Do Investors Care about Credit Ratings? An Analysis through the Cycle[†]

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Abstract

We investigate how the credit cycle affects the link between bond spreads and credit ratings. Using a simple model of the credit assessment process, we show that when the debt market is more opaque, the information content of ratings deteriorates, creating an incentive for investors to increase the amount spent on private information. We test this hypothesis empirically. Results show that when market opaqueness (proxied by the spread between Aaa- and Baa-rated bonds) increases, the explanatory power of ratings and other control variables deteriorates as investors increasingly price in non-public information.

JEL classification: G12, G15, G24

Keywords: Bond, Credit spread, Rating, Opaqueness

[†] The authors are grateful for helpful comments and suggestions from Iftekhar Hasan (the editor), two anonymous referees, Ed Altman, Viet Do, Gerry Drives, Veljko Fotak, Blaise Ganguin, Phil Molyneux, Loriana Pelizzon, Klaus Schaeck, Rafael Schiozer, and the participants at the 2010 Financial Management Association Annual Meeting in New York, the 2010 Midwest Financial Association Annual Meeting in Las Vegas, and seminars at Università Bocconi, Ca' Foscari University of Venice, and Bangor University. All errors remain the authors'.

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1 INTRODUCTION

Bond ratings provide financial market participants with judgements on the likelihood that bondholders will suffer losses due to a delay in interest or principal payment, debt restructuring, or bankruptcy. But how reliable are ratings as indicators of credit standing? Do investors have an incentive to go beyond ratings, conveying additional information into bond spreads? Does such an incentive depend on market conditions?

Extensive evidence supports the idea of a tight relation between bond spreads and several measures of credit risk, including ratings, during the last 25 years (for a review, see Gonzalez et al., 2004). However, spreads also reflect other bond characteristics, such as maturity, size, currency of denomination, liquidity, and so forth.[1] Along with ratings, these issue characteristics represent easy-to-observe information. Nonetheless, a certain amount of hidden information could be relevant in pricing a bond. The incentive to gather and price such additional information may become stronger as the debt market grows more opaque, that is, when the information content of ratings becomes poorer (i.e., when the agency ratings' ability to assess issuer creditworthiness worsens).

In this paper we analyse the effects on bond pricing of changes in market opaqueness and in the information content of ratings. The idea is simple: If the information content of ratings is poorer, bond investors should invest more in additional information; hence ratings and any other easy-to-observe issue characteristics should lose part of their ability to explain bond credit spreads.

Using a simple model of the credit assessment process under uncertainty, we verify that the incentive to invest in additional information becomes stronger when the information content of ratings is poorer. In the model, investors choose the optimal (costly) investment in additional private information to improve their ability to distinguish between good and bad issuers. This

[1] Based on CDS spreads, Collin-Dufresne *et al.* (2001) find that monthly spread changes are principally driven by local supply/demand shocks that are independent of both credit risk factors and standard proxies for liquidity. Expected recovery rates in case of default also prove relevant in explaining credit spreads (Altman, 1989).

investment in additional private information increases when ratings become less effective in forecasting future defaults.

The impact of ratings on bond spreads across the credit cycle is then empirically investigated. Using a heteroscedastic regression model, we look at the factors affecting the spread dispersion unexplained by ratings and other easy-to-observe characteristics. We find that such unexplained dispersion increases for bonds issued during phases of higher market-wide uncertainty, supporting the hypothesis that investors collect and impound additional information into spreads when opacity increases. Our chief proxy for the degree of market opaqueness is the quality spread (QS), measured by the difference between secondary-market yields on Baa- and Aaa-rated bonds. However, our results are robust to the use of alternative proxies for market opaqueness, such as the average dispersion of analyst forecasts, the downgrades-to-upgrades ratio (i.e., the number of rating downgrades divided by the number of rating upgrades), and the Standard & Poor's (S&P) 500 volatility index (VIX).

The paper proceeds as follows. Section 2 describes the main variable used to capture the stance of the credit market and provides first evidence of its relationship with the information content of agency ratings. Section 3 develops a model of ratings-based investment in risky bonds under uncertainty. Section 4 describes the methodology and the data sources, summarizes the sample characteristics, and presents the results of the empirical analysis; a number of robustness checks are also provided. Section 5 concludes by focusing on the policy implications.

2 QS AND THE INFORMATION CONTENT OF RATINGS

As stated above, in this paper we investigate how the link between bond spreads and credit ratings changes under different market conditions. Among the many variables that can be used to describe the stance of the credit market, we focus on the credit curve's steepness, that is, the QS. We compute the QS as the difference between secondary-market yields on seasoned corporate bonds rated Baa and Aaa by Moody's. We take monthly averages of daily data points, downloaded from FRED, the database of the Federal Reserve Bank of St. Louis. Moody's tries to include bonds with remaining maturities as close as possible to 30 years and drops bonds if the remaining life falls below 20 years, if the bond is susceptible to redemption, or if the rating changes. Figure **1** plots the QS from January 1919 to December 2008. When this spread is narrow – as it used to be during the 1990s and the first half of the last decade – Baa-rated issuers can tap the bond market without having to pay a substantial premium. A wider QS indicates that investors are 'flying to quality' and request higher compensation to lend to lower-quality companies. Previous studies have shown that the QS tends to rise during business cycle contractions and fall during expansions (Chen, 1991; Fama and French, 1989) and is positively related to volatility in stock market returns (Lindset and Westgaard, 2007), suggesting that it is not only associated with an increase in (investor-perceived) credit risk, but also – and more generally – with a higher uncertainty in asset prices and company values. In addition, as shown by Chen et al. (2009), the QS is positively correlated to dividend yields (i.e., it increases when stock prices decrease more than dividends) and negatively correlated to various measures of leverage (debt over total assets) for Baa-rated companies (meaning that such companies can build up debt when the QS is low but must deleverage as the QS increases).

Insert Figure 1 approximately here

Summing up, an increase in the QS signals that the real economy is experiencing a downturn, credit is becoming more expensive (and leverage shrinks) for Baa-rated companies, market returns are becoming more volatile, and stock prices are decreasing more than dividends. Furthermore, according to Mishkin (1990, 1991), increases in the QS can be viewed as the result of changes in the 'lemon's' discount on securities prices caused by asymmetric information. Examining the historical evidence on financial crises, Mishkin (1991) claims that when adverse selection increases in financial markets, there should be a large rise in borrowers' interest rates for which reliable information on their characteristics is substantially difficult to obtain, that is, for which there is a serious asymmetric information problem. On the other hand, there would be a much smaller effect on borrowers' interest rates for which there is almost no asymmetric information problem because it is easy to obtain information about their characteristics. Since low-quality borrowers are more likely to be firms for which information about their characteristics is difficult to obtain, while high-quality borrowers are more likely to be those for which the asymmetric information problem is least severe, a rise in the spread between interest rates for low- and high-quality borrowers can provide information on when the adverse selection problem becomes more severe in debt markets. Hence, according to Mishkin (1991), the QS can be interpreted as a measure of informational opaqueness. Consistent with this view, we now show that an increase in QS can be associated with a decrease in the predictive power of ratings.

Figure 2 represents the distribution by rating grade of good and bad borrowers rated by Moody's in 1970–2003;[2] to each rating grade, we attach an estimated probability of default (PD), based on its long-run default frequency.

Insert Figure 2 approximately here

One can see that good (bad) issuers tend to cluster around low (high) PD values. In other words, as the PD on the horizontal axis increases, bad issuers become more frequent in relative terms; there is, however, a considerable overlap between the two groups.

In times of high QS, the discriminatory power of ratings deteriorates. This is shown in Figure 3, which reports the distribution by rating grade (i.e., by estimated PDs) for good and

[2] This is based on a dataset of 68,862 issuer–year pairs. Bad issuers are defined as issuers defaulting seven years after the rating is observed (seven years being close to the average maturity of the bonds included in our empirical sample). This explains why the last year used is 2001, since we need to wait seven years and check whether a default took place. The PDs associated with different rating classes are based on the default rates, on a seven-year horizon, experienced by the issuers in our sample and are consistent with long-term averages published by Moody's.

bad borrowers in low- and high-QS years.[3] Comparing the two panels, one can see how the informational content of ratings changes according to debt market opaqueness. While the distribution for good issuers does not experience any dramatic shift, ratings and PDs associated with bad borrowers become significantly more disperse in high-QS years, since a larger share of future defaults comes from relatively high-quality buckets.[4]

Accordingly, in high-QS years the average estimated PD assigned by rating agencies to bad issuers decreases and approaches the average estimated PD of good borrowers[5] (see Table 1)[6]. The evidence in Figure 3 suggests that, in high-QS years, companies become harder to evaluate for rating agencies; in other words, the informational content of ratings is poorer because of an increase in borrower opaqueness.[7]

Insert Figure 3 approximately here

Insert Table 1 approximately here

[3] We rank years in 1970–2001 according to QSs and then denote as low-QS years those below the first quartile and as high-QS years those above the third quartile.

[4] The coefficient of variation of the PD distribution for bad borrowers increases from 55% to 70% when moving from low- to high-QS years. A standard chi-squared test of the equality of distributions leads to rejection of the hypothesis that the PD distribution for bad borrowers remains unchanged when moving from low-QS to high-QS years, with a 99.9% confidence level.

[5] A slight decrease in the average assessed PD is also found for good borrowers when moving from low- to high-QS years. The result may seem counterintuitive; however, this could be an effect of the flight to quality witnessed in high-spread periods, when medium- to low-quality issuers leave the market and the average rating improves.

[6] Evidence that the behaviour of rating agencies may be affected by the state of the economy is found, e.g., by Kräussl (2005) with reference to emerging markets.

[7] One can argue that in high-QS years, ratings perform worse because they are, on average, 'stale' (due to fewer new issues taking place). Our empirical test focuses on primary-market spreads to ensure that staleness does not affect our results; furthermore, agencies monitor ratings after issuance and may change them if new information arises, so that stale ratings can actually be considered to be 'reaffirmed' by agencies on a regular basis.

3 A SIMPLE MODEL OF RATINGS-BASED INVESTMENT IN RISKY BONDS

3.1 Investment based on ratings

Consider an investor wishing to invest in a bond; let $\tilde{p}$ be the issuer's PD *as estimated* by the investor. Since the investor does not observe all the information required to produce a correct assessment of this PD, $\tilde{p}$ is stochastic. The investor may choose to rely solely on the issuer's rating, in which case the investor's estimate of the issuer's PD, $\tilde{p}$, will be equal to the historical default rate of the rating bucket where the issuer has been assigned by the rating agency.

Now assume there are two types of issuers: bad issuers, who will default before the final maturity of the bond (we denote them by *D*), and good ones, who will not (denoted by $\neg D$). Ratings are correct on average, meaning that μ_D, the mean $\tilde{p}$ assigned by the rating agency to a bad issuer, is greater than $\mu_{\neg D}$, the mean $\tilde{p}$ assigned to a good one. However, PDs attached to bad and good issuers are subject to noise (with standard deviations s_D and $s_{\neg D}$, respectively), so that a good issuer can end up with a high estimated $\tilde{p}$ and vice versa. These volatilities can depend on several factors, namely, they can increase in high-QS years, when companies are more difficult to evaluate. We denote by $F\left(p;\mu_i,s_i\right)$ the cumulative distribution function of the PDs attached by the rating agency to an issuer of type $i \in \left\{D,\neg D\right\}$.[8]

A rational investor wishing to use ratings as a guideline will set some maximum threshold *k* and refrain from investing in bonds issued by borrowers with an estimated PD greater than *k*. Assuming that the investor is risk neutral, *k* is chosen to minimize the expected cost of errors.

[8] A suitable representation for F(·) is provided by the beta distribution, which can be easily constrained between zero and one (unlike, e.g., the Gaussian distribution). A beta distribution is used in the examples shown in the figures.

This involves minimizing the cost of not lending to a good borrower, $C\left(\neg L\middle|\neg D\right)$, plus the cost of lending to a bad one, $C\left(L\middle|D\right)$, each one weighted by its probability[9]:

$$\begin{aligned}&\min_k C\left(\neg L\middle|\neg D\right)\cdot pr\left(\neg L\cap\neg D\right)+C\left(L\middle|D\right)\cdot pr\left(L\cap D\right)=\\&=\min_k C\left(\neg L\middle|\neg D\right)\cdot pr\left(\neg L\middle|\neg D\right)\cdot pr\left(\neg D\right)+C\left(L\middle|D\right)\cdot pr\left(L\middle|D\right)\cdot pr\left(D\right)=\\&=\min_k r\cdot\left[1-F\left(k;\mu_{\neg D},s_{\neg D}\right)\right]\cdot\left(1-PD\right)+LGD\cdot F\left(k;\mu_D,s_D\right)\cdot PD\end{aligned} \qquad [1]$$

where *PD* is the unconditional *PD* of the average issuer (i.e., the average quality of the population from which the issuer is drawn), *r* denotes the spread earned by the investor if the investor chooses to lend, and *LGD* is the expected loss rate on the bond in the event of default.

Based on the empirical data in Figure 2 and Table 1,[10] a spread of 0.675%, and an expected LGD of 62.46%,[11] Figure **4** shows cost levels associated with different thresholds of *k*. It can be seen that the optimal value for *k* is 3.18%, with an associated expected cost of 31 basis points (bps), that is, 31 cents for every $100 of the bond's face value.

Insert Figure 4 approximately here

3.2 Investment based on ratings and private information

To make credit risk assessment more precise and reduce the expected cost associated with wrong decisions, the investor may decide to complement the rating with some (costly) private information gathered and processed independently. We assume that such private information

[9] Since $C\left(L\middle|\neg D\right)=C\left(\neg L\middle|D\right)=0$, those two cases can be ignored.

[10] Based on sample moments, two beta distributions are fitted for the estimated PDs of good issuers (mean 6.64%, standard deviation 10.19%) and bad issuers (mean 27.11%, standard deviation 14.20%). The unconditional seven-year PD for a generic, rated borrower is set accordingly to the sample seven-year default rate (8.65%).

[11] These are the average spread and LGD of the data used in the empirical test reported in Section 4.

can reduce the volatility[12] of the distributions seen in Figure 1 from s_i to $\sigma_i < s_i$, based on the following:

$$\sigma_i = s_i \cdot f(c) \text{ with } i \in \{D, \neg D\} \qquad [2]$$

where $f(\cdot)$ is a function of the cost c borne by the investor to produce extra information, such that

- $f(\cdot)$ is decreasing (volatility can be decreased by spending more in private information),
- $\lim_{c \to +\infty} f(c) = 0^+$ (uncertainty cannot be removed completely, no matter how much the investor pays), and
- $f(0) = 1$ (investors choosing not to pay for private information will end up with $\sigma_i = s_i$).

A suitable representation for $f(\cdot)$ is

$$f(c) = e^{-h \cdot c} \qquad [3]$$

where h is a positive parameter expressing the investor's screening abilities. A high value for h means that volatility can be significantly reduced at a small cost c; a low h implies that, to achieve a perceptible decrease in volatility, the investor needs to bear a relatively high cost. As stated by Li et al. (2009), 'though investors observe the same set of public information, they differ in their abilities to analyse the information…. This heterogeneity can create information disparity among traders similar to the effect of private information in the traditional sense'.

To decide how much to spend in private information before investing a given amount I in a bond,[13] the investor solves the following cost minimization problem (which generalizes [1] by adding the cost c of private information):

$$\begin{aligned} &\min_{k,c} C(\neg L|\neg D) \cdot pr(\neg L \cap \neg D) + C(L|D) \cdot pr(L \cap D) + \frac{c}{I} \\ &= \min_{k,c} r \cdot \left[1 - F\left(k; \mu_{\neg D}, s_{\neg D} \cdot f(c)\right)\right] \cdot (1 - PD) + LGD \cdot F\left(k; \mu_D, s_D \cdot f(c)\right) \cdot PD + \frac{c}{I} \end{aligned} \qquad [4]$$

[12] This assumption is justified by the fact that, otherwise, all investors would stop producing private information and content themselves with agency ratings.

[13] In the example of Figure 5 the issue size I is set equal to \$4 million.

Insert Figure 5 approximately here

Figure 5 enhances the example in Figure 4 by showing the total expected costs associated with different levels of c (assuming that the optimal threshold k is chosen, conditional on each value for c). The two lines in the figure represent two different investors: h_{high} denotes an investor with high screening abilities and h_{low} denotes an investor with low screening abilities.[14] While the former finds it optimal to spend some positive amount c in private information (thereby reducing his or her expected cost of error from 31 bps to 22 bps), the latter ends up spending $c = 0$, that is, relying solely on the agency rating (the minimum expected cost associated with $c = 0$ is equal to 31 bps, as in Figure 4).

When an investor finds it optimal to spend significantly on c, the investor's assessment of the issuer's PD will be based on a considerable amount of private information and could therefore differ from that implied by the agency rating. Accordingly, as more private information is gathered and used, the spread requested to underwrite the bond may significantly deviate from the average 'fair' spread for the issuer's rating grade.

3.3 Private information and QSs

In high-QS years, when the debt market is more opaque and more difficult to evaluate, the information content of ratings deteriorates. This creates an incentive for investors to increase the amount c spent on private information. Figure 6 focuses on the case of an investor with high screening abilities[15] and shows how the investor's incentives to spend on private information

[14] The values for h in equation [3] are set, respectively, to 70 (h_{low}) and 140 (h_{high}).
[15] Since investors with high screening abilities have lower expected costs than investors with low screening abilities (and can therefore afford to buy bonds at higher prices, all other things being equal), one may expect the former to prevail in the market for corporate bonds, 'crowding out' the latter. Hence, it seems natural to focus on the behaviour of investors with high screening abilities.

change in low- and high-opaqueness periods: This is done by solving [4] again, after plugging in the values for μ_D and $\mu_{\neg D}$ in high- and low-QS years, as seen in Table 1.[16]

Insert Figure 6 approximately here

The graph shows that in high-QS years the investor has an incentive to spend more on private information to limit the increase in the cost associated with expected errors.[17] In our example, expected unit costs would rise by 13 bps (from 28 bps to 41 bps) if the investor were to rely only on ratings (see intercepts), but the increase can be limited to 5 bps (from 21 bps to 26 bps, see the minima) by raising the optimal amount of *c*.[18]

In high-QS years, since the amount of private information used by investors increases, the yield requested to underwrite a bond may significantly deviate from the average fair spread for the bond's rating grade. In other words, after controlling for any significant covariate effect, one should witness a stronger dispersion in the prices and yields of bonds issued by equally rated companies.

4 EMPIRICAL TEST

4.1 Research methodology

To determine whether the information content of ratings changes according to bond market conditions, that is, whether different degrees of opaqueness in the market affect the spread's unexplained dispersion, we employ the heteroscedastic regression (maximum likelihood approach) proposed by Harvey (1976). This model extends the linear regression by also

[16] We also use empirical values for s_D and $s_{\neg D}$ in low- and high-QS years (13.95% and 12.48%, respectively, for s_D; 11.12% and 7.73%, respectively, for $s_{\neg D}$).

[17] This is consistent with the fact that the financial crisis spurred a number of new scoring tools, which are considered complementary to agency ratings and are provided for a fee by firms such as Morningstar, Audit Integrity, and RiskMetrics.

[18] In our numerical example, the optimal *c* increases from \$6,800 (low-QS years) to \$9,050 (high-QS years).

parametrizing the unexplained variance as a function of exogenous variables. This model can be regarded as made up of two equations, with the first explaining the mean of the dependent variable and the second representing the residual variance of the dependent. The spread at issuance is the dependent variable of the first equation, with ratings and other observable issue characteristics as explanatory variables. We refer to this equation as the *spread equation*. The second equation determines the factors affecting the precision of the spread model; it is therefore called the *variance equation*. Since the parameters of the spread and variance equations are assumed to be uncorrelated, they can be treated separately as far as selection and interpretation are concerned. Cerqueiro et al. (2011) use this approach to identify the determinants of the dispersion of loan rates. Iannotta (2011) also uses this heteroscedastic regression model to determine whether bond investors price hidden information.

The spread equation is

$$\begin{gathered}\mathrm{SPREAD} = f\,(Rating\,, \mathrm{MATU}, \mathrm{AMOUNT}, \mathrm{BID\_ASK}, \mathrm{SUBO}, \mathrm{COUPON}, \\ \mathrm{SHORT\_RATE}, \mathrm{SLOPE}, \mathrm{QS}, Control) + \varepsilon\end{gathered} \qquad [5]$$

The dependent variable is SPREAD, that is, the difference between the bond yield at issuance and that of a Treasury security with same maturity and currency. The variable *Rating* is the Moody's, S&P, and Fitch Ratings (Fitch) issue rating. We take the average of Moody's, S&P, and Fitch issue ratings and convert them into a numerical scale (Aaa/AAA/AAA is 1, Aa1/AA+/AA+ is 2, etc.), which we call AVGRATING. We then define a set of dummy variables (D_RAVGRATING*i*), each one equal to one if the issue falls in the *i*th rating category[19] and zero otherwise. We prefer to use these D_RAVGRATING*i* dummies, rather than AVGRATING, in our multivariate model. While the latter would have been more parsimonious

[19] We define RAVGRATING as the rounded average rating, that is, when the average value is not an integer, we round to the lower value (less risky). Each dummy variable D_RAVGRATING*i* is defined according to such a rounded average.

and easier to read, the former can capture any nonlinear relationship between ratings and spreads. In fact, the coefficient for each dummy variable measures the difference in credit spread between that rating and the top rating (i = 1, or Aaa/AAA/AAA), which is omitted from the regression to avoid perfect collinearity. The term AVGRATING is used instead in our descriptive statistics.

Insert Table 2 approximately here

The term MATU is the number of years to maturity of the issue; AMOUNT, defined as the natural log of the euro-equivalent amount (face value) of the issue, can be seen as both an indicator of scale economies in the origination process and a proxy for secondary-market liquidity. Liquidity is also measured by BID_ASK, the bond's bid–ask average spread on the secondary market in the first three months after the issuance date. By using this variable as a proxy for the liquidity premium, we assume that investors underwriting a bond on the primary market can foresee with reasonable accuracy the spread between bid and ask quotes that will prevail on the market after the issuance has been carried out.[20] The variable SUBO is a dummy equal to one if the issue is subordinated and zero otherwise. The term COUPON is the coupon rate. Since in most countries capital gains are paid at the time of sale, bonds with lower coupons may be more valuable because some taxes are postponed until the time of sale and because the bondholder has control over the time when these taxes are paid. The term SHORT_RATE is the three-month risk-free rate[21]: As shown by Collin-Dufresne et al. (2001), the short rate can be seen as the drift of the stochastic process followed by the borrower's assets, so it is expected to have a negative impact on credit spreads (since risk-neutral probabilities of default decline as the short rate increases). The term SLOPE is the difference between 10-year and three-month

[20] The term BID_ASK is scaled by the bond's mid-price. Alternative measures for liquidity are tested in Section 4.3.
[21] Rates refer to the end of the month when each bond was issued. Since the bonds in our sample are denominated in various currencies, different rates can be used for the same month: US dollar rates are used for all currencies, accounting for less than 3% of our sample.

yields on government bonds. If short rates are mean reverting, a higher slope signals that they are likely to increase (so credit spreads should adjust downwards). In addition, a higher slope can suggest a relatively stronger economic cycle and thus higher expected recoveries on defaulted bonds and therefore, again, lower credit spreads.[22] The term QS is the QS, measured by the difference between secondary-market yields on Baa- and Aaa-rated bonds, as calculated by Moody's on a worldwide basis. A positive coefficient is expected since higher QS levels are typically associated with an increase in investor-perceived credit risk. The term *Control* is a set of control variables that includes year-of-issuance dummies, country dummies, currency dummies,[23] and a dummy variable (D_bank) equal to one if the issuer is a commercial or investment bank and zero otherwise.

We include a dummy for bank issuers to assess whether unexplained variance tends to be larger for this category of issuers. We have no strong a priori expectations of this, since the results in the previous literature are mixed. Morgan (2002) argues that the banking industry may indeed be relatively more opaque than others, since split ratings tend to occur more often for banks than for non-bank obligors. Flannery et al. (2004) find that large banks have very similar trading properties to non-financial firms and that analysts' forecasts suggest that bank assets are not more opaque but just more 'boring'. The authors also find that in times of crisis both large and small banks exhibit a sharp increase in opacity.

The regressors in equation [5] do not include any company controls, for example, financial ratios and other accounting measures. The idea is that all publicly available information, such as ratios and financial statements, is expected to be already embedded in the ratings, since rating agencies carefully analyse financial data when assessing issuers.[24]

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[22] Again, see Collin-Dufresne et al. (2001).
[23] No dummies are created for currencies and countries that account for fewer than 10 observations. The currencies in our sample are the Australian dollar (19 observations), the Canadian dollar (eight), the Danish Krone (five), the euro (1,318), the British pound (481), the Japanese yen (13), the Norwegian Krone (eight), the New Zealand dollar (three), the Swedish krona (seven), the Singapore dollar (11), and the US dollar (424). Further details on the sample are in Table 2.
[24] See, for example, S&P (2005).

More relevant for the purpose of this paper is the variance equation of the heteroscedastic regression model:

$$
\begin{aligned}
Ln(\mathrm{SPREADVAR}) = f\,(&Rating, \mathrm{MATU}, \mathrm{AMOUNT}, \mathrm{BID\_ASK}, \mathrm{SUBO}, \mathrm{COUPON}, \\
&\mathrm{SHORT\_RATE}, \mathrm{SLOPE}, \mathrm{QS}, Control)
\end{aligned}
\qquad [6]
$$

The dependent variable is SPREADVAR, that is, the spread variance unexplained by the spread equation. The same variables determining the mean level of spreads can also affect their unexplained dispersion, so explanatory variables are the same as used in the spread equation. The key variable here is QS. As far as QS is considered a measure of informational opaqueness, it should positively affect the residual variance.

4.2 Data sources and sample

The data are from Dealogic DCM Analytics, which reports information on issuers (nationality, industry, etc.) and issues (spread at issuance; Moody's, S&P, and Fitch ratings; maturity; size; currency; etc.). We collect spreads at issuance for all fixed-rate, coupon-paying, non-convertible, non-perpetual, and non-callable bonds issued in 1999–2008 by private sector issuers in the Eurobond market (2,297 bonds). We use primary-market data to avoid rating staleness. If we did use secondary-market data, where some issues were rated several months or years earlier, any decrease in the explanatory power of ratings may just be due to the fact that, when QSs go up, fewer new bonds are issued and therefore ratings become less up-to-date.

Table 2 and Table 3 provide further information on the sample by country and by rating grade, respectively.

Insert Table 2 approximately here

Insert Table 3 approximately here

4.3 Empirical results

4.3.1 Descriptive analysis

Table 4 looks at issue ratings (AVGRATING) and QSs (QS). The sample is split into two equally sized sub-samples (below and above the median) across several dimensions (AVGRATING, MATU, AMOUNT, SUBO, QS); *t*-tests on subsample means are then carried out.

Unsurprisingly, worse-rated bonds exhibit a larger average spread at launch and higher spread dispersion. More interestingly, we find that, while ratings do not differ (in terms of mean and standard deviation) between high- and low-QS periods, spreads at launch are higher and more variable in high-QS months. This supports the idea that investors tend to look beyond ratings in pricing bonds when bond markets exhibit a larger QS and a higher degree of opaqueness.

Insert Table 4 approximately here

4.3.2 Multivariate analysis

We conduct a multivariate analysis to check for any effect of the QS on the unexplained variance in credit spreads. We run multiplicative heteroscedastic regressions of spreads (reported in Table 5 and Table 6) on the sets of covariates described in Section 4.1. Most pairwise correlations between independent variables (not shown here to save space) are well below 50%; the variance inflation factors are mostly below five. The only two regressors that appear strongly correlated are SHORT_RATE and SLOPE, but we retain them both for consistency with previous studies (Collin-Dufresne et al., 2001).

Table 5 shows the results for the spread equation, while Table 6 focuses on the variance equation. Ratings are measured through a set of dummy variables (D_AVGRATING2, D_AVGRATING3, etc.) with ratings from 14 to 21 grouped into just one dummy (D_AVGRATING14_21) because of the low number of observations available.

Moving from model (1) to model (4) in Table 5, we keep the spread equation unchanged and try four different specifications for the variance equation (note that each time a different model is estimated for the variance, the coefficients in the mean equation must also be updated).

Regarding the spread equation, rating dummies are positive and monotonically increasing (as well as significant at the 1% level), indicating that spreads rise as ratings worsen (Aaa being the base case). The term D_bank has a negative impact, suggesting that bank bonds, all other things being equal, pay a slightly lower spread. Here MATU has a positive coefficient, as expected, and is statistically significant at the 1% level. The term AMOUNT has a positive (and statistically significant) effect on spreads, consistent with McGinty (2001), who shows that even though most large corporate bond issues are liquid, this is not always the case and some large issues may actually be poorly traded. The coefficient for BID_ASK is positive, as expected, suggesting that illiquid bonds must pay a premium.[25]

Insert Table 5 approximately here

The positive and strongly significant coefficient for SUBO indicates that investors require a higher risk premium on subordinated bonds than that implicit in the ratings (notwithstanding the fact that subordinated issues get worse ratings than senior bonds issued by the same obligor). The term COUPON has a positive and strongly significant sign. As discussed by Elton et al. (2001), this is due to the different tax treatment of coupons and capital gains. Since capital gains are paid at maturity or upon sale, bonds with larger coupons may be less valuable (hence may

[25] As an alternative to BID_ASK, we tested two other liquidity measures: the absolute bid/ask (not standardized by the mid-price) and the number of days, in the three months following bond issuance, when quotes for the bond are available on the Bloomberg database. Both measures gave results (unreported) that are qualitatively similar to those for BID_ASK. An additional liquidity measure, the spread on CDSs having the bond issuer or its parent company as the reference entity, could not be tested because it caused a severe drop in the number of observations (since most issuers did not have a credit default swap associated with them).

offer a higher spread) because fewer taxes are postponed and the bondholder has less control over when these taxes are paid. The SHORT_RATE and SLOPE variables have a negative effect on spreads, consistent with the motivations discussed in Section 4.1. Finally and unsurprisingly,[26] QS has a positive and statistically significant coefficient.

Table 6 reports results for the *variance* equation of the heteroscedastic regression model. The coefficients for the D_AVGRATING dummies are roughly increasing, indicating greater unexplained variance for worse-rated bonds. This result supports the hypothesis that investors discriminate more as the quality of the issue worsens and put additional 'due diligence' effort on lower-quality bonds. The D_bank dummy does not seem to exert any significant effect on the spread residual variance.

Model (2) in Table 6 introduces a number of issue-specific features, such as maturity, size, liquidity, subordination, and coupons. The coefficients for MATU, BID_ASK, and COUPON are positive and significant at the 1% level, thus indicating that investor reliance on issue ratings decreases with maturity, illiquidity, and the size of coupons. The term SUBO has no clear effect on unexplained variance.

Insert Table 6 approximately here

Model (3) in Table 6 adds SHORT_RATE and SLOPE; both have a strong negative effect on the spread residual variance. As rates go up and credit risk decreases, investors seem to rely more strongly on ratings; the opposite is true when low rates signal a drop in expected growth and a possible economic downturn.

Model (4) tests the key variable of our analysis. As expected, QS, our measure of credit market opaqueness, seems to be a relevant factor in explaining spread residual variance. The coefficient is positive and significant at 1%. This indicates that the predictive power of ratings

[26] Like the dependent variable, QS is affected by movements in the credit spread curve, so its significance in the mean equation was largely expected. The focus of our study is, rather, on the role of QS in the variance equation.

decreases as the credit market becomes more opaque. Given an associated coefficient of 0.511, a jump of 200 bps in the QS would cause the unexplained variance in the mean equation to increase by 102.2, that is, by about 10 bps in terms of the standard deviation of the residual of the bond spread model.

This is consistent with the hypothesis that investors' efforts to find and price additional information increase when the informative content of ratings and any other easy-to-observe information is lower.[27]

4.4 Robustness checks

4.4.1 Alternative proxies for market-wide opaqueness

It can be argued that other variables exist that may be used instead of QS to account for opaqueness. Accordingly, we rerun all our regressions after replacing QS with three alternative indicators. The first indicator is the coefficient of variation, CV (standard deviation divided by the mean) of the earnings per share forecasts issued by security analysts during the month when each issue in our sample took place (source I/B/E/S). For example, if an issue occurred on January 20, 2005, we look at all earnings per share forecasts (for the following end-quarter, i.e., end March) issued in January 2005 by all stock analysts covered by I/B/E/S. For each security we compute the standard deviation and divide it by the mean; we then take the average of these coefficients of variation across all shares included in I/B/E/S. When corporate profits are easy to forecast, such an average coefficient of variation (CV) is comparatively low, and it surges in times of greater opaqueness, when estimates issued by different analysts (for the same security) tend to differ more markedly from each another. Within our sample, CV shows a 77%

[27] Another way to show the link between QS and the unexplained variance of our model involves running our regression (the 'mean equation') twice on two separate subsamples after ranking our sample by increasing values of QS. The first sample includes only observations below the first quartile (low QS) while the second includes observations above the third quartile (high QS). The R-squared value of the mean equation decreases from 0.922 to 0.887, confirming that a higher QS value has a negative impact on the explanatory power of ratings.

correlation with QS, meaning that both variables capture a similar phenomenon, although from different angles.

The second alternative to QS is the downgrades-to-upgrades ratio (D2UR), that is, the number of downgrades issued by Moody's during the quarter when each issue in our sample took place divided by the number of upgrades issued by Moody's during the same quarter. For example, if an issue occurred on January 20, 2005, we take all downgrades issued by Moody's from January to March 2005 and divide them by the upgrades issued the same quarter. The ratio increases when credit analysts become more concerned about the future outlook; hence it provides an alternative way of capturing negative market phases in the credit market. Within our sample, D2UR shows a 92% correlation with QS.

The third alternative is the VIX, as reported by Bloomberg. The VIX is often referred to as a fear index. The idea is that higher aggregate uncertainty should be related with higher stock market volatility. Within our sample, the VIX shows a 62% correlation with QS.

We replace QS with each of these three different proxies, either in the variance equation only or in both the mean and variance equations. The results (not reported here to save space) show that our key finding (that greater opaqueness leads to an increase in the share of market yields that is not explained by ratings) holds, irrespective of the variable used.

4.4.2 Structural change in the mean equation

If investors fly to quality during times of high QS, then the coefficients of the credit rating dummies can change. Such a change could also be due to the fact that credit ratings tend to remain stable across the cycle, so investors may increase grade-specific credit spreads in a downturn to account for deterioration in macro variables (Amato and Furfine, 2004; Jacobson et al., 2012). Such a structural shift in the mean equation could be an alternative explanation to our finding that the relation between bond spreads and credit ratings weakens as the QS increases.

To address this issue, we create a dummy variable that takes a value of one whenever QS is above its median and zero otherwise. We then interact this dummy with all the explanatory variables in our model. The results (unreported) confirm the existence of a structural change in the mean equation over the credit cycle. The sensitivity of bond spreads to credit ratings turns out to be much lower in high-QS times. This further supports our finding that ratings are less informative during times of distress in financial markets. Furthermore our key result still holds, since unexplained variance is again found to increase with QS.

4.4.3 Focusing on issuers where rating is a better estimate of credit quality

Our study is based on primary-market data to avoid rating staleness. However, it is well known that the decision of whether and when to issue a bond is not random and can be based on the issuer's credit quality. For example, opaque firms may find it too costly to issue bonds when markets are in distress (Chemmanur and Fulghieri, 1994), so the pool of issuers may be of higher quality in times of distress, which can bias the relationship between QS and unexplained variance in credit spreads. To address this concern, we check whether our results change when we focus on a subsample of issuers for which the ratings are a cleaner estimate of true firm true credit quality. Hence we rerun our regressions after dropping issuers that received split ratings. The results (not reported here to save space) show that our key finding is confirmed: Indeed, the coefficient for QS in the variance equation increases slightly and remains strongly significant.

5 CONCLUSIONS

In this paper we discuss, both theoretically and empirically, the relationship between spreads on newly issued bonds and QSs. We find that when bond markets are more opaque, the information content of ratings deteriorates and investors spend more on non-public information when setting credit spreads.

Several technical and policy implications follow from our findings. First, the standard approach to rating performance may need to be changed. Currently, default rates associated with different grades are computed starting from empirical data covering wide time windows (ranging from 20 to 100 years). But if ratings perform differently under different credit market conditions, then agencies and investors may want to carry out separate estimates of default rates in high- and low-QS periods, to stress-test rating performance, and check that rating performance remains adequate in periods of high market opaqueness and flight to quality.

Second, fund managers and other institutional investors investing in corporate bonds may want to increase their stock picking when the QS is high. In fact, when the QS is low, bond spreads are mostly driven by public information (such as ratings and other easy-to-observe variables), so there is little scope for proprietary research. When the QS increases investors who can process private information effectively may secure profits by anticipating future price movements.

Finally, our findings indicate that the debate on rating agencies and investor protection may become more productive if policy makers were to explicitly recognize the different roles played by agencies in different phases of the credit cycle.

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Table 1. Mean PDs for different issuers and different periods

	Mean PD (bad)	Mean PD (good)	Difference
Low-QS years	29.95%	7.34%	22.61%
High-QS years	18.18%	4.83%	13.35%
All years	27.11%	6.64%	20.47%

This table is based on a dataset of 68,862 issuer–year pairs during 1970–2003. Each issuer has an estimated PD, based on the long-run default frequency of its rating grade. Bad (good) issuers are defined as issuers defaulting (not defaulting) within seven years after the rating is observed. Source: Moody's.

Table 2. Sample descriptive statistics (by country)

COUNTRY	No. of issues	SPREAD (bp)		MATU (years)	Face value (euro, M)	COUPON (%)	SUBO (No. of issues)
		Mean	Std. dev.	Mean	Mean	Mean	
Argentina	10	452.21	133.22	4.35	140	9.36	0
Australia	66	79.89	78.86	5.12	489	5.14	1
Austria	27	62.22	29.99	7.04	564	5.12	1
Brazil	11	569.28	178.62	3.58	162	9.64	0
Cayman Islands	31	106.15	36.81	7.08	647	5.85	1
Finland	11	116.36	45.89	8.44	696	5.49	0
France	247	108.55	80.57	8.30	844	5.18	9
Germany	153	63.26	61.95	6.43	782	4.91	11
Ireland	57	89.85	83.64	7.29	851	5.14	2
Italy	56	105.06	59.20	10.24	1,500	5.26	10
Japan	13	56.13	18.73	12.76	530	4.92	0
Jersey	14	71.60	48.89	6.35	448	5.26	0
Luxembourg	52	201.27	175.53	7.60	690	5.98	6
The Netherlands	451	112.23	123.11	7.14	798	5.43	12
Russian Federation	44	460.68	163.51	4.58	323	8.75	0
Singapore	13	157.39	147.11	9.01	918	6.60	2
South Korea	12	171.08	102.91	5.66	338	5.40	0
Spain	18	88.90	47.16	8.05	1,940	4.70	1
Sweden	35	127.89	95.18	7.70	671	5.49	0
United Kingdom	435	118.36	68.98	11.01	688	5.58	46
United States	368	98.92	90.55	7.32	790	5.24	16
Virgin Islands (British)	10	312.25	150.22	8.95	557	7.01	0
Other countries	163	206.45	198.20	6.79	498	6.36	7
Total	2,297	122.71	123.27	7.96	744	5.52	125

The sample includes 2,297 bonds issued during 1999–2008. The variables are defined as follows:

SPREAD	The difference between the bond yield at issuance and that of a Treasury security with the same maturity and currency.
MATU	Years to maturity of the issue.
Face value	The euro-equivalent amount (face value) of the issue.
COUPON	The coupon rate.
SUBO	A dummy variable that equals one if the bond is subordinated and zero if it is senior.

Table 3. Sample descriptive statistics (by rating category)

RAVGRATING	No. of issues	SPREAD (bp)		MATU (years)	Face value (euro, M)	COUPON (%)	SUBO (No. of issues)
		Mean	*Std. Dev.*	*Mean*			
1	441	54.69	40.01	6.01	618	4.76	5
2	113	66.52	48.73	6.06	606	4.99	4
3	187	82.62	65.01	7.75	726	5.05	8
4	238	86.43	61.84	10.03	868	5.22	36
5	252	84.05	55.86	9.39	787	5.18	36
6	295	120.07	78.42	9.04	802	5.66	22
7	201	125.61	88.46	8.62	944	5.49	10
8	247	143.23	88.39	8.43	895	5.66	3
9	123	162.72	83.72	8.84	815	5.98	1
10	63	197.90	76.52	7.86	596	6.00	0
11	23	313.16	156.65	6.21	413	7.39	0
12	24	405.19	116.52	4.57	301	8.37	0
13	35	445.86	155.27	4.58	294	8.63	0
14	32	557.33	142.90	4.17	198	9.80	0
15	13	621.68	143.81	5.44	333	10.73	0
16	8	579.01	169.89	6.06	405	9.95	0
19	1	920.00	-	7.00	196	13.5	0
21	2	500	-	5.00	200	8.375	0
Total	2,297	122.71	123.27	7.96	744	5.52	125

The sample includes 2,297 bond issued during 1999–2008. Variables are defined as follows:

RAVGRATING The rounded average issue rating (converted into a numerical scale where Aaa/AAA/AAA is equal to one). When the average value is not an integer, it is rounded to the lower (less risky) value.

SPREAD The difference between the bond yield at issuance and that of a Treasury security with the same maturity and currency.

MATU Years to maturity of the issue.

Face value The euro-equivalent amount (face value) of the issue.

COUPON The coupon rate.

SUBO A dummy variable that equals one if the bond is subordinated and zero if it is senior.

Table 4. Average spread and rating by issue characteristics

		AVGRATING		MATU		Face value		SUBO		QS	
		Below	*Above*	*Below*	*Above*	*Below*	*Above*	*Yes*	*No*	*Below*	*Above*
No. of issues		1,181	1,116	1,168	1,129	1,313	984	125	2,172	1,161	1,136
SPREAD	Mean	71.71	176.68	121.16	124.32	125.68	118.75	122.31	122.73	110.41	135.28
	(t-test)	(0.000)**		(0.539)		(0.182)		(0.970)		(0.000)**	
	Std. dev.	54.58	149.90	141.84	100.56	140.02	96.44	60.29	125.95	115.23	129.84
	(Levene's test)	(0.000)**		(0.000)**		(0.000)**		(0.000)**		(0.000)**	
AVGRATING	Mean	-		4.88	5.93	5.46	5.32	4.92	5.43	5.38	5.42
	(t-test)			(0.000)**		(0.324)		(0.009)**		(0.739)	
	Std. dev.			3.74	2.75	3.70	2.76	1.46	3.40	3.32	3.33
	(Levene's test)			(0.000)**		(0.000)**		(0.000)**		(0.926)	

The sample includes 2,297 bond issued during 1999–2008. Here *Below* and *Above* indicate sub-samples for which the corresponding variable is equal to and below or above the sample median, respectively. Reported are the *t*-test (*p*-value) for equality of the mean and Levene's test (*p*-value) for equality of the variance.

The variables are defined as follows:

SPREAD	The difference between the bond yield at issuance and that of a Treasury security with same maturity and currency.
AVGRATING	The average issue rating (converted into a numerical scale where Aaa/AAA/AAA is equal to one).
MATU	Years to maturity of the issue.
Face value	The euro-equivalent amount (face value) of the issue.
SUBO	A dummy variable that equals one if the bond is subordinated and zero if it is senior.
QS	The spread between the average yields paid on Aaa- and Baa-rated corporate bonds.

The superscripts ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 5. Multiplicative heteroscedastic regression of SPREAD on issue characteristics and QS (spread equation)

	(1)	(2)	(3)	(4)
D_RAVGRATING2	5.15*	2.12	1.10	1.44
	(0.011)	(0.267)	(0.541)	(0.431)
D_RAVGRATING3	12.63**	8.98**	8.28**	8.30**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING4	12.09**	9.52**	9.12**	9.00**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING5	15.82**	12.99**	13.05**	12.99**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING6	27.36**	24.08**	23.71**	23.26**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING7	39.36**	33.97**	33.49**	33.20**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING8	47.65**	42.43**	43.11**	42.94**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING9	57.70**	50.55**	52.11**	51.43**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING10	96.29**	88.17**	88.11**	88.27**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING11	136.07**	111.92**	105.41**	106.83**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING12	207.74**	193.51**	179.80**	181.65**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING13	232.92**	209.81**	203.85**	206.12**
	(0.000)	(0.000)	(0.000)	(0.000)
D_RAVGRATING14-21	311.96**	290.81**	275.52**	277.40**
	(0.000)	(0.000)	(0.000)	(0.000)
D_bank	-4.465**	-4.256**	-3.125**	-3.041**
	(0.000)	(0.000)	(0.003)	(0.003)
MATU	0.383**	1.308**	1.436**	1.442**
	(0.000)	(0.000)	(0.000)	(0.000)
AMOUNT	3.052**	3.422**	3.350**	3.503**
	(0.000)	(0.000)	(0.000)	(0.000)
SUBO	12.121**	14.417**	13.670**	14.215**
	(0.000)	(0.000)	(0.000)	(0.000)
COUPON	32.92**	30.696**	29.622**	29.750**
	(0.000)	(0.000)	(0.000)	(0.000)
BID_ASK	122.80*	640.268**	581.670**	622.781**
	(0.012)	(0.000)	(0.000)	(0.000)
SHORT_RATE	-3.616**	-28.746**	-28.799**	-29.233**
	(0.000)	(0.000)	(0.000)	(0.000)
SLOPE	-24.508**	-21.334**	-21.752**	-22.215**
	(0.000)	(0.000)	(0.000)	(0.000)
QS	20.662**	29.772**	23.747**	19.964**
	(0.000)	(0.000)	(0.000)	(0.000)

This table reports the regression coefficients and *p*-values (in parentheses). The dependent variable is the issue spread (SPREAD). Equations are estimated with the (maximum likelihood) multiplicative heteroscedastic regression model.
The explanatory variables are defined as follows:

D_RAVGRATING2… D_RAVGRATING14-21	Dummy variables that equal one if the rounded average issue rating (RAVGRATING) falls in the corresponding rating category and zero otherwise (rating categories 14–16, 19, and 21 are grouped into a single category, D_RAVGRATING14-21).
D_bank	A dummy variable that equals one if the issuer is a bank (either commercial or investment) and zero otherwise.
MATU	Years to maturity of the issue.
AMOUNT	The natural log of the euro-equivalent amount (face value) of the issue.
SUBO	A dummy variable that equals one if the bond is subordinated and zero if it is senior.
COUPON	The coupon rate.
BID_ASK	The bond's bid–ask average spread on the secondary market in the first three months after the issuance date, scaled by the bond's mid-price (in yield terms).
SHORT_RATE	The three-month risk-free rate.
SLOPE	The difference between 10-year and three-month yields on government bonds.
QS	The spread between the average yields paid on Aaa- and Baa-rated corporate bonds.

We also control for year, country, and currency fixed effects. We do not report these variables' coefficients for ease of exposition. The superscripts ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 6. Multiplicative heteroscedastic regression of SPREADVAR on issue characteristics and QS (variance equation)

	(1)	(2)	(3)	(4)
D_RAVGRATING2	-0.005 (0.974)	-0.219 (0.181)	-0.236 (0.148)	-0.189 (0.248)
D_RAVGRATING3	-0.273* (0.043)	-0.510** (0.000)	-0.439** (0.001)	-0.403** (0.003)
D_RAVGRATING4	0.034 (0.783)	-0.413** (0.001)	-0.433** (0.002)	-0.397** (0.002)
D_RAVGRATING5	0.194 (0.110)	-0.244 (0.051)	-0.110 (0.380)	-0.082 (0.510)
D_RAVGRATING6	0.297* (0.012)	-0.099 (0.425)	-0.143 (0.253)	-0.170 (0.175)
D_RAVGRATING7	1.193** (0.000)	0.518** (0.000)	0.427** (0.003)	0.458** (0.002)
D_RAVGRATING8	1.148** (0.000)	0.645** (0.000)	0.629** (0.000)	0.646** (0.000)
D_RAVGRATING9	1.430** (0.000)	0.810** (0.000)	0.705** (0.000)	0.702** (0.000)
D_RAVGRATING10	2.125** (0.000)	1.358** (0.000)	1.234** (0.000)	1.267** (0.000)
D_RAVGRATING11	2.691** (0.000)	1.855** (0.000)	1.541** (0.000)	1.629** (0.000)
D_RAVGRATING12	2.838** (0.000)	1.715** (0.000)	1.680** (0.000)	1.699** (0.000)
D_RAVGRATING13	3.340** (0.000)	2.071** (0.000)	1.667** (0.000)	1.679** (0.000)
D_RAVGRATING14-21	3.626** (0.000)	1.663** (0.000)	1.169** (0.000)	1.225** (0.000)
D_bank	-0.074 (0.328)	-0.026 (0.751)	0.031 (0.699)	0.055 (0.500)
MATU	-	0.049** (0.000)	0.050** (0.000)	0.052** (0.000)
AMOUNT	-	-0.073 (0.085)	-0.102* (0.016)	-0.928* (0.029)
SUBO	-	0.225 (0.135)	0.129 (0.392)	0.152 (0.314)
COUPON	-	0.329** (0.000)	0.462** (0.000)	0.452** (0.000)
BID_ASK	-	57.997** (0.000)	47.472** (0.000)	45.058** (0.000)
SHORT_RATE	-	-	-0.911** (0.000)	-0.729** (0.000)
SLOPE	-	-	-0.597** (0.000)	-0.449** (0.000)
QS	-	-	-	0.511** (0.000)
Obs.	2,297	2,297	2,297	2,297
χ^2	(0.000)	(0.000)	(0.000)	(0.000)
VWLS R^2	0.834	0.834	0.840	0.839
Pseudo R^2	0.235	0.242	0.246	0.247

This table reports the regression coefficients and *p*-values (in parentheses). The dependent variable is the unexplained spread variance (SPREADVAR). Equations are estimated with the (maximum likelihood) multiplicative heteroscedastic regression model. The term χ^2 denotes the *p*-value of the chi-squared test for the null hypothesis that all the coefficients jointly equal zero. The explanatory variables are defined as follows:

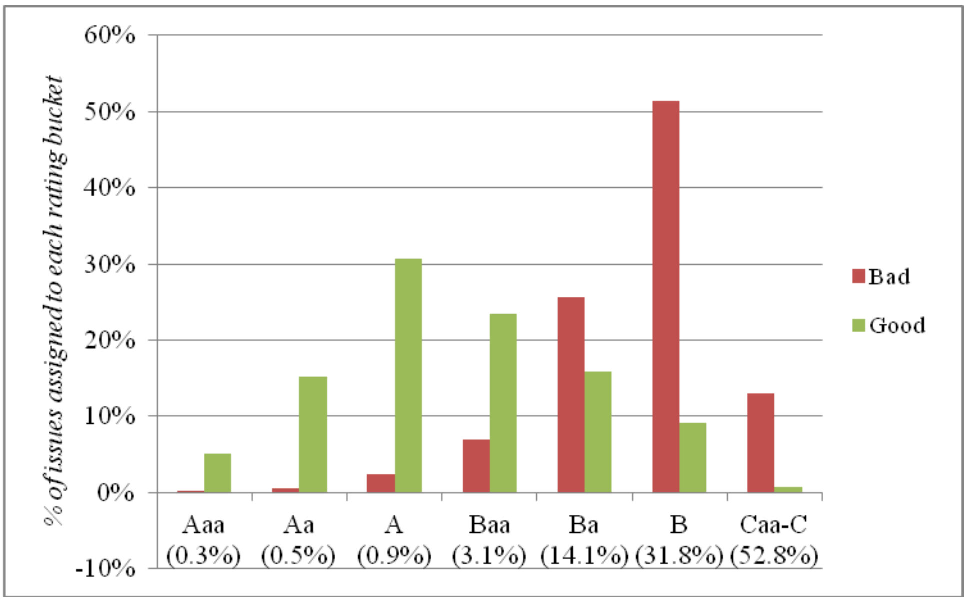
D_RAVGRATING2… D_RAVGRATING14-21	Dummy variables that equal one if the rounded average issue rating (RAVGRATING) falls in the corresponding rating category and zero otherwise (rating categories 14–16, 19, and 21 are grouped into a single category, D_RAVGRATING14-21).
D_bank	A dummy variable that equals one if the issuer is a bank (either commercial or investment) and zero otherwise.
MATU	Years to maturity of the issue.
AMOUNT	The natural log of the euro-equivalent amount (face value) of the issue.
SUBO	A dummy variable that equals one if the bond is subordinated and zero if it is senior.
COUPON	The coupon rate.
BID_ASK	The bond's bid–ask average spread on the secondary market in the first three months after the issuance date, scaled by the bond's mid-price (in yield terms).
SHORT_RATE	The three-month risk-free rate.
SLOPE	The difference between 10-year and three-month yields on government bonds.
QS	The spread between the average yields paid on Aaa- and Baa-rated corporate bonds.

We also control for year, country, and currency fixed effects. We do not report these variables' coefficients for ease of exposition. The superscripts ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Figure 1. QS, January 1919 to December 2008

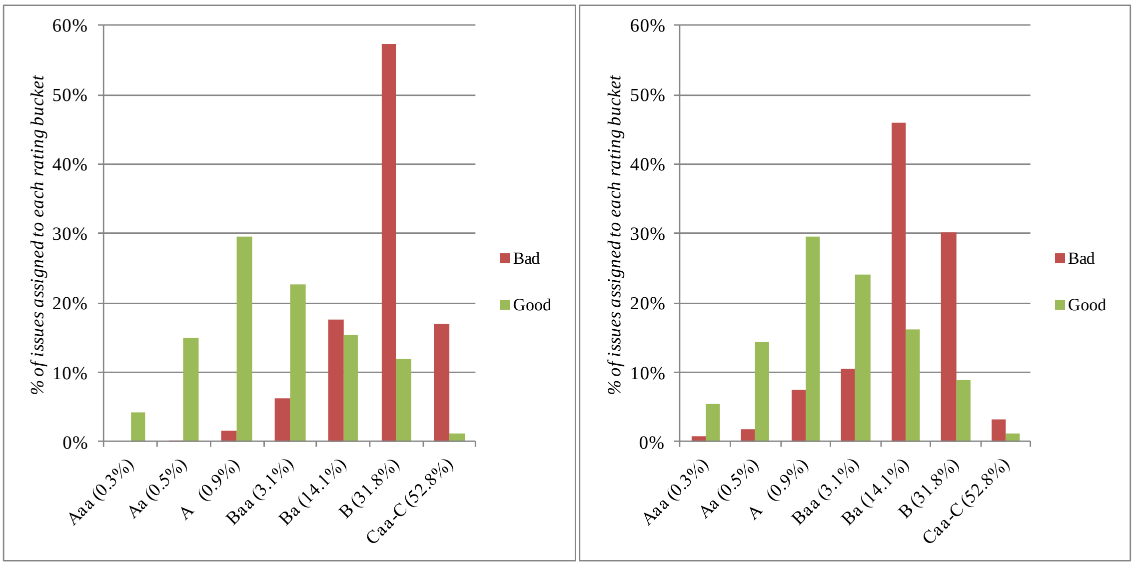
This graph plots the QS from January 1919 to December 2008. The QS is computed as the difference between secondary-market yields on seasoned corporate bonds rated Baa and Aaa by Moody's. We compute the monthly averages of the daily data points, collected from FRED, the database of the Federal Reserve Bank of St. Louis. Moody's tries to include bonds with remaining maturities as close as possible to 30 years and drops bonds if the remaining life falls below 20 years, if the bond is susceptible to redemption, or if the rating changes.

Figure 2. Ratings (and estimated seven-year PDs) associated by Moody's with bad and good issuers, 1970–2001



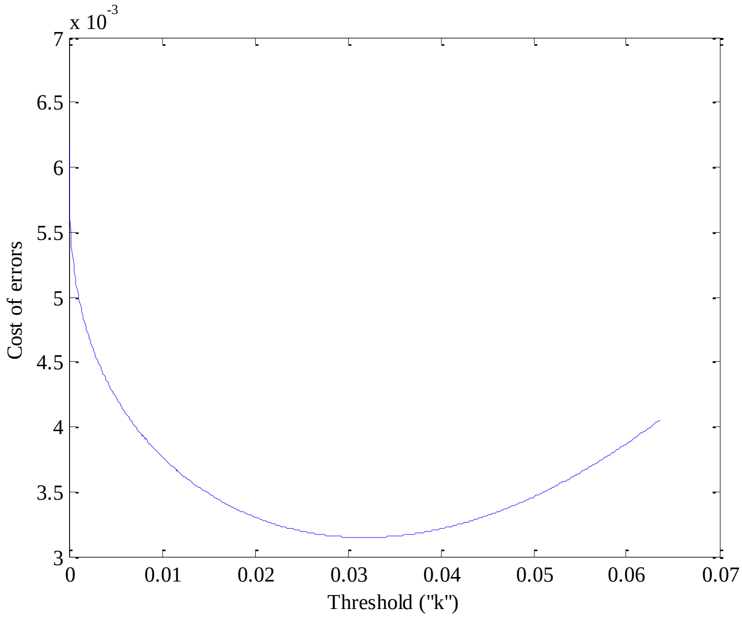
This figure shows the distribution of bad and good issuers over rating categories in a dataset of 68,862 issuer–year pairs during 1970–2001. Bad (good) issuers are defined as issuers defaulting (not defaulting) within seven years after the rating is observed. For example, about 50% of bad issuers have a B rating, while about 30% of good issuers have an A rating. Source: Moody's.

Figure 3. PDs (on a seven-year horizon) associated by Moody's ratings with bad and good issuers in low-QS years (left panel) and high-QS years (right panel)



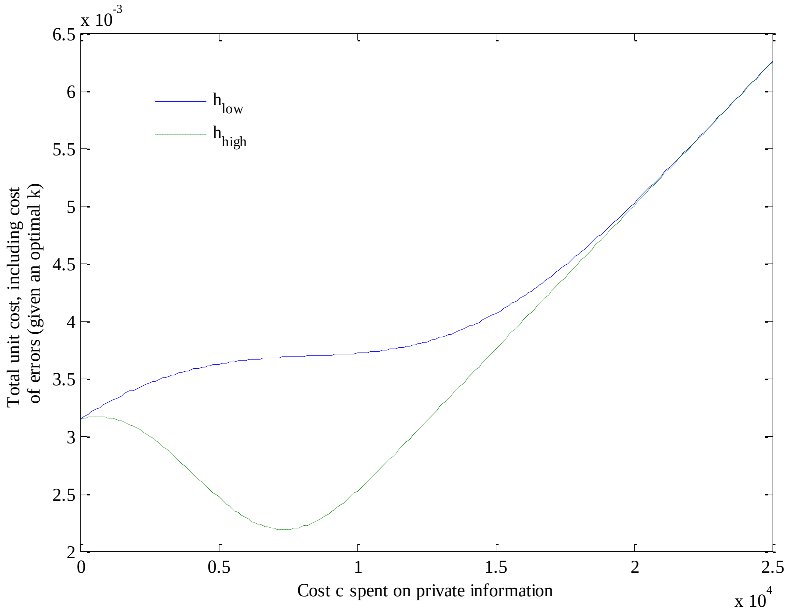
This figure shows the distribution of bad and good issuers over rating categories in a dataset of 68,862 issuer–year pairs during 1970–2001. Bad (good) issuers are defined as issuers defaulting (not defaulting) within seven years after the rating is observed. Source: Moody's.

Figure 4. Choice of the optimal threshold *k*



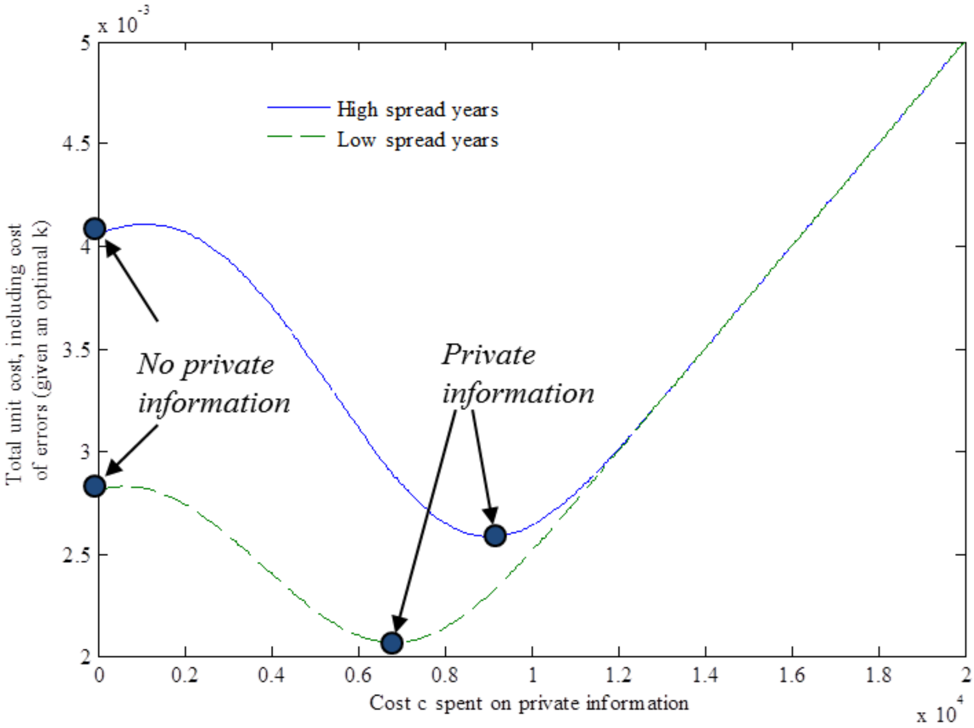
This figure shows an example of the optimal (cost-minimizing) PD threshold *k* above which a rational investor will decide not to buy a risky bond.

Figure 5. Cost of private information *c* borne by investors with different screening abilities



This figure exemplifies how different types of investors choose their optimal investment c on private information before deciding whether to buy a risky bond.

Figure 6 - Cost of private information *c* borne by an investor (with high screening abilities) at different stages of the credit cycle



This figure shows how the amount spent on private information by rational investors can increase in high-QS years.