Very Preliminary
Comments Welcome

Bank Regulation, Credit Ratings, and Systematic Risk

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Abstract

A model is presented that shows how current regulations create incentives for banks to take systematic risks. When (Basel Accord) capital standards or (FDIC) insurance premiums are based on a bank's physical default probability or expected default losses, a bank can increase its shareholder value by making loans and investing in bonds that have relatively high systematic risk. Such an incentive occurs because, holding expected default losses constant, credit spreads are higher for systematically risky debt as they reflect risk-neutral, rather than physical, expected default losses. If credit ratings are based on physical expected default losses, then credit rating-based regulation, such as the Basel II and III "Standardized Approach," will subsidize banks' systematically risky investments.

Using an international sample of almost 4,000 bonds, we test whether credit rating based-regulation can create the bank moral hazard predicted by our model. First, we estimate each bond issuer's debt beta, a measure of the debt's systematic risk, and find that it positively affects the bond's credit spread, even after controlling for the bond's credit rating. In contrast, the idiosyncratic risk of the issuer's debt has no impact on its bond's credit spread after accounting for the bond's credit rating. Second, credit ratings only partially reflect systematic risk. If a bank chooses bonds within a given credit rating that have above median credit spreads, the systematic risk of its investments rises by an economically significant amount. Third, while Moody's and S&P do not differ significantly in their assessments of systematic risk, the likelihood of a split rating (disagreement between raters over the same issue) decreases with the issuer's beta.

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1. Introduction

Government regulation of banks is pervasive, and its rationale stems from two factors: the inherent fragility of banks; and the negative externalities from bank failures. Banks provide liquidity by issuing demand deposits and also act as delegated monitors by making loans to opaque borrowers. This combination of loan-making and deposit-taking makes banks vulnerable to runs, as they finance relatively illiquid loans with liquid demand deposits. Individual bank fragility can, in turn, trigger contagious runs, even on healthy banks, culminating in system-wide failures with a consequent disruption of credit flows to the rest of the economy.

Government insurance of deposits can be effective in preventing bank runs, thereby avoiding systemic bank failures and their negative spillovers to the rest of the economy. However, deposit insurance and other government assistance, such as central bank lending facilities, can create incentives for banks to take excessive risks. If unchecked, this moral hazard may lead to large losses by governments when bailing out insolvent banks. Bank regulation aims to mitigate moral hazard through the setting of capital standards and, in some cases, deposit insurance premia. However, for regulation to be effective, it must be risk-based in a manner that neutralizes moral hazard incentives.

The current regulatory framework of risk-based capital and deposit insurance might actually create a particular form of moral hazard. Specifically, regulation that sets capital and/or insurance premia to cover expected default losses may encourage banks to take excessive systematic risk; that is, to make loans and invest in bonds that are highly likely to suffer losses simultaneously during an economic downturn. As shown by Kupiec (2004) and Pennacchi (2006), such moral hazard occurs if regulators measure the risk of a bank's assets based on their physical (actual) expected default losses, rather than their risk-neutral expected default losses which reflect the assets' systematic risks.

For example, under Basel II capital regulations, as well as in the new Basel III framework, a bank's required capital is set according to either external or internal credit ratings. If credit ratings are based on physical - rather than risk-neutral – expected default losses, credit rating based regulation effectively will undercharge banks for their cost of funding systematically risky investments. As a result, banks will have an incentive to make loans and invest in bonds that have the highest systematic risk within each rating class. This occurs because theory predicts that such systematically risky loans and bonds have the highest yields (credit spreads) within each rating class.

In summary, banks' moral hazard incentive to increase systematic risk is based on the theory that loan and bond credit spreads reflect risk-neutral expected default losses while regulators set capital requirements and/or deposit insurance premia based on credit ratings that reflect physical expected default losses. Such regulation-induced moral hazard would be particularly devastating to banking system stability because banks would herd into the most systematically risky investments, making simultaneous bank failures particularly sensitive to economic downturns. Critical empirical questions regarding the validity of this theory are whether credit spreads truly reflect systematic risk and, if so, whether credit ratings also account for systematic risk to the same degree. If credit ratings do not incorporate systematic risk to the same extent as credit spreads, then the theory's main premise would be upheld. These issues are the focus of our paper.

Whether credit rating agencies' ratings criteria are designed to discriminate between systematic and nonsystematic risk is not clear. Moody's and Standard & Poor's (S&P) claim that their ratings are assigned "through the cycle:" ratings reflect the ability of a firm to survive a cyclical downturn. But accounting for systematic risk requires that if two firms had the same overall probability of default (PD) and loss given default (LGD) but one was relatively more likely to default during an economic downturn, then that one should receive a lower quality rating. S&P, whose credit ratings are stated to reflect PDs, recently introduced a stability criterion to its rating methodology: a lower rating is assigned if "an issuer or security has a high likelihood of experiencing unusually large adverse changes in credit quality under conditions of moderate stress (for example, recessions of moderate severity, such as the U.S. recession of 1982 and the U.K. recession in the early 1990s or appropriate sector-specific stress scenarios)" (Standard & Poor's 2010). S&P's revision appears to be the first time that it penalizes issuers for systematic versus nonsystematic risk. Moody's, whose ratings are viewed to reflect expected default losses (PD×LGD), has not announced a similar change in its general ratings methodology.

Regarding the link between credit spreads and systematic risk, Elton, Gruber, Agrawal, and Mann (2001) analyzed secondary market corporate bond spreads over the period 1987 to 1996. For bonds of a given credit rating and maturity, they find that monthly changes in a bond's credit spread are significantly related to

Fama and French (1993) risk factors. This is suggestive evidence that corporate bond credit spreads may embed a systematic risk component, even after controlling for their credit rating.[1] More recently, Coval, Jurek, and Stafford (2009) show that particular fixed-income securities can have high quality credit ratings but also high systematic risk. They demonstrate that highly-rated structured bonds, such as senior asset-backed, mortgage-backed, and collateralized debt obligation tranches, reallocate payoffs of the underlying assets from states with high marginal utility to states with low marginal utility, thereby increasing systematic risk.[2] They also argue, however, that fixed income investors tended to price these securities based on credit ratings that only reflect physical probabilities of default. Their empirical evidence suggests that while these bonds had high systematic risk, their credit spreads failed to compensate investors for this risk. But using a different calibration methodology, Collin-Dufresne, Goldstein, and Yang (2010) present opposite evidence that the credit spreads of these highly-rated structured bonds did fully reflect their systematic risk.

The aforementioned papers do not specifically address whether credit ratings measure purely physical (actual) expected default losses or whether they distinguish between systematic and nonsystematic default losses. Such an analysis is conducted by Hilscher and Wilson (2010) who find that S&P issuer ratings are related to some measures of systematic default risk. Although they show that systematic risk also is strongly related to credit spreads, they do not test whether spreads reflect systematic risk beyond that implied by credit ratings.

In this paper, we use a standard structural credit risk model to show how banks have an incentive to choose high systematic risk loans and bonds if regulatory capital standards and deposit insurance premia are based on physical expected default losses, as might be the case when they are tied to credit ratings. To examine the validity of this incentive, we address three empirical questions. First, we check that credit spreads actually impound systematic risk (as measured by the issuer's debt beta), after controlling for credit ratings. Second, we investigate whether credit ratings reflect systematic risk, either fully, partially, or not at all. Third, we analyze differences between Moody's and S&P in their assessment of systematic risk.

[1] While they attempt to control for default probabilities, it may be possible that changes in credit spreads reflect changes in expected default losses that are correlated with systematic risk factors.

[2] Using a different model, Wojtowicz (2011) arrives at a similar result for collateralized bond obligations.

Our empirical tests are conducted on an international sample of 3,924 bonds issued during the 1999 to 2010 period. The data comprise credit spreads and issue credit ratings at the time each bond is underwritten, along with characteristics of each bond and issuer. Three main results emerge. First, the issuer's debt beta positively affects its bond's credit spread, even after controlling for the bond's credit rating. In contrast, the idiosyncratic risk of the issuer's debt has no impact on credit spreads after accounting for credit ratings. As such, ratings seem to not incorporate (at least not fully) the issuer's systematic risk, while they reflect idiosyncratic risk. This result holds even when excluding bonds issued during the financially turbulent period of 2008 to 2010. Second, for the sample as a whole, credit ratings seem to not account for systematic risk. This result, however, is entirely driven by bonds issued during the financial crisis, when the average level of systematic risk for debt was abnormally high and only top-rated issuers were able to tap bond markets. As a result, in those years bonds with high ratings are associated to extremely high systematic risk. When dropping bonds issued during 2008 to 2010, we find that ratings reflect some information about the issuer's systematic risk. Nonetheless, the fact that bond investors require a systematic risk premium, after controlling for credit ratings, suggest that raters do not fully account for systematic risk (at least not as much as do investors). Third, while Moody's and S&P do not differ significantly in their assessments of systematic risk, the likelihood of a split rating (disagreement between raters over the same issue) decreases with the issuer's beta. We explain this finding with the fact the fundamentals of high-beta issuers are more strongly correlated with systematic factors, which raters are more likely to agree on compared to firm-specific factors.

The paper proceeds as follows. Section 2 presents the model and discusses why current bank regulation creates incentives to take excessive systematic risk. Section 3 describes our sources of data and presents summary sample characteristics. In Section 4 we address the question of whether credit spreads reflect an issuer's systematic risk. In Section 5 we look at the impact of the issuer's systematic risk on its credit ratings, while in Section 6 we test for any difference between Moody's and S&P's assessment of systematic risk. Section 7 concludes.

2. The model

The model developed in this section predicts that the current structure of bank regulation creates incentives for banks to take excessive systematic risk and thus provides motivation for our subsequent empirical tests. It considers a setting where a regulated bank chooses a portfolio of multiple bonds and loans. The model has similar implications to the binomial model in Pennacchi (2006) but uses the framework of Merton (1974, 1977) and Galai and Masulis (1976) which better guides our empirical work.

Consider a continuous-time model of a bank that issues government-insured deposits and is subject to risk-based capital standards. At the initial date 0, the bank has insured deposits of D_0 upon which it pays the competitive, default-free interest rate of r. The bank's shareholders also contribute initial equity capital equal to K_0. Therefore, the bank initially has $D_0 + K_0$ available to invest in a portfolio of default-risky bonds and loans whose date 0 value is denoted $A_0 = D_0 + K_0$. The bank's portfolio is allocated to the debt of firms in m different industries, where each of the firms has a capital structure that satisfy the assumptions in Merton (1974). Appendix A shows that if the portfolio's proportions invested in the m different industries are kept constant over time, then the rate of return on this portfolio can be written as

$$\begin{aligned}\frac{dA_t}{A_t} &= \mu dt + \sum_{i=1}^{m} \sigma_{A,i} dz_i \\ &= \mu dt + \sigma dz\end{aligned} \tag{1}$$

where $\sigma_{A,i}$ is the volatility of returns from the bank's loans and bonds of firms in industry i, dz_i is the Brownian motion process specific to firm asset returns in industry i, $dz_i dz_j = \rho_{ij} dt$, $\sigma^2 = \sum_{j}^{m} \sum_{i=1}^{m} \sigma_{A,j} \sigma_{A,i} \rho_{ij}$, and $dz \equiv \frac{1}{\sigma} \sum_{i=1}^{m} \sigma_{A,i} dz_i$. In addition, if the Capital Asset Pricing Model (CAPM) holds, Appendix A shows that the expected rate of return on the bank's asset portfolio satisfies the CAPM relationship

$$\mu = r + \varphi_M \sum_{i=1}^{m} \omega_i \beta_i \tag{2}$$

where φ_M is the excess expected return on the market portfolio of all assets, ω_i is the bank's proportion of total assets held in bonds and loans of firms in industry i, and β_i is the average debt beta of firms in industry i. Appendix A details how debt betas are calculated based on Galai and Masulis (1976).

A government regulator sets a risk-based capital standard and a deposit insurance premium for the bank. The bank's insurance premium is determined at date 0 but payable at a future date T, which also is the time that the bank is audited by the regulator. Let p be the (continuously-compounded) annual insurance premium rate per deposit. The premium to be paid at date T equals $D_T(e^{pT}$-1), so that the total amount of deposits plus insurance premium payable at date T is $D_T e^{pT} = D_0 e^{(r+p)T}$.[3] Similar to Merton (1977), if at the audit date $A_T < D_0 e^{(r+p)T}$, the bank is declared to have failed and is closed or merged with another institution. The government regulator/deposit insurer incurs any loss required to pay off insured deposits.

These assumptions imply that there are three claimants on the bank's assets: depositors, bank shareholders, and the government regulator/insurer. Because insured depositors obtain a default-free claim that pays the competitive default-free rate r, the date 0 value of their claim on the bank's assets is always worth D_0. Denote the date 0 values of claims on the bank's assets by shareholders and by the government regulator as E_0 and G_0, respectively. Then

$$A_0 = D_0 + K_0 = D_0 + E_0 + G_0 \tag{3}$$

or $K_0 = E_0 + G_0$. When capital standards and/or deposit insurance premiums are set fairly, $G_0 = 0$, so that $E_0 = K_0 = A_0 - D_0$; that is, the value of the shareholders' claim on the bank equals the funds that they contribute. If $G_0 < 0$, so that $E_0 > K_0$, then a government subsidy transfers value to the bank's shareholders. In general, the value of the regulator's claim can be computed as

$$\begin{aligned} G_0 &= A_0 - D_0 - E_0 \\ &= e^{-rT}\mathrm{E}^Q\left[A_T - D_T\right] - e^{-rT}\mathrm{E}^Q\left[\max\left(A_T - D_T e^{pT}, 0\right)\right] \\ &= e^{-rT}\mathrm{E}^Q\left[\min\left(D_T\left(e^{pT}-1\right), A_T - D_T\right)\right] \\ &= D_0\left(e^{pT}-1\right) - e^{-rT}\mathrm{E}^Q\left[\max\left(D_T e^{pT} - A_T, 0\right)\right] \end{aligned} \tag{4}$$

where $\mathrm{E}^Q[\cdot]$ denotes the "risk-neutral" or Q-measure expectations operator. It computes expectations based on the risk-neutral asset return process

$$\frac{dA_t}{A_t} = r dt + \sigma dz^Q \tag{5}$$

[3] This insurance premium structure makes it analogous to a credit spread on deposits if deposits were uninsured. In the absence of deposit insurance and regulation, uninsured depositors would set the credit spread, p, to make the date 0 fair value of their default-risky deposits equal D_0, the amount they contribute initially.

Equation (4) shows that the claim of the government regulator/insurer equals the value of its premium income, $D_0(e^{pT} - 1)$, minus the value of a put option written on the bank's assets, $e^{-rT}\mathrm{E}^Q[\max(D_T e^{pT} - A_T, 0)]$. If $G_0 = 0$, so that there is no subsidy, equation (4) implies that the present value of the insurance premium revenue must equal the value of losses from the bank's failure:

$$\begin{aligned} D_0\left(e^{pT}-1\right) &= e^{-rT}\mathrm{E}^Q\left[\max\left(D_T e^{pT}-A_T,0\right)\right] \\ &= D_0 e^{pT} N\left(-d_2\right)-\left(K_0+D_0\right)N\left(-d_1\right) \\ &= Put\left(K_0+D_0, D_0 e^{pT}, T\right) \end{aligned} \tag{6}$$

where $d_1 = \left[\ln\left(\left(K_0+D_0\right)/\left(D_0 e^{pT}\right)\right)+\sigma^2 T\right]/\left(\sigma\sqrt{T}\right)$, $d_2 = d_1 - \sigma\sqrt{T}$. Equation (6) is a relationship between the bank's required capital, K_0, and its deposit insurance rate, p, that leads to no government subsidy to the bank. It equates the present value of premiums to the value of a put option written on assets currently worth $A_0 = K_0 + D_0$, having an exercise price with present value $D_0 e^{pT}$, and a time until maturity of T.

Importantly, the current structure of capital requirements and deposit insurance appears fundamentally different from equation (6) because they are based either on external credit ratings or physical, rather than risk-neutral, expected default losses. Under the Basel II and III "Standardized Approach," credit risk weights which determine capital requirements are linked to external bond and loan credit ratings. For example, credit risk weights are 20%, 50%, 100%, and 150% for corporate claims rated AAA to AA-, A+ to A-, BBB+ to BB-, and below BB-, respectively. Under Basel's "Internal Ratings Based (IRB) Approach," which is followed by the largest globally-active banks, credit risk capital charges are calibrated to a Value at Risk (VaR) formula. This formula requires that banks estimate their own bonds' and loans' physical probabilities of default (PD) and losses given default (LGD).[4] With these physical inputs and a Basel-chosen portfolio correlation estimate, IRB capital charges are determined.[5] Even Basel capital requirements for "market" (as

[4] Under the "Foundation" IRB approach, regulators fix LGD for corporate claims. For example, it is 45% for all senior, unsecured bonds and loans. Under the "Advanced" IRB approach, guidelines recommend that banks estimate a bond or loan's "downturn" LGD, which reflects losses that are expected to occur if default happens during an economic downturn. Use of downturn LGDs may in principle differentiate between high and low systematic risk claims, but since PDs are not conditioned on a downturn, the VaR capital requirement is unlikely to fully incorporate systematic risk.

[5] Basel standards require sufficient initial capital, K_0, such that there is no more than a 0.1% physical probability of losses exceeding this initial capital over a one-year horizon. The VaR capital requirement formula assumes a portfolio correlation value that differs between types of credit risky claims. In principle, this correlation value could distinguish

opposed to “credit”) risks might rely on external credit ratings. In 2008 the Swiss Federal Banking Commission required that UBS report the key causes of its severe losses during the crisis. UBS’s report to shareholders (UBS, 2008) is uniquely insightful as to the risk management practices of large banks. It states that external credit ratings were used to determine “the relevant product-type time series to be used in calculating VaR” (p. 20). Moreover, an over-reliance on credit ratings, which appears to be common across the industry, was found to be a primary cause of UBS’s losses as “a comprehensive analysis of the portfolios may have indicated that the positions would necessarily perform consistent with their ratings” (p. 39).

In addition, risk-based deposit insurance premia, such as those set by the Federal Deposit Insurance Corporation (FDIC), generally are calibrated to cover expected losses, where expectations of losses are, again, calculated using physical probabilities, not risk-neutral probabilities.[6] Therefore, rather than capital charges and deposit insurance premia being set such that premiums cover risk-neutral expected losses from bank failures, the spirit of actual capital standards and deposit insurance premia would, instead, be consistent with a relation where premiums cover physical expected losses:

$$\begin{aligned} D_0\left(e^{pT}-1\right) &= e^{-rT}\mathrm{E}^P\left[\max\left(D_T e^{pT}-A_T,0\right)\right] \\ &= D_0 e^{pT}N\left(-d_2^P\right)-\left(K_0+D_0\right)e^{(\mu-r)T}N\left(-d_1^P\right) \\ &= Put\left(\left(K_0+D_0\right)e^{(\mu-r)T},D_0 e^{pT},T\right) \end{aligned} \tag{7}$$

between claims with high and low systematic risk claims. However, the Basel rule’s correlation value is the same for broad classes of bonds and loans. For corporate bonds and loans, the correlation value varies between 8% and 24%, but the variation is a function only of the borrowing firm’s annual sales (greater for firms with more than €50 million in sales) and the bank’s estimated physical PD, where correlation is higher for lower PDs. See BCBS (2005). Fitch Ratings (2008) finds no empirical support for the Basel rule’s inverse relationship between PDs and portfolio correlation (systematic risk). As will be reported in our empirical work, neither do we find an inverse relationship between a firm’s systematic risk (debt beta) and its probability of default (as reflected in its credit rating).

[6] For example, see *Federal Register* 76 (38) February 25, 2011 which details amendments to the Federal Deposit Insurance Act made to comply with the Dodd-Frank Act. An underlying principle for setting premiums (assessments) is stated on page 10700: “Under the FDI (Federal Deposit Insurance) Act, the FDIC’s Board of Directors must establish a risk-based assessment system so that a depository institution’s deposit insurance assessment is calculated based on the probability that the DIF (Deposit Insurance Fund) will incur a loss with respect to the institution.” The FDIC’s statistical failure probability models, on which its premium schedule is based, use physical, rather than risk-neutral, probabilities of bank failures.

where $d_1^P = \left[\ln\left(\left(K_0 + D_0\right) e^{(\mu - r)T} / \left(D_0 \left(1 + pe^{-rT}\right)\right)\right) + \sigma^2 T \right] / \left(\sigma\sqrt{T}\right), d_2^P = d_1^P - \sigma\sqrt{T}$, and E^P[·] is the "physical" or P-measure expectations operator that computes expectations based on the physical asset return process in equation (1). Computing expectations under the physical, rather than risk-neutral, probability measure leads to the same Black-Scholes put option pricing formula as (6) except that the underlying asset value $\left(K_0 + D_0\right)$ is everywhere replaced with the underlying asset value $\left(K_0 + D_0\right) e^{(\mu - r)T}$. Because put options are decreasing functions of the value of the assets on which they are written, when $\mu > r$, the value of the put option in equation (7) is less than that in equation (6):

$$Put\left(\left(K_0 + D_0\right) e^{(\mu - r)T}, D_0 e^{pT}, T\right) < Put\left(K_0 + D_0, D_0 e^{pT}, T\right) \quad \text{if } \mu > r \tag{8}$$

An implication of inequality (8) is that when a regulator uses equation (7) to set insurance rates, p, and capital standards, K_0, they are lower than what would be required to satisfy the no-subsidy relationship in equation (6), so that from equation (4), $G_0 < 0$. In turn, equation (3) implies $E_0 = K_0 – G_0 > K_0$, so that the subsidy provided by the regulator accrues to the bank's shareholders. Specifically, since shareholders' equity has a payoff analogous to a call option, its value is

$$\begin{aligned} E_0 &= e^{-rT} \mathrm{E}^Q \left[\max\left(A_T - D_0 e^{(r+p)T}, 0\right)\right] \\ &= \left(K_0 + D_0\right) N\left(d_1\right) - D_0 e^{pT} N\left(d_2\right) \end{aligned} \tag{9}$$

and since $\partial\left(E_0 - K_0\right) / \partial K_0 = N\left(d_1\right) - 1 < 0$ and $\partial\left(E_0 - K_0\right) / \partial p = -pD_0 e^{pT} N\left(d_2\right) < 0$, when capital standards and/or insurance premia are lowered under regulations based on physical default expectations, a subsidy flows to bank shareholders. The greater is (μ - r), the greater is the difference between the put option in equation (6) versus that in equation (7) and the greater is the government subsidy transferred to shareholders.

Indeed, one now sees from equation (2) that bank shareholders can increase the subsidy that accrues to them by raising the systematic risk of their bond and loan portfolio, $\mu - r = \varphi_M \sum_{i=1}^{m} \omega_i \beta_i$. This can be done by done by selecting greater portfolio weights, ω_i, in industries where the average debt beta of firms are relatively high. Alternatively, within an industry, a bank might select those bonds and loans of firms with relatively high debt betas, thereby raising the average debt beta in that industry, β_i. Such portfolio decisions need not change the overall volatility of the bank's asset portfolio, σ, but even if they do, the relative subsidy for any given level of portfolio volatility, σ, still increases.

While our model suggests that banks will intentionally take excessive systematic risk in order to increase shareholder value, it is possible that more naïve banks will do so unintentionally. Why? Note that controlling for physical expected default losses, bonds or loans with greater systematic risk will have larger credit spreads or yields to maturity. This is because if the debt beta of the i^{th} bond or loan is β_i, its expected rate of return is $r + \varphi_M\beta_i$. All else equal (including expected default losses), higher systematic risk in the form of a higher debt beta raises the expected rate of return of the bond or loan, which must lower its price relative to its promised payment, thereby raising its yield and credit spread.

Thus, if a naïve bank subject to credit rating-based capital charges simply chooses bonds and loans that have the highest credit spread or yield for a given credit rating, it will automatically pick relatively high beta bonds and loans. By simply selecting top-yielding bonds and loans within a given rating class, the bank may inadvertently be loading up on systematic risk and, in turn, receiving a greater government subsidy.

The next sections consider whether the main assumptions of our model have empirical validity. We examine the relationships between credit spreads, credit ratings, and systematic risk based on an international sample of bonds which we now describe.

3. Data

We obtained data on bond issues over the 1999 to 2010 period from DCM Analytics, which reports information on each bond issuer (nationality, industry, etc.) and each bond issue's characteristics (credit spread, credit rating, years to maturity, face value, maturity date, currency, etc.). Since agencies assign the issue rating at the time of issuance, our use of primary market data overcomes the problem of stale ratings. In other words, issue ratings should impound all of the information available to the rating agency at the time of issuance. In contrast, issuer ratings might reflect new information only with a lag. Similarly, secondary market credit spread data might reflect information about the issuer ahead of the credit rating agency.

Our sample is restricted to fixed-coupon bonds that are non-convertible, non-perpetual, and non-callable. The initial sample consists of 9,691 bonds that have complete information about the issue. We focus on investment grade issues, which reduce the sample to 7,413 bonds.

We then use Bloomberg to match each bond ISIN code with the issuer's corresponding stock ISIN code. Our final sample consists of 3,924 bonds issued by 620 listed firms, mostly from North America, Europe and Japan. For each bond we collected from Bloomberg the issuer's stock returns for the 52 weeks prior to the bond's issuance date along with the contemporaneous weekly returns of the MSCI World Index. As a robustness check, we repeated our analysis by using the issuer's domestic stock index rather than the MSCI World, with no relevant change in our main findings. We employ a standard market model to estimate the issuer's stock beta. While the stock beta reflects shareholders' systematic risk, the theoretically appropriate measure of the systematic risk faced by the firm's bondholders is the firm's debt beta. Moreover, bond credit spreads should reflect debt betas. We follow Galai and Masulis (1976) to derive the firm's debt beta from its equity beta (see Appendix A), assuming a debt maturity of 10 years. As a robustness check, we also computed debt betas with maturities of 1 and 5 years, and the main results of the paper are confirmed. We also compute the equity residual volatility as a measure of idiosyncratic risk. From this variable we derived debt residual volatility (see Appendix A for methodological details).

Table 1 provides mean values of the relevant issue and issuer characteristics by rating class (Panel A) and by year (Panel B). For summary statistics we use letter ratings (AAA/Aaa, AA/Aa, A/A, etc.) as opposed to notch-level ratings (AAA/Aaa, AA+/Aa1, AA/Aa2, AA-/Aa3, etc.) to have a greater number observations per rating class. A bond's credit spread is defined as the difference between the bond's yield at issuance and the yield on a Treasury security of the same maturity and currency of denomination. As expected, the average credit spread at issuance is monotonically increasing as ratings worsen. There are only 132 issues with top ratings of AAA/Aaa, with an average credit spread of about 80 basis points (bp). BBB/Bbb –rated bonds, the worst class among investment grade issues, have an average credit spread of almost twice as much at 149 bp. Top-rated bonds also have a much shorter maturity of 4.8 years compared to the 8.1 year maturity of all other rating classes. Should ratings reflect systematic risk, one would expect worse-rated bonds to have higher beta. In fact, top rated bonds tend to have greater betas (both stock and debt) and residual volatility compared to bonds with worse ratings. However, the reason that AAA/Aaa bonds have remarkably larger betas is that the majority were mostly issued by financial institutions during the years 2008 to 2009 (99 out of 132) at the height of the financial crisis when systematic risk was abnormally high. Figures 1 and 2 plot the average of issuers' equity and debt betas for the entire 1999 to 2010 sample and also for the sample excluding issues that took place during the financial crisis (year 2008 and beyond). Issuers of top-rated bonds have much lower betas when dropping observations in 2008 and beyond. Moreover, taking the financial crisis out of the picture, debt betas are clearly increasing as rating worsens. Equity betas of the issuer have a less clear pattern, as even excluding the financial crisis, they appear relatively stable across rating classes.

Turning to the time evolution of the main sample variables, we observe that the mean credit spread decreases from 104 bp in 1999 to a minimum of 46 bp in 2005; then it keeps increasing to the maximum of 215 bp during the financial crisis year of 2009. The mean spread during the 1999 to 2005 period is 82.8 bp as opposed to 146.9 bp from 2006 to 2010. Interestingly, the mean rating shows the opposite trend. The mean rating is 6.2 (about A/A2) during the 1999 to 2005 period, while it is about one notch better (A+/A1) from 2006 through 2010. This pattern presumably reflects a "flight to quality" during the financial crisis when only high-quality issuers were able to tap debt markets. Figures 3 and 4 show the time series evolution of equity and debt betas. Equity betas average 1.17 in year 1999 and tend to decrease to a minimum of 0.69 in 2006. Starting in 2007 it constantly increases to a maximum of 1.3 in 2010. Average debt betas follow a similar pattern, although they are relatively more variable. From a level of 0.15 in 1999, debt betas steadily drop to 0.01 in year 2005 and 2006. They then increase dramatically to 0.22 in 2009. This substantial rise reflects, in part, that debt betas rise as the net worth of the issuers declines.

4. Do credit spreads reflect issuers' systematic risk beyond that implied by credit ratings?

4.1. A preliminary test

A simple way to determine whether credit spreads reflect systematic risk beyond any systematic risk reflected in credit ratings is to compare the mean spreads for bonds having different systematic risk across different rating classes. We define bonds with high (*low*) systematic risk those having betas higher than (*lower than or equal to*) the sample median. We exclude bonds rated AAA/Aaa for which we have a limited number of observations (132). Table 2 reports the mean spreads for bonds with high and low systematic risk for the three different rating classes: AA, A, and BBB. We also control for whether the bond's maturity was 10 years or less versus greater than 10 years. The rationale for doing so might be that issuers' systematic risk influences the bond maturity that they choose, and it may be maturity, rather than systematic risk, that is reflected in spreads.

In Panel A of Table 2, bonds are classified according to their issuer's equity beta. Within the same rating class, bonds of issuers with high systematic risk pay a much larger spread. For example, the average AA bond with maturity less than 10 years and low systematic risk pays about 67 bp. Equally-rated bonds with high systematic risk pay an average of 107 bp. The 40 bp difference is statistically significant at the 1% level. Similar significant differences emerge in the other rating classes, irrespective of maturity. The only exception is the BBB class with maturities exceeding 10 years: however, there are only 107 bonds with such features, of which 36 (*71*) have high (*low*) systematic risk. When excluding bonds issued in the years 2008 and beyond, we obtain similar results, although the magnitude of the systematic risk premium is smaller. The spread difference between bonds with high versus low equity betas (across all rating classes) is about 36 bp for the whole sample, while it drops 15.2 bp when excluding the financial crisis period.

As shown in Panel B of Table 2, the results are similar when classifying bonds according to their issuer's debt beta, though the spread difference between high versus low systematic risk bonds appears even larger. The systematic risk premium (across all rating classes) is about 56 bp (compared to 36 bp based on equity betas). As before, the spread difference between bonds with high and low debt betas drops when excluding bonds issued in the 2008 to 2010 period, from 56.5 bp to 19.6 bp.

4.2. A bond picking exercise

Penati and Protopapadakis (1988) develop a theory predicting that banks might increase their systemic risk (as opposed to systematic risk) to benefit from implicit government protection. The idea is that the likelihood of a government bailout increases if many banks get into trouble together. The government reaction to the recent financial crisis confirms their prediction. Many banks have been bailed out by their national governments through provisions that range from the guarantee of uninsured debt to equity capital injections. Since borrowers with higher systematic risk tend to default together (in bad times), banks might increase their *systemic* risk by intentionally lending to borrowers with higher *systematic* risk.

Our argument is different. We claim that capital charges or deposit insurance premia based on credit ratings can lead banks to take more systematic risk, even if they are not bailed out but are allowed to fail. They do so because regulation does not discriminate between defaults in good versus bad times, but credit spreads do. Banks can increase their shareholder value by selecting bonds and loans with the highest credit spreads for a given credit rating, which leads to more systematic risk that is ignored by regulations. Indeed, banks may not intentionally choose to load on high systematic risk investments, but they may do so simply by investing in the top-yielding bonds and loans within a given rating class (and amount of required capital). The bank may naively believe that such selections exploit market inefficiencies.

To show how this mechanism can work, we categorize all bonds in our sample by year of issuance, maturity (lower versus higher than 10 years), currency (Euro, US Dollar, and Yen), and credit rating. To be consistent with the Standardized Approach of Basel II, we use ratings at the letter level (as opposed to the notch level) and merge AAA-rated bonds with AA-rated bonds.[7] For each category that has at least five issues, we rank bonds based on their credit spreads and compute the average debt beta of bonds with credit spreads above the median of the category (high-spread bonds). We then compare this value with the average debt beta of all the bonds in the category. Table 3 reports the result of this exercise. Panels A and B show betas for bonds with maturities of 10 years and less versus greater than 10 years, respectively. In most of the categories, the average beta of high-spread bonds is higher than the average beta of all of the bonds in the category. For example, suppose that in the year 2003 a bank had to choose among Euro-denominated, A-rated bonds with maturities of 10 years or less. The average beta of bonds with credit spread above the median is 0.192 compared to an average beta of 0.133 for all the bonds with analogous features. Similarly, for U.S. dollar-denominated issues, the average BBB-rated high-spread bond issued in 2007 has a debt beta of 0.062, while the entire category has an average beta of 0.040. Results are similar when looking at bonds with longer maturities (Panel B).

We compute the ratio of the average beta of high-spread bonds to the average beta of all the bonds within the

[7] Recall that Basel II's Standardized Approach assigns risk weights of 20%, 50%, 100%, and 150% to corporate claims rated AAA to AA-, A+ to A-, BBB+ to BB-, and below BB-, respectively. These risk weights are likely to be only a crude proxy for bonds' expected default losses. However, our test of whether the choice of high credit spread bonds within a given rating class results in relatively high systematic risk does not depend on these chosen risk weights.

same category. If choosing a high-spread bond had no relationship with the debt beta, the natural log of this ratio should have an unconditional value of zero. In Table 4 we report the results of a t-test, conducted for all the categories, as well as for categories with the same currency. We can reject the hypothesis that mean log ratios are equal to zero both when looking at all categories together and for categories with the same currency. The results in Table 4 show that if a bank simply selected bonds with credit spreads above the median for any given Basel II credit rating category, it would be investing in bonds having debt betas (systematic risk) approximately 20% above average. This appears to be an economically significant increase in systematic risk relative to random bond selection.[8]

So far, the evidence suggests that bond investors require a credit spread premium for bonds with higher systematic risk within the same rating class. In other words, credit ratings appear not to capture all of the systematic risk reflected in credit spreads. However, to control for other issue and issuer characteristics that might influence credit spreads, we next move to more formal multivariate statistical tests. We start by investigating whether credit spreads impound the issuers' systematic risk when controlling for credit ratings as well as other issue and issuer characteristics. We then test whether credit ratings at least partially account for systematic risk and whether there is any difference between Moody's and S&P in their assessment of systematic risk.

4.3. Regression analysis

To test whether bond investors price the systematic risk of an issuer's debt, we run a regression of credit spreads on the bond issuer's (debt) beta, controlling for credit ratings, and other issue and issuer characteristics. Specifically, consider the following specification:

$$Spread_{i,t} = f\left(Rating, Debt\ Beta, \ln\left(Debt\ Residual\ Volatility\right), Controls\right) + \varepsilon_{i,t} \tag{10}$$

where:

[8] If we had more observations on bonds (which might be possible by including secondary market spreads and credit ratings on previously-issued bonds), we could repeat this exercise with bonds in each category divided by credit spreads into quartiles, quintiles, or deciles, rather than just above and below the median. It is likely that if banks selected, say, the highest spread decile of bonds for a given rating category, their exposure to systematic risk would be even greater.

Spread	The bond's credit spread, equal to the difference between the bond's yield at issuance and that of a Treasury security having the same maturity and currency.
Rating	Indicator variables for issue ratings (at the notch level). AAA/Aaa is the excluded variable.
Debt Beta	The issuer's debt beta estimated for the 52 weeks preceding the issue.
Debt Res. Vol.	The issuer's debt residual volatility estimated for the 52 weeks preceding the issue.
Controls	Issue's and issuer's characteristics that might affect the credit spread (including the issue face value, maturity, issuer's country, year, and currency fixed effects). A detailed description of control variables is reported in the Appendix B.

We estimate OLS regressions with robust standard errors clustered at both the year and the issuer level. Table 5 reports results. In Column 1 we include only ratings and control variables. Rating dummies are all strongly significant and increase monotonically as the bond's rating worsens. Despite the recent criticism about the accuracy and timeliness of rating agencies, our empirical evidence indicates that credit ratings are an important determinant of bond yield spreads. For example, a AA+/Aa1 rated bond pays about 74 bp more than AAA/Aaa bond (the excluded category), while the credit spread of a BBB-/Bbb3 rated bonds is about 211 bp larger than a top-rated bond. In Column 2 we include the debt beta, whose coefficient is positive and strongly significant. Controlling for credit ratings, for a 0.1 variation in the issuer's debt beta investors require about 10.8 bp. Notably, the idiosyncratic volatility of the issuer's debt is not significant (Column 3), presumably because it is entirely captured by credit ratings. Indeed, in unreported results, we find that the coefficient of the debt residual volatility become significant when dropping rating dummies.

To sum up, our results suggest credit spreads required by bond investors incorporate systematic risk beyond any systematic risk reflected in credit ratings. In contrast, controlling for credit ratings, credit spreads do not appear to additionally reflect the issuer's idiosyncratic risk. Put another way, credit ratings seem to be based on physical expected default losses, while investors value bonds based on risk-neutral expected default losses.

Earlier we noted that bonds issued during the financial crisis have better issue ratings, notwithstanding a remarkably higher systematic risk. The association between good ratings and high systematic risk observed from 2008 to 2010 might bias our results, leading to an over-estimate the systematic risk premium required by investors. We thus run regressions excluding bonds issued in the years 2008 and beyond. Results are reported in Column 4 of Table 5. Two main findings emerge.

First, the credit risk premium relative to AAA/Aaa bonds are much smaller for all rating classes, reflecting the ease of tapping debt markets in the pre-crisis era. For example, while in the whole sample the average BBB-/Bbb3 bond pays about 211 bp more than a AAA/Aaa rated bond, excluding the financial crisis the figure drops to 76 bp, roughly the same as a AA+/Aa1 in the whole sample. In addition, when excluding the financial crisis a AA+/Aa1 bond does not have a significantly higher credit spread than a top-rated bond. In particular, credit spreads for the whole AA/Aa rating class (including bonds with ratings equal to AA+/Aa1, AA/Aa2, AA-/Aa3) are not statistically different from that of a AAA/Aaa bond if we exclude 2008 to 2010. Therefore, it seems that in the pre-crisis era bond investors relied on credit ratings mostly to discriminate between just the best and the worst of investment-grade bonds. This result is particularly relevant in light of banks' capital regulation. Under Basel II and III, claims rated from AAA to AA- have the same risk weight (20% for claims on corporates). Based on our evidence, this approach proves correct in "normal" times: in contrast, under stress conditions, investors clearly discriminate between a AAA bond and each notch-level rating within the AA class.

Second, although strongly significant, the coefficient of the debt beta variable is smaller compared to the whole sample regression (67.8 versus 108.8). It is therefore plausible that a structural increase in the systematic risk premium required by investors occurred as a result of the financial turbulence. In Column 5 we test the effect of the interaction between a dummy for the financial crisis years (2008-10) and the issuer's debt beta. As expected, the interaction term is positive and strongly significant, suggesting that investors required a much higher systematic risk premium after 2008.[9]

For robustness, we estimated debt betas and residual volatilities by assuming a maturity of 5 years (instead of 10 years) and re-ran all the regressions. The main findings are all confirmed.

[9] From analyzing the term structure of credit default swap (CDS) spreads, Berg (2010) also finds a rise in the short-term systematic risk premium during the crisis. The term structure CDS spreads is consistent with a mean-reverting process for this risk premium.

4.4. Controlling for liquidity

If for some reason bond investors are reluctant to trade securities with high systematic risk, newly issued bonds might be expected to be more illiquid in the future if the issuer has a higher debt beta. Since credit ratings do not account for bond liquidity, what we label a systematic risk premium might actually be a liquidity risk premium. In the regressions reported in Table 5, we controlled for a number of issue characteristics, including the issue size, which should proxy for the bond's secondary market liquidity. We nonetheless conduct an additional test, controlling for a bond's *observed* liquidity in the secondary market. A commonly used measure of liquidity is the relative bid-ask spread (Chordia et al. 2005; Goyenco and Ukhov, 2009), which is computed as follows:

$$Bid - Ask\ Spread = \frac{Ask - Bid}{\frac{1}{2}\left(Ask + Bid\right)} \times 100 \tag{11}$$

where *Ask* and *Bid* are the quoted ask and bid prices for a given day.

For each bond in our sample, we searched Bloomberg for its bid and ask quotes for each day over the first 60 trading days following its issuance. From these quotes we computed the average relative bid-ask spread, deleting any daily observations with a spread equal to zero or negative. We were able to find and compute the average relative bid-ask spread, *Avg Bid-Ask Spread*, for a subsample of 2,395 bonds (out of the total sample of 3,924 bonds).

For this 2,395 bond subsample, regressions similar to those reported in Table 5 were run except that the variable *Avg Bid-Ask Spread* was also included as a control. By using this control for expected illiquidity, we implicitly assume that investors purchasing a bond on the primary market can foresee with reasonable accuracy the spread between bid and ask quotes that will prevail on the secondary market. The results of these regressions are reported in Table 6. As expected, larger secondary market bid-ask spreads are associated with a higher credit spread in the primary market.[10] But most importantly, our previous main findings are all confirmed. Credit spreads reflect debt systematic risk even after controlling for credit ratings,

[10] Of course while we have defined the bond's credit spread as the difference between its yield and that of an equivalent maturity government bond, our tests imply that this spread reflects both credit and liquidity risks.

just as strongly as before when the bid-ask spread was excluded. Moreover, controlling for illiquidity shows that the systematic risk premium still dramatically increased during the financial crisis.

To sum up, the evidence thus far suggests that investors account for systematic risk to a greater extent than what is reflected in credit ratings. However, we cannot reject the hypothesis that ratings at least partially impound information about the issuer's systematic risk. Indeed, it is possible that investors assign a different weight to systematic risk than raters do. In the next section we check whether issue ratings reflect issuers' systematic risk by running regressions of ratings on the issuers' debt betas, volatilities, and other issue and issuer controls.

5. Do credit ratings reflect issuers' systematic risk?

From statements by credit rating agencies, issue ratings would seem to reflect a bond's physical probability of default, as would be the case if raters considered only the issuer's total default risk and not whether default tends to occur during economic expansions versus economic recessions. In contrast, if raters differentiated between idiosyncratic and systematic default risk, then ratings might reflect risk-neutral probabilities of default if defaults in bad economic times were weighted more heavily than defaults in good economic times.

Both Moody's and S&P claim that normal fluctuations in economic activity and the consequent effects on the credit quality of an issuer or issue are impounded into their credit ratings. In other words, ratings are assigned "through the cycle." Whether this approach includes an assessment of systematic risk is unclear. On the one hand, an evaluation of the possible adverse consequences of an economic slowdown on a credit rating would arguably imply an analysis of the bond's systematic risk. On the other hand, if raters place probabilities on the likely occurrence of different economic scenarios equal to their physical (actual), rather than risk-neutral, probabilities, then their calculations of expected default or expected default losses will not equal risk-neutral expected default or default losses. For example, an issuer with high systematic risk might be considered extremely vulnerable to a recession, but if the probability of a recession is not weighted greater than its physical probability, ratings will not reflect risk-neutral expected default losses.

Recently, S&P announced new ratings criteria (Standard & Poor's, 2008, 2010) that suggests they may be switching from using physical default probabilities to something akin to risk-neutral ones. The President of S&P, Deven Sharma, summarized this change with the statement "Under S&P's new criteria,…we may feel that two securities have similar default risk, but if we believe one is more prone to a sharp downgrade in periods of economic stress, it will be rated lower initially." Such a rating methodology might have the potential to place greater weight on default losses during an economic downturn.

To investigate the information content of credit ratings, we first compute the average issue rating (*Avg Rating*), equal to the average of Moody's and S&P's issue ratings converted into a numerical scale (AAA/Aaa = 1, AA+/Aa1 = 2, …, BBB-/Bbb3 = 10). We then run the following OLS regression, with robust standard errors clustered at both the year's and the issuer's level:

$$Rating_{i,t} = f\left(Debt\ Beta, \ln\left(Debt\ Residual\ Volatility\right), Controls\right) + \varepsilon_{i,t} \tag{12}$$

Results are reported in Table 7. In Column 1 we exclude the residual volatility of the issuer's debt and only analyze the effect of systematic risk. The coefficient of the debt beta variable enters positive and significant. Recall that a higher value of *Rating* indicates a worse issue rating. Notably, however, when including the issuer's idiosyncratic risk, the debt beta becomes insignificant (Column 2). Results are very similar when replacing the idiosyncratic (residual) volatility of the issuer's debt with the total volatility of the issuer's debt (Column 3).

As noted earlier, the financial crisis produced two relevant effects on the bond market, which are clearly detectable in our sample: i) only issuers of good quality could access the market, thus resulting in better average issue ratings; and ii) the average systematic risk of issuers increased dramatically. As a result, during the crisis bonds with good ratings are associated with very high issue betas, therefore possibly biasing our results towards the finding that ratings do not account for systematic risk. Indeed, by focusing on the sub-sample of bonds issued before 2008, a different picture emerges. Ratings do reflect systematic risk (Column 4), even when controlling for the residual or total volatility of the issuer's debt (Columns 5 and 6). Results (unreported) are unchanged when using debt and residual volatility estimated for a 5-year horizon (instead of

10 years). This result, coupled with that discussed in the previous section, suggests that raters partially account for systematic risk, but not as much as bond investors.

It is nonetheless possible that the granularity of the discrete rating scale does not accurately reflect a continuous variable such as the systematic risk of the issuer's debt. However, the same discrete rating scale seems to properly capture the level of the debt's idiosyncratic and total risk, which also are continuous. Whether it is a matter of granularity of rating scales or rather an under-weight of systematic risk by raters is not a pivotal question for our study. Indeed, in one case or the other, a capital regulation based on credit ratings would generate an incentive for banks to take more systematic risk.

By using *Avg_Rating* as the dependent variable of an OLS regression we implicitly assume that ratings are cardinal measures of risk; that is, the risk difference between rating classes is constant. While this assumption may be implausible, it does not seem to drive our results. Indeed, we re-run regressions using an ordered probit model. To limit the number of cases in the dependent variable, we rounded the *Avg_Rating* variable to the closest integer. Results, reported in Columns 7 and 8 of Table 7, confirm our main findings. Excluding bonds issued during the financial crisis, issue ratings reflect both systematic and either idiosyncratic or total risk.

6. Do raters differ in assessing systematic risk?

As mentioned earlier, during the recent financial crisis, S&P announced a relevant change in its rating rules, introducing a criterion based on stability (Standard & Poor's, 2008, 2010). According to the new criterion, ratings (both issuer and issue) are assigned not only based on the current credit quality, but also depending on its expected stability in a stress scenario. In particular, a worse rating is assigned if there is a "high likelihood ... of unusually large adverse changes in credit quality under conditions of moderate stress" (Standard & Poor's 2010). For each rating class, S&P defines a maximum expected deterioration (i.e., a maximum down-grade) under conditions of moderate stress. If the issuer or issue is believed to fall below that maximum, then a worse rating is assigned.

According to this newly adopted criterion, S&P's ratings should reflect the tendency of a firm's (or security's) credit quality to deteriorate in bad times, regardless of the expectations about the economy. One could argue that before this change, S&P did not assess systematic risk at all. Moody's did not react to the S&P's announcement with an analogous change in its rating criteria. This might introduce a wedge between the two agencies over ratings assigned from 2008 on. Alternatively, it is possible that Moody's already assessed systematic risk, at least to a given extent. To check whether raters differ in their assessment of systematic risk, we run regressions of ratings on debt beta by using Moody's and S&P's ratings separately. Results, reported in Columns 1-8 of Table 8, are similar to those obtained in the previous section. When dropping bonds issued during the financial crisis, both Moody's and S&P reflect issuers' systematic risk.

An alternative way to test for any difference between the two raters related to systematic risk is to analyze the likelihood of a split rating and the issuer's beta. Split ratings occur when raters assign different ratings to the same bond issue. If one rater does assess systematic risk while the other does not, the frequency of split ratings should increase with the issuer's systematic risk. We therefore run a probit regression to test whether the likelihood of a split rating depends on the issuer's systematic risk. The dependent variable takes the value of 1 if Moody's and S&P's ratings differ, zero otherwise. Explanatory variables are those used in equation (10). We include rating dummy variables as previous studies find that split ratings tend to increase as rating worsens (Morgan, 2002; Iannotta, 2006).

Columns 9-10 of Table 8 report results obtained with the whole sub-sample of double-rated bonds (those for which it is possible to observe split ratings). Surprisingly, the issuer's debt beta enters *negatively* and it is strongly significant. When dropping observations from the financial crisis (Columns 11-12), the result is qualitatively similar. The negative sign of the debt beta coefficient might be explained by the fact the firms with higher systematic risk are more exposed to the same fundamental factors on which raters are more likely to agree. The probability of default of an issuer with high systematic risk tends to be more related to economy-wide variables. In contrast, it is plausible that the probability of default of issuers with low systematic risk is more related to firm-specific factors. Under the assumption that raters disagree more on firm-specific (as opposed to economy-wide) factors, higher systematic risk should result in a lower frequency of split ratings, as we observe. More importantly, these results do not support the hypothesis that Moody's and S&P differ in their assessment of issuers' systematic risk.

7. Conclusions

Our model predicts that if credit spreads reflect the systematic risk of a borrower's debt but the debt's credit rating does not, then credit rating-based capital requirements and deposit insurance create incentives for banks to take excessive systematic risk. Our empirical analysis of corporate bond spreads and ratings confirms that credit spreads embed the systematic risk of the bond's issuer, even after controlling for the bond's rating. Moreover, banks can significantly increase the systematic risk of their investments by simply by choosing bonds with the highest credit spreads for any given credit rating. Applied to structured finance, the model can explain why some banks may have been active securitizers of loans yet retained the highly-rated, but systematically risky, tranches of these securitizations on their balance sheet (Erel, et al., 2011).

What regulatory reforms might address this moral hazard? One reform advocated by some academics and regulatory economists is to reduce the distortions of directly regulating banks by placing greater reliance on market discipline.[11] If a bank is required to obtain some funding from investors who are not *de jure* or *de facto* insured by the government, credit spreads on such bank debt should account for the systematic risk of the bank's investments.[12] Credit spreads on uninsured debt would then, at least partially, penalize a bank that took excessive systematic risk. In addition, regulatory capital requirements and supervisory actions might better respond to systematic risk if they were made dependent on the credit spreads or credit default swap spreads of this uninsured bank debt, as Hart and Zingales (2010) advocate.

A reform based on market discipline may be limited to the largest banks that have access to uninsured sources of funding. Moreover, the abolition of a government's de facto bailout policy may not be credible for the largest of banks. Many *ex ante* political statements have been violated by *ex post* government interventions, as the experience of the recent financial crisis appears to confirm. Furthermore, if the likelihood of a public-sector bailout is greater when shocks affecting banks are systematic ones, credit spreads on bank debt may fail to reflect systematic risks, thereby undermining market discipline.

Thus, additional reforms that directly change the setting of risk-based capital and deposit insurance would be

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[11] See Flannery (1998) for a review.

[12] In our model, if the bank's debt were uninsured and fairly priced, the debt's fair credit spread, p, would satisfy equation (6).

desirable. Indeed, the Basel Committee on Banking Supervision (2009) already has recognized that risk-weights for securitized and "resecuritized" (i.e., CDO) tranches need to be raised to reflect their greater risk.[13] In the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 has mandated that "Federal regulatory agencies must remove references to, or requirements to rely on, credit ratings from all regulations, and substitute alternative standards of credit-worthiness." Decreasing the reliance on credit ratings may be beneficial if an improved risk measure can be substituted. Indeed, as our analysis suggests, greater use of credit spreads on loans and securities for setting capital requirements and deposit insurance premiums represents a likely improvement.[14]

[13] These changes affect risk-weights for securitizations and resecuritizations under both the "Standardized Approach" based on external credit ratings and for the IRB Approach. Thus far, no major changes were recommended for risk-weights on corporate claims.

[14] Credit spreads may be refined to adjust for possible liquidity and tax effects. Empirical work by Morgan and Ashcraft (2003) supports the use of credit spreads on commercial and industrial loans as a predictor of future bank health.

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APPENDIX A – Model Details

The model in Section 2 considers a bank whose assets are a fixed-income portfolio composed of corporate debt issued by a large number of different firms. Each firm's capital structure satisfies the assumptions of the corporate debt model of Merton (1974). Specifically, if firm i has date t assets worth $A_{i,t}$ and has issued of a single zero-coupon bond or loan that promises to pay B_i in τ_i periods, then the date t value of firm i's debt, $D_{i,t}$, equals

$$D_{i,t} = A_{i,t} N\left(-d_{1,i}\right) + B_i e^{-r\tau_i} N\left(d_{2,i}\right) \tag{A1}$$

where $d_{1,i} = \left[\ln\left(A_{i,t} / B_i\right) + \left(r + \frac{1}{2}\sigma_i^2\right)\tau_i\right] / \left(\sigma_i \sqrt{\tau_i}\right)$, $d_{2,i} = d_{1,i} - \sigma_i \sqrt{\tau_i}$, and σ_i is the volatility of the return on firm i's assets. The standard deviation of the return on this default risky debt, $\sigma_{d,i}(\tau_i)$, equals

$$\sigma_{d,i}\left(\tau_i\right) = N\left(-d_{1,i}\right) \frac{A_{i,t}}{D_{i,t}} \sigma_i \tag{A2}$$

Equation (A2) shows that the volatility of firm i's default-risky debt changes over time. However, suppose that the bank holds the risky debt of many similar firms in firm i's industry, where a firm in firm i's industry is assumed to have assets driven by the same Brownian motion as that of firm i, say dz_i. The bank is assumed to purchase and sell bonds of firms in industry i and/or make new loans and not renew maturing loans to firms in the industry so that it keeps the relative exposure of its total assets to this industry constant, equal to $\sigma_{A,i}$. For example, if the average volatility of the loans and bonds of industry i held by the bank equals $\overline{\sigma}_i$ and the bank's total asset portfolio weight to debt in industry i is ω_i, then $\sigma_{A,i} = \omega_i \overline{\sigma}_i$. Thus, the bank can adjust either ω_i and/or $\overline{\sigma}_i$ to keep $\sigma_{A,i}$ constant. If it holds bonds and loans of firms in m different industries, this re-balancing behavior implies that the bank's total assets satisfy the process given in equation (1) of the text.

Let us maintain the Merton (1974) assumptions and also assume there is a single priced risk factor determining assets' expected rates of return, consistent with the Capital Asset Pricing Model (CAPM).[15] Specifically, let the economy's stochastic discount factor be of the form $dM_t/M_t = -rdt - \theta dz_M$. Then

$$\mu = r + \theta \sum_{i=1}^{m} \sigma_{A,i} \rho_{i,M} \tag{A3}$$

where $dz_i dz_M = \rho_{i,M} dt$. In the context of the CAPM, $\theta = \varphi_M / \sigma_M$ is the Sharpe ratio of the market portfolio, equal to the expected excess return on the market portfolio, φ_M, divided by the market portfolio's standard deviation of return, σ_M. Thus, from equation (A3), the bank portfolio's expected rate of return can be rewritten as equation (2) in the text where $\beta_i = \bar{\sigma}_i \sigma_M \rho_{i,M} / \sigma_M^2$ is the beta of the average loan or bond from industry i that is held by the bank.

Next we outline how debt betas can be calculated for an individual firm. Let $\beta_{A,i} = \sigma_i \sigma_M \rho_{i,M} / \sigma_M^2$ be the asset beta of firm i. Galai and Masulis (1976) show that the firm's equity beta ($\beta_{E,i}$) and debt beta (β_i) satisfy:

$$\begin{aligned} \beta_{E,i} &= \frac{\partial E_{i,t}}{\partial A_{i,t}} \frac{A_{i,t}}{E_{i,t}} \beta_{A,i} = N\left(d_{1,i}\right) \frac{A_{i,t}}{E_{i,t}} \beta_{A,i} \\ \beta_i &= \frac{\partial D_{i,t}}{\partial A_{i,t}} \frac{A_{i,t}}{D_{i,t}} \beta_{A,i} = N\left(-d_{1,i}\right) \frac{A_{i,t}}{D_{i,t}} \beta_{A,i} \end{aligned} \tag{A4}$$

where $E_{i,t} = A_{i,t} - D_{i,t}$ is the market value of the firm's shareholders equity. The above implies

$$\beta_i = \beta_{E,i} \frac{E_{i,t}}{D_{i,t}} \frac{N\left(-d_{1,i}\right)}{N\left(d_{1,i}\right)} = \beta_{E,i} \frac{E_{i,t}}{A_{i,t} - E_{i,t}} \left[\frac{1}{N\left(d_{1,i}\right)} - 1 \right] \tag{A5}$$

Based on equation (A5), a firm's debt beta could be computed from its equity (stock) beta and the market value of the firm's equity, $E_{i,t}$, if we also know the market value of the firm's assets, $A_{i,t}$, and the volatility of the firm's assets, σ_i. Similar to Marcus and Shaked (1984), we solve for $A_{i,t}$ and σ_i by using information on the market value of the firm's total equity, $E_{i,t}$, as well as an estimate of the equity's total volatility, call it $\sigma_{E,i}$:

[15] It would be straightforward to extend the model to an economy with multiple risk factors.

$$
\begin{aligned}
E_{i,t} &= A_{i,t} N\left(d_{1,i}\right) - B_i e^{-r\tau_i} N\left(d_{2,i}\right) \\
\sigma_{E,i} &= \frac{A_{i,t}}{E_{i,t}} N\left(d_{1,i}\right) \sigma_i
\end{aligned}
\tag{A6}
$$

The two equations in (A6) are two non-linear equations in the two unknowns, $A_{i,t}$ and σ_i. We take τ_i = 10 years and B_i equal to the book value of the firm's debt. For robustness, we also estimate firms' debt betas assuming τ_i = 5 years.

The firm's debt beta is the measure of the bond's systematic risk premium that theory predicts should be incorporated in the bond's credit spread. The bond's credit spread should approximately equal expected default losses plus the bond's beta times the expected excess return on the market. Assuming the expected excess return on the market is constant, then the beta of the bond is the appropriate measure to include in a spread regression.

APPENDIX B – Variable Description

Spread	The bond's credit spread, i.e. the difference between the bond yield at issuance and that of a Treasury security with same maturity and currency.
Rating	Indicator variables for issue ratings (at the notch level).
Avg_Rating	The average of Moody's and S&P's rating (at the notch level) converted into a numerical scale (AAA/Aaa = 1, AA+/Aa1 = 2, …, BBB-/Bbb3 = 10).
Split	An indicator variable that takes value 1 if Moody's and S&P's ratings are different, zero otherwise.
Debt Beta	The issuer's debt beta. It is derived from the issuer's *Equity Beta* as shown in Appendix A. We get the *Equity Beta* by using the weekly returns of the issuer's stocks and the MSCI World Index in a standard market model estimated on the 52 weeks preceding each issue. From this model we also get the *Equity Residual Volatility*.
Debt Res. Vol.	The issuer's debt residual volatility, estimated from the *Equity Residual Volatility* as shown in Appendix A.
Debt Tot. Vol.	The issuer's debt total volatility, estimated from the *Equity Total Volatility* as shown in Appendix A.

Controls include issue's and issuer's characteristics

Issue's characteristics

Face Value	The natural log of the USD equivalent face value of issue.
Maturity	The natural log of the years to maturity of the issue.
Seniority	A dummy variable equal to 1 if the issue is subordinated and zero otherwise.
International Mkt	A dummy variable equal to 1 if the issue is a eurobond and zero otherwise.
Negative Pledge	A dummy variable that equals 1 if the bond issue has a negative pledge clause and zero otherwise. The negative pledge clause avoids the possibility for the issuer to use part of its assets as collateral for future debt obligations.

Reg D	A dummy variable equal to 1 if the issue is Regulation D and zero otherwise.
Reg S	A dummy variable equal to 1 if the issue is Regulation S and zero otherwise.
Rule 144a	A dummy variable equal to 1 if the issue is Rule 144a and zero otherwise.
Fungible	A dummy variable equal to 1 if the issue is fungible and zero otherwise.
Force majeure	A dummy variable equal to 1 if the issue has a force majeure clause and zero otherwise.
Shelf registration	A dummy variable equal to 1 if the issue is shelf-registered and zero otherwise.
Cross-default	A dummy variable that equals 1 if the bond issue has a cross-default clause and zero otherwise. The cross-default clause avoids the possibility of selective default on the part of the issuer. If the issuer is insolvent on one loan or bond issue, it is automatically considered as insolvent on all other loans and obligations.
Year	Year fixed effects.
Currency	Currency fixed effects.
Avg Bid-Ask Spread	The average bid-ask spread over the 60 trading days following the issuance of each bond. This variable is available for 2,395 bonds (out of 3,924 bonds of the whole sample).

Issuer's characteristics

Size	The natural log of the USD equivalent issuer's market capitalization.
Country	Country fixed effects.

Figure 1 – Equity Beta by Credit Rating

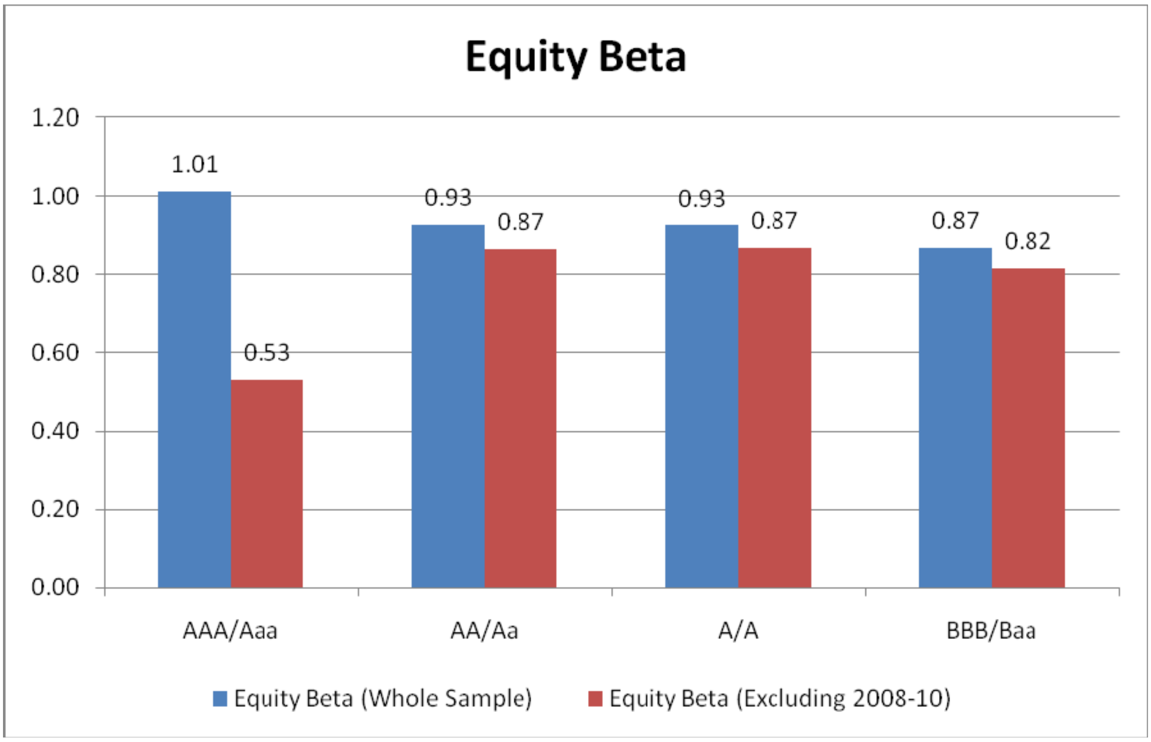

Figure 2 – Debt Beta by Credit Rating

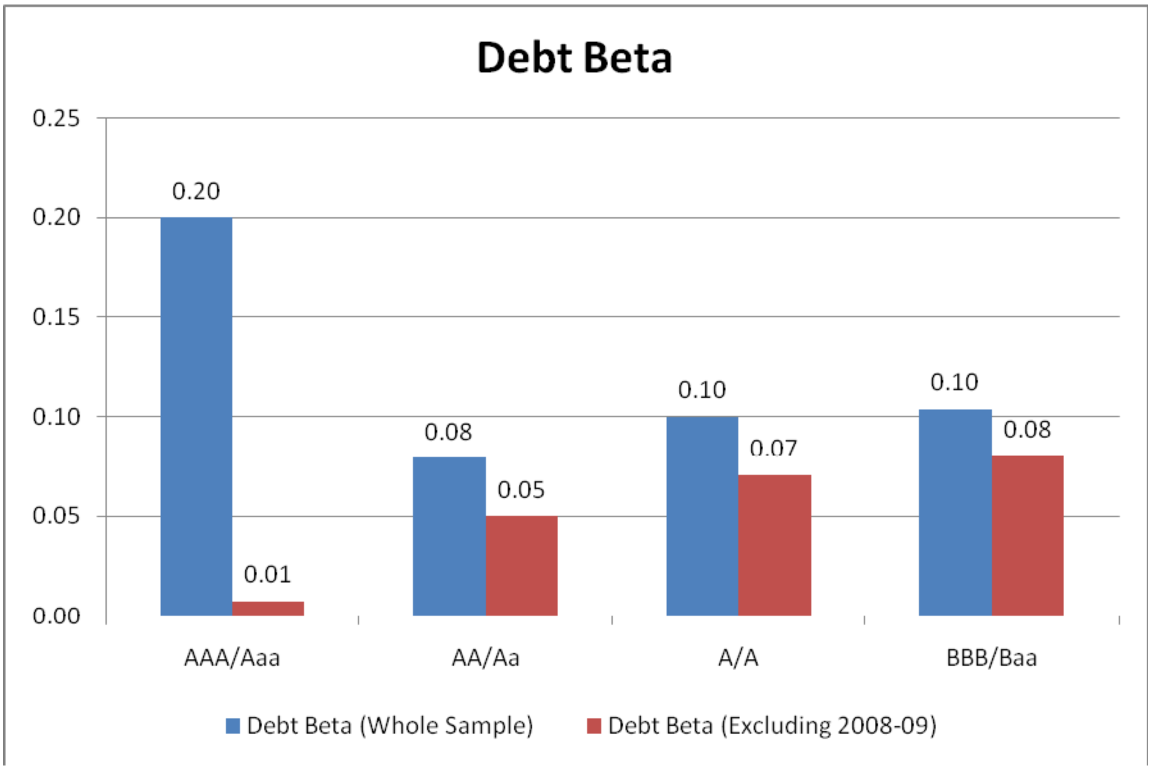

Figure 3 – Equity Beta by Year

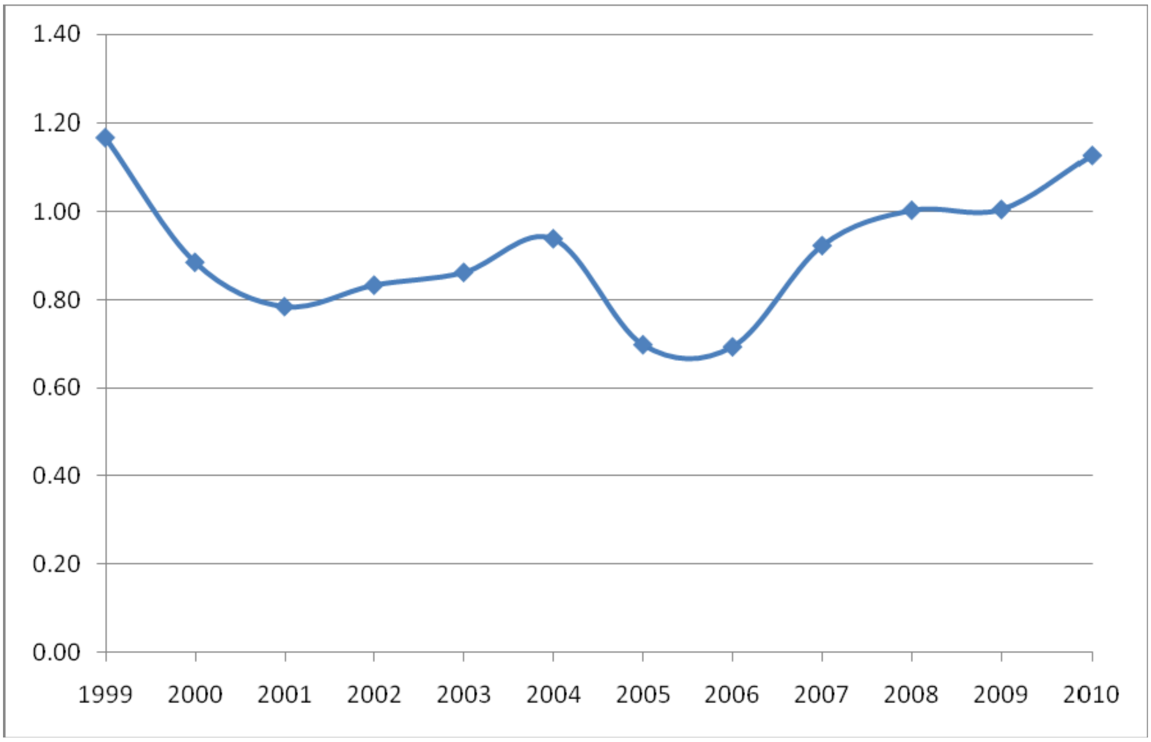

Figure 4 – Debt Beta by Year

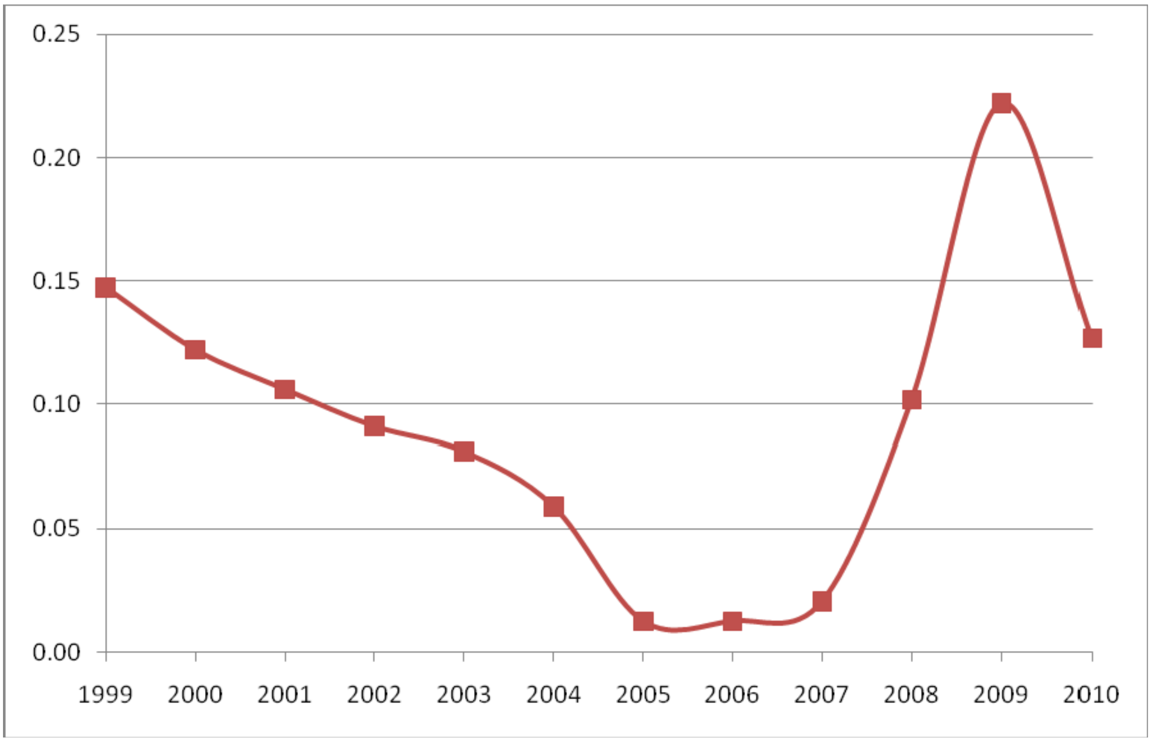

Table 1 – Summary Statistics
Detailed variable description is reported in Appendix B.

Panel A - Variable Mean by Credit Rating
Mean Values

Rating	Obs.	Spread	Maturity (years)	Face Value (USD, m)	Equity			Debt		
					Beta	Res. Vol.	Tot. Vol.	Beta	Res. Vol	Tot. Vol.
AAA/Aaa	132	80.696	4.816	1,820	1.01	6.07	7.67	0.20	1.03	1.35
AA/Aa	1,156	88.196	7.805	889	0.93	3.65	4.47	0.08	0.34	0.43
A/A	1,587	114.824	8.440	864	0.93	3.99	4.82	0.10	0.44	0.56
BBB/Baa	1,049	149.052	8.010	661	0.87	4.33	5.04	0.10	0.54	0.64
Total	3,924	114.982	8.016	849	0.91	4.05	4.87	0.10	0.46	0.57

Panel B – Variable Mean by Year

Year	Obs.	Spread	Rating	Maturity (years)	Face Value (USD, m)	Equity			Debt		
						Beta	Res. Vol	Tot. Vol.	Beta	Res. Vol	Tot. Vol.
1999	158	104.399	5.542	9.097	836	1.17	4.56	5.46	0.15	0.52	0.64
2000	219	112.078	5.423	7.397	974	0.89	4.90	5.51	0.12	0.61	0.71
2001	337	114.036	6.223	8.022	1,030	0.79	4.74	5.26	0.11	0.54	0.63
2002	305	93.989	6.595	9.229	776	0.83	4.22	4.91	0.09	0.46	0.53
2003	376	72.113	6.711	8.768	606	0.86	4.16	4.83	0.08	0.42	0.49
2004	275	49.578	6.319	7.740	547	0.94	3.23	3.62	0.06	0.21	0.24
2005	284	45.704	5.989	7.806	521	0.70	2.46	2.67	0.01	0.05	0.05
2006	292	60.414	5.783	9.052	735	0.69	2.61	2.86	0.01	0.06	0.06
2007	353	77.982	5.191	8.990	796	0.92	2.67	3.12	0.02	0.06	0.07
2008	393	173.703	4.826	7.672	997	1.00	4.19	5.10	0.10	0.45	0.56
2009	554	215.625	5.270	6.645	1,120	1.00	5.72	7.72	0.22	1.13	1.55
2010	378	149.292	5.533	7.207	988	1.13	4.09	5.25	0.13	0.46	0.60
Total	3,924	114.982	5.750	8.016	849	0.91	4.05	4.87	0.10	0.46	0.57

Table 2 – Mean Credit Spreads by Credit Ratings – High vs. Low Systematic Risk

This table reports the mean *Spread* for bonds with different ratings and maturity. Bonds are split according to their Equity Beta (Panel A) and Debt Beta (Panel B). Detailed variable description is reported in Appendix B. ***, **, * indicate statistical significance (1%, 5%, 10%, respectively) of the t-test for the equality of the mean *Spread* for bonds with beta below and above the median.

Panel A – Equity Beta

All Issues (3,924 Bonds)								
Maturity	Equity Beta below median (0.867)				Equity Beta above median (0.867)			
	AA	A	BBB	Total	AA	A	BBB	Total
≤ 10 years	66.78	93.25	125.28	95.06	106.52***	130.14***	166.88***	132.55***
> 10 years	71.16	115.44	175.29	116.36	124.23***	148.69***	191.19	149.92***
Total	67.48	96.86	131.67	98.28	108.14***	131.97***	168.66***	134.11***
Excluding 2008-10 (2,599 Bonds)								
Maturity	Equity Beta below median (0.799)				Equity Beta above median (0.799)			
	AA	A	BBB	Total	AA	A	BBB	Total
≤ 10 years	47.00	69.88	83.19	68.09	67.62***	85.65***	91.258*	82.36***
> 10 years	70.78	107.37	108.62	96.40	101.98***	113.08	184.20***	127.72***
Total	51.05	76.10	85.99	72.34	72.07***	88.84***	100.50***	87.58***

Panel B – Debt Beta

All Issues (3,924 Bonds)								
Maturity	Debt Beta (10Y) below median (0.038)				Debt Beta (10Y) above median (0.038)			
	AA	A	BBB	Total	AA	A	BBB	Total
≤ 10 years	65.68	77.47	119.45	84.19	114.11***	144.87***	165.86***	143.04***
> 10 years	73.55	108.80	167.84	110.49	128.36***	162.52***	202.070*	162.59***
Total	66.87	82.68	126.19	88.25	115.40***	146.53***	168.41***	144.72***
Excluding 2008-10 (2,599 Bonds)								
Maturity	Debt Beta below median (0.020)				Debt Beta above median (0.020)			
	AA	A	BBB	Total	AA	A	BBB	Total
≤ 10 years	51.22	64.86	85.06	64.98	67.84***	90.48***	88.44	85.05***
> 10 years	74.18	100.17	131.21	96.94	106.71***	124.740**	156.027*	129.90***
Total	55.01	70.91	91.24	70.11	72.68***	94.26***	94.34	89.75***

Table 3 – Debt Beta of Bonds with High Spreads

Sample bonds are categorized by year of issuance, currency (Euro, US Dollar, and Yen), and credit rating. For each category with at least five issues, bonds are ranked based on their credit spreads and the average debt beta is computed for All of the bonds in the category versus only those bonds with Spreads Above the Median. (high-spread bonds). This table reports the mean *Debt Beta.* Panel A reports debt beta values for bonds with maturities of 10 years and less while Panel B reports debt beta values for bonds with maturities greater than 10 years. Values in bold indicate that the mean debt beta for high-spread bonds is greater than mean debt beta for all bonds in the category.

Panel A –Years to Maturity ≤ 10 years

Year	Sub-sample	EUR			USD			JPY		
		AAA-AA	A	BBB	AAA-AA	A	BBB	AAA-AA	A	BBB
1999	Spread above Median	**0.224**	**0.158**	**0.158**	**0.228**	**0.189**	**0.232**	**0.123**	0.060	
	All	0.219	0.142	0.145	0.142	0.161	0.150	0.064	0.060	
2000	Spread above Median	0.057	**0.110**	0.046	**0.192**	**0.247**	0.180	**0.268**	**0.110**	
	All	0.062	0.099	0.063	0.144	0.177	0.187	0.203	0.105	
2001	Spread above Median	**0.099**	**0.151**	**0.187**	**0.166**	**0.202**	**0.196**	**0.208**	**0.112**	0.099
	All	0.070	0.114	0.127	0.100	0.155	0.150	0.130	0.070	0.104
2002	Spread above Median	**0.190**	0.126	**0.254**	**0.064**	**0.087**	0.055	**0.033**	0.033	**0.144**
	All	0.098	0.138	0.185	0.047	0.061	0.102	0.020	0.053	0.109
2003	Spread above Median	**0.092**	**0.192**	**0.233**	**0.042**	**0.102**	**0.230**	**0.034**	0.061	**0.078**
	All	0.077	0.133	0.157	0.039	0.093	0.130	0.034	0.070	0.072
2004	Spread above Median	**0.025**	0.018	**0.067**	**0.006**	**0.031**		**0.019**	0.044	**0.134**
	All	0.014	0.033	0.039	0.004	0.021		0.014	0.101	0.121
2005	Spread above Median	**0.002**	**0.014**	**0.010**	**0.002**	**0.011**	0.003	**0.005**	0.010	**0.048**
	All	0.002	0.008	0.008	0.001	0.006	0.008	0.004	0.012	0.033
2006	Spread above Median	**0.006**	**0.005**	**0.009**	**0.002**	**0.005**	**0.091**	**0.017**	**0.038**	**0.032**
	All	0.003	0.004	0.007	0.001	0.003	0.065	0.012	0.034	0.024
2007	Spread above Median	**0.021**	**0.013**	0.006	**0.019**	**0.022**	**0.062**	**0.045**	**0.054**	**0.073**
	All	0.014	0.012	0.007	0.012	0.015	0.040	0.030	0.042	0.047
2008	Spread above Median	0.099	**0.106**	**0.069**	0.090	**0.093**	0.015	**0.097**	0.140	**0.336**
	All	0.120	0.078	0.042	0.181	0.061	0.039	0.073	0.152	0.260
2009	Spread above Median	**0.242**	**0.254**	**0.295**	0.221	**0.413**	**0.218**	0.138	**0.241**	**0.371**
	All	0.237	0.231	0.265	0.244	0.361	0.135	0.138	0.233	0.370
2010	Spread above Median	**0.189**	0.119	**0.137**	**0.180**	**0.178**	**0.255**	**0.073**	0.073	0.117
	All	0.152	0.121	0.112	0.133	0.169	0.172	0.059	0.083	0.117

Panel B - Maturity > 10 years

Year	Sub-sample	EUR			USD			JPY		
		AAA-AA	A	BBB	AAA-AA	A	BBB	AAA-AA	A	BBB
1999	Spread above Median					**0.195**				
	All					0.124				
2000	Spread above Median					**0.216**				
	All					0.147				
2001	Spread above Median					0.124				
	All					0.156				
2002	Spread above Median					**0.147**		0.010	**0.034**	
	All					0.117		0.032	0.026	
2003	Spread above Median		**0.175**		**0.101**	**0.102**				0.034
	All		0.139		0.072	0.087				0.037
2004	Spread above Median					0.012			**0.041**	
	All					0.016			0.026	
2005	Spread above Median		**0.000**					**0.002**	0.082	
	All		0.000					0.002	0.091	
2006	Spread above Median		**0.009**			**0.003**		0.015	**0.043**	
	All		0.007			0.002		0.016	0.040	
2007	Spread above Median				**0.010**	**0.017**	0.007	**0.030**	**0.072**	
	All				0.006	0.011	0.014	0.020	0.061	
2008	Spread above Median				**0.094**	**0.110**	**0.057**	**0.038**	**0.167**	
	All				0.071	0.060	0.035	0.026	0.114	
2009	Spread above Median		**0.099**	**0.082**	**0.309**	**0.204**	**0.329**	**0.154**		
	All		0.084	0.054	0.192	0.201	0.239	0.100		
2010	Spread above Median		**0.173**		**0.091**	**0.115**	0.006			
	All		0.092		0.045	0.082	0.010			

Table 4 – Average Beta of Bonds with High Spreads – t-test

For each category reported in Table 3 we compute the ratio of the average beta of high-spread bonds to the average beta of all the bonds within the same category. This table reports the mean log ratios. ***, **, * indicate statistical significance (1%, 5%, 10%, respectively) of the t-test for the equality of the mean log ratios to zero.

Maturity	EUR	USD	JPY	Total
≤ 10 years	0.190***	0.183***	0.129***	0.169***
> 10 years	0.341***	0.219***	0.108	0.201***
Total	0.212***	0.196***	0.123***	0.178***

Table 5 – Regression of Credit Spread on Ratings and Debt Systematic Risk

Reported are coefficients of OLS regressions with robust standard errors clustered both at the year and issuer level. The dependent variable is *Spread*, i.e. the difference between the bond yield at issuance and that of a Treasury security with same maturity and currency. Detailed variable description is reported in Appendix B. Coefficient for control variables are not reported for ease of exposition. ***, **, * indicate significance at 1%, 5%, 10% level, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Whole Sample			**Excluding 08-10**	**Whole**
AA+/Aa1	73.641***	82.059***	82.158***	3.797	75.990***
	(0.000)	(0.000)	(0.000)	(0.826)	(0.001)
AA/Aa2	83.889***	92.379***	92.150***	5.477	81.549***
	(0.000)	(0.000)	(0.000)	(0.648)	(0.001)
AA-/Aa3	109.311***	111.737***	111.650***	17.742*	98.391***
	(0.000)	(0.000)	(0.000)	(0.057)	(0.000)
A+/A1	117.662***	119.570***	119.276***	21.217**	107.155***
	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)
A/A2	133.765***	134.584***	134.284***	31.379***	121.631***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A-/A3	152.259***	154.257***	153.903***	42.027***	139.632***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB+/Baa1	182.061***	182.894***	182.433***	57.829***	166.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB/Baa2	199.850***	196.790***	196.316***	62.452***	178.798***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB-/Baa3	211.318***	208.639***	208.109***	76.344***	188.046***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt Beta		108.781***	105.424***	67.799***	41.618**
		(0.000)	(0.001)	(0.000)	(0.045)
ln (Debt Residual Volatility)			0.432	0.803	2.555
			(0.831)	(0.419)	(0.103)
Crisis (2008-10)					93.842***
					(0.000)
Debt Beta × Crisis					228.267***
					(0.002)
Obs.	3,924	3,924	3,924	2,599	3,924
Adj. R^2	0.610	0.623	0.623	0.642	0.601

Table 6 – Regression of Credit Spread on Ratings and Debt Systematic Risk (Bid-Ask Spread)

Reported are coefficients of OLS regressions with robust standard errors clustered both at the year and issuer level. The dependent variable is *Spread*, i.e. the difference between the bond yield at issuance and that of a Treasury security with same maturity and currency. Detailed variable description is reported in Appendix B. Coefficient for control variables are not reported for ease of exposition. ***, **, * indicate significance at 1%, 5%, 10% level, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Whole Sample			**Excluding 08-10**	**Whole**
AA+/Aa1	87.790**	100.594**	100.418**	-4.890	92.318**
	(0.016)	(0.011)	(0.011)	(0.726)	(0.020)
AA/Aa2	99.555***	113.670***	114.855***	3.097	104.580***
	(0.006)	(0.003)	(0.004)	(0.731)	(0.008)
AA-/Aa3	119.208***	129.359***	130.239***	13.445*	117.376***
	(0.003)	(0.002)	(0.002)	(0.063)	(0.008)
A+/A1	119.658***	128.089***	129.438***	16.726**	119.009***
	(0.002)	(0.002)	(0.002)	(0.018)	(0.006)
A/A2	137.262***	143.876***	145.402***	24.437***	135.210***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.003)
A-/A3	146.725***	153.758***	155.407***	37.334***	142.834***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB+/Baa1	169.333***	174.518***	176.557***	55.574***	162.262***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB/Baa2	190.508***	191.277***	193.208***	57.731***	179.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB-/Baa3	206.119***	207.675***	209.928***	88.358***	192.440***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt Beta		131.123***	139.492***	75.937***	65.137***
		(0.000)	(0.000)	(0.000)	(0.001)
ln (Debt Residual Volatility)			-1.185	-0.063	0.819
			(0.513)	(0.939)	(0.578)
Crisis (2008-10)					106.996***
					(0.000)
Debt Beta × Crisis					299.626***
					(0.000)
Avg Bid-Ask Spread	103.655***	89.896***	90.439***	61.144***	112.314***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	2,395	2,395	2,395	1,732	2,395
Adj. R2	0.641	0.659	0.659	0.662	0.637

Table 7 – Regression of Avg Rating on Debt Systematic Risk

Reported are coefficients of OLS regressions (Columns 1-6) and ordered probit (Columns 7-8) with robust standard errors clustered both at the year and issuer level. The dependent variable is *Avg_Rating*, i.e. the average of Moody's and S&P's issue ratings, converted into numerical scale (AAA/Aaa = 1, AA-/Aa1 = 2, …, BBB-/Bbb3 = 10). Detailed variable description is reported in Appendix B. Coefficient for control variables are not reported for ease of exposition. ***, **, * indicate significance at 1%, 5%, 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS						Ordered Probit	
	Whole Sample			Excluding 2008-10				
Debt Beta	1.875***	0.917	0.883	2.947***	1.682***	1.627***	1.259***	1.219***
	(0.006)	(0.202)	(0.218)	(0.000)	(0.002)	(0.003)	(0.000)	(0.000)
ln (Debt Residual Volatility)		0.123***			0.155***		0.109***	
		(0.000)			(0.000)		(0.000)	
ln (Debt Total Volatility)			0.121***			0.153***		0.108***
			(0.000)			(0.000)		(0.000)
Obs.	3,924	3,924	3,924	2,599	2,599	2,599	2,599	2,599
Adj. R^2	0.474	0.482	0.481	0.523	0.537	0.537	0.186	0.186

Table 8 – Moody's vs. S&P's ratings

Reported are coefficients of OLS regressions (Columns 1-8) and probit regressions (Column 9-12) with robust standard errors clustered both at the year and issuer level. In Columns 1-4 the dependent variable is the rating of Moody's (Columns 1-2 and 5-6) or S&P's (Columns 3-4 and 7-8) converted into a numerical scale (AAA/Aaa = 1, AA+/Aa1 = 2, …, BBB-/Bbb3 = 10). In Columns 9-12 the dependent variable is *Split*, that is equal to 1 if Moody's and S&P's ratings for the same issue are different, zero otherwise. Detailed variable description is reported in Appendix B. Coefficient for control variables are not reported for ease of exposition. ***, **, * indicate significance at 1%, 5%, 10% level, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Whole Sample				**Excluding 2008-10**				**Whole Sample**		**Excluding 2008-10**	
	Moody's		**S&P's**		**Moody's**		**S&P's**		**Split**			
Debt Beta	0.664	0.631	0.553	0.527	1.527***	1.451***	1.441***	1.391**	-1.033***	-1.004***	-1.554**	-1.531*
	(0.494)	(0.516)	(0.472)	(0.493)	(0.002)	(0.005)	(0.008)	(0.012)	(0.003)	(0.004)	(0.048)	(0.053)
ln (Debt Residual Volatility)	0.136***		0.128***		0.190***		0.160***		-0.015		-0.013	
	(0.002)		(0.000)		(0.000)		(0.000)		(0.426)		(0.666)	
ln (Debt Total Volatility)		0.134***		0.126***		0.188***		0.158***		-0.019		-0.015
		(0.002)		(0.000)		(0.000)		(0.000)		(0.304)		(0.606)
Obs.	2,658	2,658	3,715	3,715	1,472	1,472	2,489	2,489	2,439	2,439	1,336	1,336
Adj. R^2	0.523	0.523	0.475	0.475	0.564	0.564	0.538	0.538	0.230	0.231	0.234	0.234