ratios do not contribute significant information to the ratings. The sign on RAPD is positive and significant, which is consistent with the expectations. We also find that the coefficient on the control variable SIC code is significant for some codes at some points in time. The variable for heteroskedasticity becomes statistically significant in some periods.

The output of the thresholds regression is given in table 6. What is apparent is that there is a strong negative time trend in the thresholds of investment grade rating categories. This confirms the test of BLM that S & P adopted stricter standards during this time period and the test does not rely on the changing intercepts alone. We find evidence for the hypothesis that the distribution of default risk matters for the assignment of ratings. The results of table 6 tend to confirm the BLM finding that rating standard is time varying and extends beyond it to show that

[14] Results of the sixty quarter-by-quarter ordered probit regressions are not included in this paper.

it is “relative”, relative to the default risk in the economy. This implies that ratings do not reflect an unconditional likelihood of default for any rating category, but only a conditional default probability depending upon the credit risk prevalent in the economy at that point in time. Moreover, even though the long term ratings are supposed to be “through the cycle” and not “point in time”, we find evidence that there is considerable overlap between the two.

Robustness check

A critique of our results could be that the results obtained in the threshold regressions are a result of the model of default that we employ, viz., Merton’s model. Merton (1974) of default has been criticized because it does not yield correct cardinal probabilities of default owing to its simplifying assumptions. Subsequent structural models have relaxed some of the assumptions and improved upon the Merton model (see Benos and Papanastasopoulos (2007)) yielding better results. Hillegeist *et al* (2004) compare the Merton model to Z-score and O-score models and find that Merton’s model outperforms the Z and O score models, so much so that they recommend researchers to use the Merton model.

We would like to point out that for our purposes the exact probability of default is not very relevant but their ordering by rating categories is. Brockman and Turtle (2003) make the same point. Table 2 and Figure 3 of our paper show that this requirement is met by the probabilities that we obtain. Still, for robustness check we employ another market based model of barrier option framework to estimate risk adjusted default probabilities. We label this the down and out call (DOC) option framework since equity in this model is obtained as a down and out call option. The details of the model are presented in Reisz and Perlich (2007). The basic formulation is given in the Appendix.

In a nutshell, DOC option model is a four-equation and four unknown model. The asset values at times t and t-1, the volatility of assets and the endogenous default barrier are all simultaneously determined from four transcendental equations using market parameters. Since traditional calculus based algorithms do not converge, we employ a genetic algorithm for obtaining convergence of the procedure. Out of our initial sample of 38408 firm quarter observations, we obtain convergence for 21684 observations. This implies a convergence rate of 56.46 %, which is comparable to Reisz and Perlich (2007) who obtain a convergence rate of 54.96% (convergence on 33037 observations out of 60110) using a mix of calculus based and search based algorithms.

Our calculations show the implied barrier value has a mean value of 32.24% of market value of assets while the median is 31.42%. Reisz and Perlich (2007) find the mean and median values of the implied barrier to be 30.53% and 27.58% respectively, while Leland and Toft (1996) report the simulated implied barrier level to be 30%. The mean and median DOC RAPD for these 21684 observations over the period 1986-2000 are 8.52% and 1.04% respectively while they equal 7.82% and 1.27% for the Merton model. The coefficient of correlation between the two RAPDs is 0.9253.

A comparison of summary statistics of the DOC option RAPD and Merton RAPD is given in Table 7 by rating class. The implied barrier rises as we descend down the rating categories, as expected.

To carry out the robustness check on our previous results, we run quarter quarter-by-quarter ordered probit regressions using DOC RAPD instead of Merton RAPD for sixty quarters over our sample period. The sample now consists of a total of 21684 firm quarter observations. After obtaining the sixty thresholds for each rating category, we carry out the SUR estimation of the thresholds against time and the location and dispersion parameters of DOC RAPD distribution. The results reaffirm [15]the earlier finding that the default risk distribution determines the thresholds for the various rating categories and that over time the thresholds have moved in a way that the BLM finding is corroborated.

Section V

Conclusion

In this paper, we study whether rating agencies follow absolute standards or relative while controlling for the industry level effects. Drawing upon existent theories on rating accuracy we provide an economic rationale why ratings might be relative and develop an empirical hypothesis. Employing a pooled ordinal probit regression, and using a market determined probability of default as an explanatory variable, we develop the model to incorporate a direct measure of RAPD in contrast to the indirect measure employed in BLM. Further econometric innovation lies in analysis of rating thresholds instead of the intercept term alone as carried out in BLM (1998) and Doherty and Phillips (2002). The analysis ensures that momentum effects are capture in the model while segregating the business cycles effect from the default cycles effect. After doing such an analysis, we find that rating standards are relative and that they do vary over time. We find that a firm's rating is dependent not only on its own risk profile but also upon the default risk of the economy. Moreover, the standards appear to have varied differently for different rating categories in a way that is consistent with anecdotal evidence. The evidence suggests the dichotomy between "point in time" vs. "through the cycle" methodologies may not be as sharp as previously assumed.

[15] Results are not attached with this version of the paper.

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Appendix: Equity as Down-and-Out Call Option

The basic Merton model assumes that the asset value of the firm at time t, V (t), follows a lognormal stochastic process of the form

$$dV_A(t) = \mu V_A(t)dt + \sigma V_A(t)dZ(t)$$

(A.1)

where μ_A and σ are constants and *Z(t)* is the standard Weiner process. The firm's liabilities have face value *F* maturing at date *T*. It is assumed that a firm's liabilities are like a zero coupon bond in this model, the Macauley duration equals the time to maturity for these liabilities. The stockholders of the firm have a call option on the firm's underlying assets. However, covenants dictate that if the value of the firm falls below a value B (the barrier) anytime between the current time *t* and maturity at time *T*, bondholders take control of the firm to reorganize or liquidate it. In this framework, bankruptcy can occur in two ways, one – when the firm asset value falls below B from above before *T*; or two- at maturity, when the firm value is above *B* but less than *F*.

Assuming that the asset process V_A is given by equation (A1), the market value of firm's equity V_E is given by the following equation[16] under the European DOC option framework:

$$V_E = V_A N(a) - Fe^{-r(T-t)} N(a - \sigma\sqrt{T-t})$$

$$- V_A(B/V_A)^{2\eta} N(b) + Fe^{-r(T-t)}(B/V_A)^{2\eta-2} N(b - \sigma\sqrt{T-t})$$

(A.2)

Where,

V_E : Value of equity

V_A : Value of underlying assets

F : Strike price of the option

r : Risk- free rate of interest

T : Date of maturity of the DOC option

σ : Volatility of assets

B : Barrier, and

$$a = \frac{\ln(V_A/F) + (r + (\sigma^2/2))(T-t)}{\sigma\sqrt{T-t}} \text{ for } F \geq B, \text{ and}$$

[16] Time subscript has been suppressed. The formula holds instantaneously. See Brockman and Turtle (2003) and Reisz and Perlich (2007) for further details.

$$a = \frac{\ln(V_A / B) + (r + (\sigma^2 / 2))(T - t)}{\sigma\sqrt{T - t}} \text{ for } F < B;$$

$$b = \frac{\ln(B^2 / V_A F) + (r + (\sigma^2 / 2))(T - t)}{\sigma\sqrt{T - t}} \text{ for } F \geq B, \text{ and}$$

$$b = \frac{\ln(B / V_A) + (r + (\sigma^2 / 2))(T - t)}{\sigma\sqrt{T - t}} \text{ for } F < B;$$

$$\eta = \frac{r}{\sigma^2} + \frac{1}{2};$$

The Brockman and Turtle implementation of this equation involves calculation of the implied barrier. Reisz and Perlich (2007) combine the above equation with the optimal hedge equation to determine the firm parameters and the implied barrier simultaneously. The optimal hedge equation is given by:

$$\sigma_E = \frac{V_A}{V_E}\Delta_B\sigma; \Delta_B = \frac{\partial V_E}{\partial V_A}$$

(A.3)

and, σ_E is stock price volatility. When $F \geq B,$ then

$$\Delta_B = N(a) + (\frac{B}{V_A})^{2\eta-2}\{\frac{Fe^{-r(T-t)}}{V_A}N(b - \sigma\sqrt{T-t}) + (2\eta - 1)[\frac{B^2}{V_A^2}N(b) - \frac{Fe^{-r(T-t)}}{V_A}N(b - \sigma\sqrt{T-t}]\}$$ e

lse, when $F < B$, then

$$\Delta_B = N(a) + (\frac{B-F}{V_A\sigma\sqrt{T-t}})e^{-r(T-t)}\{(\frac{B}{V_A})^{2\eta-2}n(b - \sigma\sqrt{T-t}) + n(a - \sigma\sqrt{T-t})\}$$

$$+ (2\eta - 1)(\frac{B}{V_A})^{2\eta}N(b) - \frac{Fe^{-r(T-t)}}{V_A}(\frac{B}{V_A})^{2\eta-2}(2\eta - 2)N(b - \sigma\sqrt{T-t}]\}$$

(A.4)

And the probability of bankruptcy is given by:

$$\text{Failure Probability} = N(\frac{(\ln B - \ln V_A) - (r - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}) +$$

$$e^{(\frac{2(r-\sigma^2/2)(\ln B - \ln V_A)}{\sigma^2})} \times$$

$$[1\text{-}N(\frac{-(\ln B - \ln V_A) - (r - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}})]$$

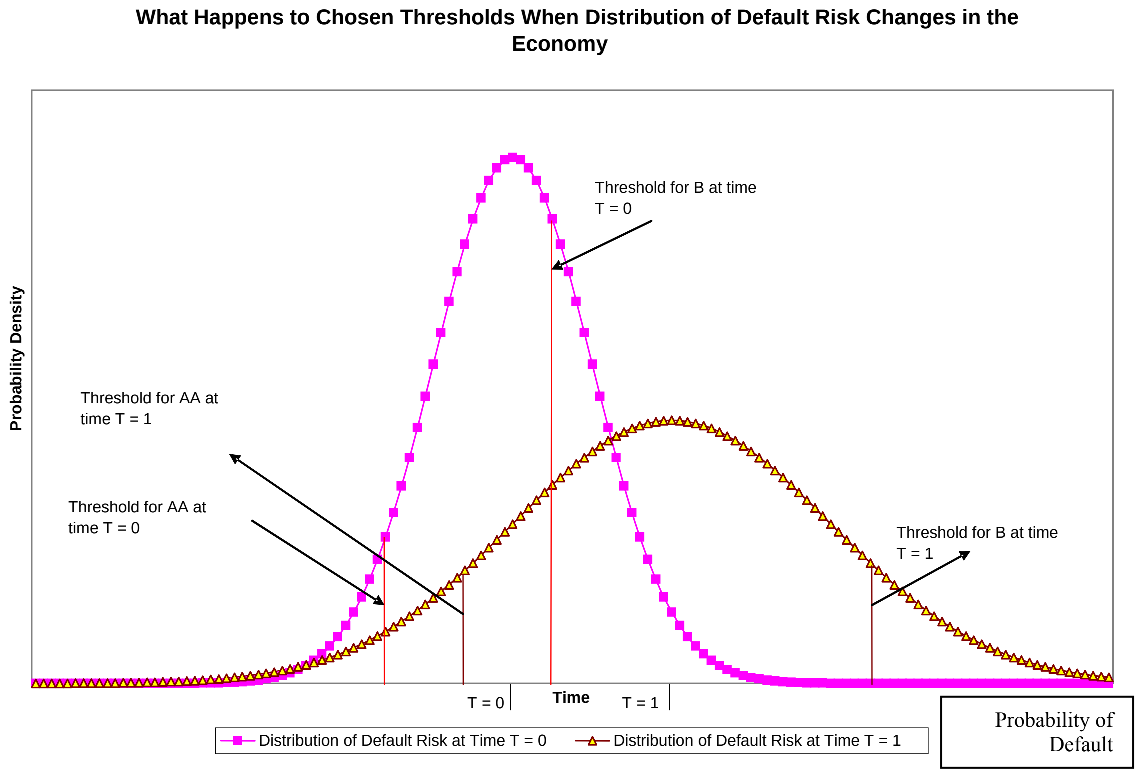
(A.5)

Specification of DOC Option Model:

The model above has 3 unknowns, viz., barrier *B*, instantaneous asset value V_A, and σ. However, there are only two equations (A.2) and (A.3). Following Reisz and Perlich (2007) we estimate the set of equations at times *t* and *t-1*, keeping the volatility σ and *B* constant, while changing V_A^t and V_A^{t-1}. Thus the system reduces to a four equations in four unknowns. Since an actual root is not found, the sum of absolute percentage errors $|\frac{V_E - DOC}{V_E}| + |\frac{\sigma_E - \sigma_{DOC}}{\sigma_{DOC}}|$ is minimized. The value of $V_A^t, B, and \sigma$ is then substituted into equation (A.5) to calculate the probability of default at time *t*.

Figure 1

What is this study about?



At time T = 0, the risk of default has a particular distribution shown above. The rating agency chooses the thresholds to categorize firms into different rating categories. At time T = 1, this distribution changes. How do the thresholds change, if at all?

Table 1

The rating categories corresponding to subordinated debt CC and C, as well as that of income bonds are not considered. The category on selective default and Suspended Bond Rating category is also deleted.

Rating	Assigned Numerical Value
AAA	1
AA	2
A	3
BBB	4
BB	5
B	6
CCC & below	7

Table 2

Pair-wise test of differences in mean and median for Risk Adjusted Probability of Default (RAPD) and Time to Maturity by rating categories based on t and Mann-Whitney-Wilcoxon Z-statistic respectively. All tests are pairwise comparisons where one letter rating category is compared to one preceding it. Numbers in brackets below mean values test for difference from zero. t test results are based on unequal variances and Z-test values reported are also two sample test statistics. All variable values are rounded to four decimal places. Panel A reports result for RAPD while Panel B for Time to Maturity of liabilities.

Panel A: RAPD by rating category

rating	N Obs	Mean	Median	Std Dev	Minimum	Maximum	t- stat for differences in means		Z- test for differences between medians	
AAA	757	0.0228 (5.24***)	0.0000	0.1196	0	0.9513				
AA	4001	0.0220 (14.16**)	0.0000	0.0982	0	0.9751	0.17		-9.2340	***
A	12150	0.0314 (32.98***)	0.0005	0.1048	0	1	-5.15	***	-24.6565	***
BBB	13476	0.0653 (55.53***)	0.0080	0.1364	0	1	-22.42	***	-41.2585	***
BB	11426	0.1522 (84.47***)	0.0697	0.1926	0	1	-40.20	***	-46.9253	***
B	7582	0.2623 (94.92***)	0.1938	0.2406	0	1	-33.37	***	-30.9870	***
CCC & below	564	0.3773 (31.57***)	0.3375	0.2838	0	1	-9.38	***	-8.1176	***
Total	49956									

***,**,*: Significant at 1%, 5% and 10% level of significance respectively.

Panel B: MaCauley Duration for time to maturity for Merton model of default by rating category

rating	N Obs	Mean	Median	Std Dev	Minimum	Maximum	t- stat for differences in means		Z- test for differences between medians	
AAA	757	3.7892 (76.78***)	3.5024	1.3579	1.3855	8.6459				
AA	4001	4.2152 (139.73***)	3.9193	1.9081	0.5570	8.8073	-7.37	***	-3.4479	***
A	12150	4.8115 (295.37***)	4.7672	1.7956	0.5000	9.5311	-17.39	***	-17.8761	***
BBB	13476	5.3115 (351.08***)	5.3219	1.7563	0.5000	9.5532	-22.49	***	-18.7152	***
BB	11426	5.5627 (324.40***)	5.7242	1.8329	0.5000	9.8029	-10.99	***	-12.8949	***
B	7582	5.7866 (261.01***)	5.9441	1.9305	0.5000	9.6496	-7.99	***	-6.1026	***
CCC & below	564	5.0967 (50.29***)	5.6378	2.4067	0.5000	9.3559	6.65	***	4.4516	***
Total	49956									

Table 3

Summary Statistics of the Risk Adjusted Probability of Default over the years 1986 to 2005 by year.

Panel A: RAPD

Fiscal Year	N Obs	Mean	Median	Std Dev	Minimum	Maximum
1986	2236	0.0711	0.0051	0.1507	0	1.0000
1987	2351	0.1363	0.0168	0.2199	0	0.9737
1988	2309	0.0793	0.0045	0.1609	0	0.9915
1989	2184	0.0610	0.0008	0.1496	0	1.0000
1990	1975	0.0831	0.0044	0.1704	0	0.9751
1991	1949	0.0762	0.0034	0.1601	0	0.9708
1992	2138	0.0755	0.0032	0.1592	0	1.0000
1993	2328	0.0757	0.0039	0.1589	0	1.0000
1994	2500	0.0665	0.0034	0.1467	0	1.0000
1995	2565	0.0722	0.0015	0.1587	0	0.9800
1996	2884	0.0798	0.0034	0.1651	0	0.9931
1997	3155	0.0919	0.0065	0.1757	0	0.9849
1998	3303	0.1479	0.0354	0.2175	0	0.9881
1999	3310	0.1719	0.0643	0.2222	0	1.0000
2000	3221	0.2076	0.1153	0.2334	0	1.0000
2001	1456	0.1780	0.0841	0.2157	0	0.9726
2002	1169	0.1986	0.1246	0.2176	0	0.9666
2003	2802	0.1129	0.0264	0.1742	0	0.8795
2004	3040	0.0823	0.0107	0.1488	0	0.9333
2005	3081	0.0664	0.0066	0.1319	0	0.8994
Total	49956					

Panel B: Time to Maturity

Fiscal Year	N Obs	Mean	Median	Std Dev	Minimum	Maximum
1986	2236	4.6140	4.5516	1.7895	0.5000	9.1946
1987	2351	4.6121	4.5635	1.8006	0.5990	9.1282
1988	2309	4.5405	4.4597	1.7698	0.5000	9.1464
1989	2184	4.6764	4.5399	1.7893	0.5645	9.1546
1990	1975	4.5935	4.5102	1.7764	0.5000	8.9295
1991	1949	4.6614	4.6634	1.7895	0.5000	9.0426
1992	2138	4.8428	4.7809	1.8060	0.5000	9.6004
1993	2328	5.2088	5.2675	1.8150	0.5000	9.8029
1994	2500	5.1385	5.2242	1.8414	0.5674	9.7714
1995	2565	5.1578	5.2334	1.8592	0.6067	9.2221
1996	2884	5.2802	5.3276	1.8830	0.5740	9.7308
1997	3155	5.2959	5.3177	1.8707	0.5000	9.4778
1998	3303	5.5203	5.6111	1.8811	0.5000	9.5311
1999	3310	5.4931	5.6180	1.8890	0.5534	9.4603
2000	3221	5.3236	5.3841	1.9177	0.5100	9.6496
2001	1456	5.5258	5.5835	1.8433	0.6753	9.4673
2002	1169	6.0328	6.2073	1.8792	0.7686	9.5532
2003	2802	5.6870	5.8266	1.8216	0.5165	9.4729
2004	3040	5.7373	5.8602	1.8528	0.5176	9.4235
2005	3081	5.6915	5.8398	1.8500	0.6148	9.5987
Total	49956					

Table 4 - Panel A
Summary Statistics of Variables Used in Ordered Probit Regressions

The Numeric Ratings are as shown in Table 1. Operating Income to Debt Ratio is the ratio of operating income before depreciation to the total long-term debt. Operating Income to Sales ratio equals operating income before depreciation to net sales ratio. Return on Assets equals Net Income plus Interest Expense divided by total assets. Long –Term debt to assets ratio is the ratio of long-tem debt on balance sheet to the total assets. Interest coverage ratio is the ratio of sum of operating income before depreciation and interest expense to interest expense. It is divided into four ranges to account for possible piecewise-linear marginal effects. The four Interest coverage ratios correspond to ranges $(-\infty, 0)$, $[0, 10)$, $[10, 20)$ and $[20, \infty)$. Cross section indicator variables equal 1 if the firm belongs to a particular one-digit SIC code. There are 10 one digit SIC codes, hence nine dummies. Log (Market Capitalization) is the natural log of market value of all shares as on the end of that quarter. Firm level RAPD is the market determined probability of default as determined by the Merton model. Total Assets is assets of the firm the square root of which is used to model heteroskedasticity.

Variable	Mean	Std Dev	Minimum	Maximum
Dependent Variable				
Numerical Code S & P Rating	4.1173	1.2742	1	7
Balance Sheet Variables				
Operating Income to Debt Ratio	0.9762	71.3061	-140.0125	14902
Operating Income to Sales Ratio	-0.0424	21.8290	-4763.1300	3.1307
Return on Assets	0.0159	0.0345	-1.9276	1.0048
Long-Term Debt to Assets Ratio	0.2943	0.1809	0	2.9890
Interest Coverage Ratio 1	4.0739	5.8839	-475.4000	5
Interest Coverage Ratio 2	2.2450	2.1673	0	5
Interest Coverage Ratio 3	1.7310	3.3515	0	10
Interest Coverage Ratio 4	11.0366	823.4780	0	175385
Control Variables (Cross - Section Indicator)				
Industry 1 Dummy	0.0679	0.2516	0	1
Industry 2 Dummy	0.2202	0.4144	0	1
Industry 3 Dummy	0.2582	0.4377	0	1
Industry 4 Dummy	0.2118	0.4086	0	1
Industry 5 Dummy	0.1303	0.3367	0	1
Industry 6 Dummy	0.0149	0.1212	0	1
Industry 7 Dummy	0.0655	0.2474	0	1
Industry 8 Dummy	0.0267	0.1611	0	1
Control Variable (Size)				
Log (Market Capitalization)	14.0854	1.6783	4.1150	20.0331
Market Determined Probability of Default				
Firm Level RAPD	0.1062	0.1853	0.0000	1.0000
Variance Parameter Proxy				
Square Root Total Assets	55.1975	45.1946	0.2074	597.6353
Total Observations: 49956				

Table 4 – Panel B

Year by Year averages of variables used in quarterly regressions. Variables are defined in Table 4- Panel A.

Variable	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Dependent Variable																				
Numerical Code S & P Rating	3.9311	4.0438	3.9996	3.9803	3.8410	3.7830	3.8433	3.9145	4.0172	4.0304	4.0947	4.1353	4.1686	4.1825	4.1857	4.2617	4.2361	4.3904	4.4704	4.4752
Balance Sheet Variables																				
Operating Income to Debt Ratio	0.2699	0.2626	0.2715	0.2635	0.3675	0.2392	0.3503	0.3903	0.3359	0.4381	0.3199	0.4320	0.2574	0.2538	0.5785	1.0676	0.4566	1.4534	8.1497	1.5439
Operating Income to Sales Ratio	0.1359	0.0785	0.1371	0.1631	0.1604	0.1522	0.1603	-0.2055	0.0090	-0.1449	0.0240	0.1706	-0.1782	0.0589	0.1571	0.1735	-0.0823	0.0377	-0.0377	-1.3874
Return on Assets	0.0149	0.0171	0.0204	0.0197	0.0178	0.0155	0.0126	0.0119	0.0140	0.0169	0.0154	0.0167	0.0144	0.0145	0.0180	0.0136	0.0132	0.0137	0.0166	0.0187
Long-Term Debt to Assets Ratio	0.2686	0.2809	0.2829	0.2918	0.2793	0.2735	0.2787	0.2787	0.2836	0.2871	0.2975	0.3028	0.3147	0.3330	0.3119	0.3118	0.3031	0.3020	0.2941	0.2824
Interest Coverage Ratio 1	4.0202	4.0890	4.1939	4.0562	3.8273	3.8387	4.0031	3.5419	4.0760	4.0143	4.0616	4.0780	4.1600	4.0766	4.1988	4.1585	3.8626	4.2240	4.2237	4.3665
Interest Coverage Ratio 2	1.9305	1.9729	2.0381	1.9108	1.9567	1.8930	2.0048	2.2229	2.3924	2.3567	2.3753	2.4153	2.2122	2.0752	2.2069	2.1151	2.3424	2.4083	2.7113	2.8276
Interest Coverage Ratio 3	1.4067	1.3187	1.2844	1.1548	1.1638	1.1874	1.3549	1.6253	1.7910	1.8549	1.8297	1.9483	1.7060	1.5093	1.6233	1.5966	1.7938	2.0750	2.6345	2.8190
Interest Coverage Ratio 4	1.6567	5.0134	8.8513	9.6379	4.8015	1.6161	10.7624	10.5056	3.6818	74.4053	15.0048	6.7836	4.3528	18.0844	5.2570	6.4943	4.1124	4.5669	6.7422	10.0011
Control Variables(Cross - Section Indicator)																				
Industry 1 Dummy	0.0429	0.0451	0.0403	0.0458	0.0572	0.0585	0.0617	0.0631	0.0668	0.0608	0.0704	0.0887	0.0775	0.0686	0.0813	0.0893	0.0924	0.0785	0.0799	0.0782
Industry 2 Dummy	0.2178	0.2203	0.2248	0.2212	0.2253	0.2391	0.2371	0.2375	0.2280	0.2203	0.2160	0.2181	0.2125	0.2196	0.2158	0.2060	0.2113	0.2170	0.2122	0.2123
Industry 3 Dummy	0.3166	0.3131	0.3049	0.2834	0.2734	0.2653	0.2521	0.2461	0.2536	0.2550	0.2490	0.2466	0.2558	0.2486	0.2391	0.2273	0.2284	0.2302	0.2474	0.2428
Industry 4 Dummy	0.1990	0.2012	0.2109	0.2184	0.2314	0.2252	0.2245	0.2135	0.2096	0.2214	0.2174	0.2016	0.2022	0.2042	0.2207	0.1971	0.2181	0.2077	0.2079	0.2149
Industry 5 Dummy	0.1261	0.1182	0.1217	0.1310	0.1251	0.1334	0.1394	0.1448	0.1416	0.1376	0.1418	0.1334	0.1390	0.1390	0.1229	0.1532	0.0992	0.1235	0.1135	0.1165
Industry 6 Dummy	0.0219	0.0208	0.0182	0.0147	0.0096	0.0092	0.0126	0.0116	0.0112	0.0133	0.0132	0.0082	0.0088	0.0115	0.0149	0.0151	0.0257	0.0228	0.0207	0.0201
Industry 7 Dummy	0.0559	0.0553	0.0563	0.0604	0.0516	0.0477	0.0458	0.0468	0.0504	0.0608	0.0624	0.0707	0.0724	0.0770	0.0792	0.0859	0.0890	0.0807	0.0780	0.0737
Industry 8 Dummy	0.0152	0.0221	0.0199	0.0215	0.0223	0.0180	0.0220	0.0331	0.0348	0.0261	0.0253	0.0279	0.0266	0.0248	0.0220	0.0213	0.0317	0.0360	0.0372	0.0364
Control Variable (Size)																				
Log (Market Capitalization)	13.3304	13.3533	13.3701	13.5225	13.6262	13.8362	13.8939	13.9894	13.9813	14.0613	14.1473	14.2690	14.2456	14.3144	14.3928	14.4204	14.4560	14.4368	14.6190	14.7583
Market Determined Probability of Default																				
Firm Level RAPD	0.0711	0.1363	0.0793	0.0610	0.0831	0.0762	0.0755	0.0757	0.0665	0.0722	0.0798	0.0919	0.1479	0.1719	0.2076	0.1780	0.1986	0.1129	0.0823	0.0664
Variance Parameter Proxy																				
Square root of Total Assets ($ million)	40.3620	40.0447	42.9537	44.1584	48.4835	50.3084	51.0849	50.4617	50.3458	52.1623	52.1399	53.7716	55.3418	58.4374	63.9024	63.5168	68.2094	68.4424	69.2673	71.6101
Total Observations:	2236	2351	2309	2184	1975	1949	2138	2328	2500	2565	2884	3155	3303	3310	3221	1456	1169	2802	3040	3081

Table 5

Results of the Pooled Ordered Probit Regression for the entire panel 1986-2000, when BLM (1998) is modified to take into account RAPD variable directly as an independent variable instead of the proxies employed by BLM. The dependent variable is the seven rating categories: AAA, AA, A, BBB, BB, B, CCC & below, numerically coded 1,..,7 respectively.

Variable (N = 49956)	**Coefficient**	**t -stat**	
Intercept	8.9605	77.1490	***
Time Dummies by Quarter (Yr86q1 to Yr05q4)			
Balance Sheet Variables			
Operating Income to Debt Ratio	0.0001	0.664	
Operating Income to Sales Ratio	-0.0003	-0.581	
Return on Assets	-1.0965	-10.956	***
Long-Term Debt to Assets Ratio	1.5093	47.639	***
Interest Coverage Ratio 1 (-Ifty,5)	-0.0186	-40.358	***
Interest Coverage Ratio 2 [5,10)	-0.0993	-30.366	***
Interest Coverage Ratio 3 [10,20)	-0.0065	-3.463	***
Interest Coverage Ratio 4 [20,Ifty)	0.0000	1.841	*
Control Variables(Cross - Section Indicator)	**8 Industry**	**Dummies**	
Control Variable (Size)			
Log (Market Capitalization)	-0.4283	-110.602	***
Market Determined Probability of Default			
Firm Level RAPD	1.2230	42.97	***
Variance Parameter Proxy			
Square root of Total Assets	-0.0007	-11.418	***
Threshold Parameter Values			
Upper Limit for AA	1.2366	56.461	***
Upper Limit for A	2.5387	96.326	***
Upper Limit for BBB	3.6431	122.373	***
Upper Limit for BB	4.7933	146.188	***
Upper Limit for B	6.7173	172.717	***
Log-Likelihood	-47368		
Pseudo R-squared	0.2605		

,,*: Significant at 1%, 5% and 10% level of significance respectively.

Table 6 – Panel A

[redacted]

Table 6 – Panel B

[redacted]

Table 7

The Table shows the comparison of Risk Adjusted Probabilities of Default (RAPD) obtained from the modified Merton model(RAPD_Merton) and from the equity as a Down-and-out Call option model (RAPD_DOC) by letter rating categories. It also shows the value of the implied default barrier as a percentage of market value of assets (MVA) obtained from the DOC option model. The barrier values are comparable to ones obtained by Leland and Toft (1996) and Reisz and Perlich (2007). The period of study is 1986-2000.

Rating Class	N	Variable	Mean	Median	Std Dev	Minimum	Maximum
AAA	318	RAPD_DOC	0.0097	0.0000	0.0508	0.0000	0.4390
		RAPD_MERTON	0.0090	0.0000	0.0427	0.0000	0.4058
		Barrier as % of MVA	0.2022	0.1716	0.1293	0.0110	0.6170
AA	1837	RAPD_DOC	0.0172	0.0000	0.0642	0.0000	0.5833
		RAPD_MERTON	0.0163	0.0001	0.0600	0.0000	0.6090
		Barrier as % of MVA	0.2562	0.2334	0.1420	0.0097	0.7533
A	5812	RAPD_DOC	0.0246	0.0007	0.0696	0.0000	0.8459
		RAPD_MERTON	0.0253	0.0012	0.0679	0.0000	0.6956
		Barrier as % of MVA	0.2946	0.2825	0.1358	0.0014	0.8010
BBB	6326	RAPD_DOC	0.0611	0.0099	0.1096	0.0000	0.9996
		RAPD_MERTON	0.0592	0.0123	0.1027	0.0000	0.8373
		Barrier as % of MVA	0.3333	0.3270	0.1355	0.0082	0.8596
BB	4578	RAPD_DOC	0.1475	0.0789	0.1696	0.0000	0.9980
		RAPD_MERTON	0.1319	0.0751	0.1491	0.0000	0.8877
		Barrier as % of MVA	0.3522	0.3430	0.1438	0.0051	0.8178
B	2638	RAPD_DOC	0.2131	0.1662	0.1941	0.0000	1.0000
		RAPD_MERTON	0.1882	0.1458	0.1700	0.0000	0.9164
		Barrier as % of MVA	0.3615	0.3572	0.1490	0.0084	0.9002

CCC & below	175	RAPD_DOC	0.2662	0.2232	0.2352	0.0000	1.0000
		RAPD_MERTON	0.2416	0.1994	0.2209	0.0000	1.0000
		Barrier as % of MVA	0.4000	0.3876	0.1632	0.0936	0.9148
Total	21684						