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Dion Bongaerts
K.J. Martijn Cremers
William N. Goetzmann

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ABSTRACT

This paper explores the role played by multiple credit rating agencies (CRAs) in the market for corporate bonds. Moody's, S&P and Fitch operate in a competitive setting with market demand for both credit information and the certification value of a high rating. We empirically document the outcome of this competitive interaction over the period 2002 to 2007. Virtually all bonds in our sample are rated by both Moody's and Standard and Poors (S&P), and between 40% and 60% of the bonds are also rated by Fitch. This apparent redundancy in information production has long been a puzzle. We consider three explanations for why issuers apply for a third rating: 'information production,' 'adverse selection' and 'certification' with respect to regulatory and rules-based constraints. Using ratings and credit spread regressions, we find evidence in favor of Certification only. Additional evidence shows that the reported certification effects are consistent with an equilibrium outcome in a market with information-sensitive and insensitive bonds. In such a setting, ratings help to prevent market breakdowns.

Dion Bongaerts
Roetersstraat 18
1018 WB Amsterdam,
Netherlands
d.g.j.bongaerts@uva.nl

K.J. Martijn Cremers
Yale School of Management
135 Prospect Street
New Haven, CT 06520-8200
martijn.cremers@yale.edu

William N. Goetzmann
School of Management
Yale University
Box 208200
New Haven, CT 06520-8200
and NBER
william.goetzmann@yale.edu

1. Introduction

Credit Rating Agencies (CRAs) produce information about the risk of fixed income securities. However, the various ways the information is used by financial, legal and regulatory entities may potentially influence the nature of the information production process. Bond ratings are not only used to assess risk, they are also used for certification, e.g. to classify securities into investment grade (IG) and high yield (HY, or junk) status. These classifications in turn influence institutional demand and serve as bright-line triggers in corporate credit arrangements and regulatory oversight. For example, regulations may mandate banks and insurance companies to keep much higher reserve capital for high yield issues than for investment grade, where the level of reserve capital required goes up in large discrete increments depending on which side of the investment grade boundary an issue lies. The institutional and regulatory importance of credit ratings to issuers and investors has raised questions about whether the current system provides the proper incentives to optimally produce reliable, value-relevant information about risk.

Almost all large, liquid US corporate bond issues are rated by both S&P and Moody's but not by Fitch. Fitch thus plays the role of a "third opinion" for large bond issues.[1] The most prevalent institutional rule used for classifying rated bonds is that, if an issue has two ratings, only the worse rating can be used to classify the issue (e.g. into investment-grade or non-investment grade). However, if an issue has three ratings, the middle rating should be used (see for example the Basel II accord or the NAIC guidelines).[2] Therefore, if S&P and Moody's ratings are on opposite sides of the investment grade boundary, the Fitch rating (assuming it is the marginal, third rating) will decide into which class the issue falls.

In light of this practice, a natural question is whether Fitch might play the role of "tie-breaker" for large bond issues, and if so, what the nature is of the "tie" being broken, specifically whether Fitch's decision seems informational or regulatory/rules-based. We thus address the question of whether the third rating agency primarily plays a certification role or an informational role in the marketplace for bond ratings. If the certification role dominates, only the weaker issuers would need a third rating. Therefore, we also investigate whether the option of a third rating leads to adverse selection effects in pricing.

[1] For smaller issues, Fitch is occasionally one of two raters. However, almost all bonds in our final sample are rated by both Moody's and S&P (see also Figure 1). Specifically, about 95% of all bonds in our database with at least 2 ratings are rated by both S&P and Moody's. This lack of cross-sectional variation in having an S&P or Moody's rating means that we can only study the implications for having Fitch as a third rating. Accordingly, we remove from our sample all bond issues that do not have ratings from both S&P and Moody's. For this sample of bond issues rated by both Moody's and S&P and using quarterly observations for 2000-2007, about 60% of observations have a Fitch rating. As a result, the main focus of our paper will be to consider the 'marginal' role of Fitch ratings, while controlling for S&P and Moody's ratings.

[2] The National Association of Insurance Commissioners (NAIC) is the organization of state insurance regulators.

To address these issues, we consider three hypotheses that could lead to demand for multiple credit ratings: An 'information production' hypothesis, a 'rating shopping' hypothesis and a 'certification' hypothesis. Under the information hypothesis, investors are averse to uncertainty, which is reduced by adding extra ratings. Under the rating shopping hypothesis, issuers 'shop' until their average rating at least conforms to their own credit assessment. Under the certification hypothesis, market and regulatory forces create a need for one or more CRAs to credibly separate issues into two types: investment grade and non-investment grade. For all three hypotheses, we derive implications which are tested in the empirical section of the paper. For example, for information production, one would not expect systematic differences in ratings across CRAs, whereas for rating shopping (by selection) and certification ('niche' rating) one would expect an extra rating to be more optimistic.[3]

For our empirical analysis, we use bond price data, issue and firm characteristics and credit ratings for U.S. corporate bond issues over the period 2000 through 2007.[4] Consistent with previous research (see for example Cantor and Packer, 1997) we find that Fitch, on average, assigns the highest (i.e., most credit-worthy) ratings, while Moody's on average assigns a lower rating than both S&P and Fitch. Given these systematic differences, we conduct further tests on the three hypotheses. A logit model predicting whether an issue is rated by Fitch finds little evidence that proxies for asymmetric information or dispersion of opinion predict a Fitch rating, which is evidence against both rating shopping and information production.

Instead, having a Fitch rating is strongly associated with S&P and Moody's ratings being on opposite sides of the investment grade boundary. This is consistent with the Fitch rating having a significant certification value as a "tie-breaking" rating agency for purposes of certification of investment grade status. Consistently, financials, which are extremely dependent on a credit rating are more likely to have a Fitch rating when Moody's and S&P disagree. However, we do not observe this pattern for other measures of uncertainty or opaqueness. However, we do not find that Fitch ratings are different from typical Fitch ratings (particularly more optimistic) in these specific cases where Fitch ratings may be the "tie breaker" for an investment grade classification, notwithstanding the significant economic consequences of Fitch's decision.

Next, we consider the impact of multiple ratings on credit spreads in order to estimate the importance of the certification and information effects. While credit ratings, in general, contain information about risk, the information about risk provided by the third rating agency (assumed to be Fitch) seems marginal. The major and critical exception is that, if they are relatively positive, Fitch

[3] Previous literature supports the plausibility of each of the three hypotheses. For example, Guentay and Hackbarth (2006) show that analyst dispersion leads to higher credit spreads, suggesting uncertainty aversion among corporate bond investors. Poon and Firth (2005) show evidence of rating shopping in unsolicited ratings, Skreta and Veldkamp (2008) suggest this is increasing in issue complexity. Sangiorgi, Sokobin and Spatt (2009) consider theoretically rating shopping and any biases in ratings if there is heterogeneity across issuers in the extent to which different raters agree. Brister et al. (1994) provide some evidence of a super-premium for high-yield bonds due to certification.

[4] Throughout the paper, we only consider the three major credit rating agencies (CRAs), ignoring all others.

ratings lead to lower credit spreads around the investment grade boundary. In particular, bond issues for which the Fitch rating pushes a bond over the investment grade threshold (i.e., where S&P and Moody's are on opposite sides of this boundary) have a credit spread that is 45 basis points lower than when it confirms the High-yield [HY] status, controlling for risk characteristics. This economically very large difference suggests that the certification effect can significantly lower the issuer's cost of capital (apart from endogeneity considerations, which do not seem obvious for the very specific case of S&P and Moody's being on opposite sides of the IG boundary, e.g., we control for various measures of uncertainty, including credit rating dispersion).

For bond issues that are not at the margin of the investment-grade classification, the certification effect of adding a Fitch rating is negative on average, increasing the credit spread by about 8 basis points when Fitch confirms the average rating given by Moody's and S&P. Thus, absent the benefit of certification, the third rating seems associated with a higher risk-adjusted cost of capital. This is consistent with a certification-related adverse selection effect and further evidence against information production as an explanation for multiple ratings.

We further investigate certification as a co-ordination mechanism for differentiating securities with respect to information sensitivity. Following Gorton and Pennacchi, (1990) and Boot and Thakor (1993), we consider a setting with two types of investors in which issues with a lower credit quality carry more uncertainty. With one type of investors having regular trading needs and only the other type able to efficiently conduct costly research to reduce uncertainty, we get a market breakdown for intermediate quality bonds. In this setting, credit ratings can restore trading by reducing the uncertainty about the value of information. Theoretically, this should lead to lower liquidity of high yield bonds, a concentration of Fitch (certification-induced) ratings around the IG-HY boundary and higher credit spreads for Fitch rated bonds especially in periods of high uncertainty when the value of certification increases. These predictions are confirmed empirically, such that the certification effects documented in this paper seem consistent with an equilibrium outcome in a market with information-sensitive (i.e., high yield) and insensitive (i.e., very high credit quality) bonds.

Taken together, our work suggests that a major function of CRAs is to certify to relatively uninformed traders that they do not face a significant informational disadvantage. Absent the IG-HY boundary certification, there might be a no-trade equilibrium due to adverse selection. In the long run, a necessary condition for the credit rating agency to have credibility about the IG-HY classification is that it produces and uses value-relevant information about the firm. A rubber-stamp without research will not serve the certification purpose in the long run, especially if the regulatory emphasis on credit ratings would change in the aftermath of the current credit crisis. Thus, the research by CRAs – to the extent that it is independently verifiable – is a means to earn the trust of the marketplace. Competition among CRAs in information-production seems a necessary condition for effective certification, even if in equilibrium the third rater does not seem to provide significant new information.

The remainder of the paper is organized as follows. Section 2 contains our motivation for the empirical tests and the various hypotheses, and also considers related literature. In section 3, we discuss the sample construction and methodology. Section 4 presents the empirical results on the three hypotheses. Section 5 explores the certification effect in more depth and section 6 concludes.

2. Motivation

2.1 Credit Rating Agencies and Regulation

There are three major credit rating agencies (CRAs) in the U.S. market: S&P, Moody's and Fitch. In addition to these big three, there are seven minor CRAs that issue credit ratings that qualify for meeting regulatory standards. While the purpose of a credit rating is to reflect the creditworthiness of an issue or issuer, the rating agencies have some discretion in the philosophy underlying their rating system and are not required to make their rating methodology public.[5]

CRAs are licensed as Nationally Recognized Statistical Rating Organizations (NRSRO) by the Securities and Exchange Commission. This official designation has a number of effects. First, CRAs are exempt from Regulation FD, allowing corporations to share value-relevant information with the rating agency without disclosing it publicly. Second, the SEC designation allows credit ratings to be used for meeting regulatory requirements that call for a minimum or an average rating value. For example, until June, 2008 the SEC required that money market mutual funds hold instruments with a credit rating in one of the two short-term higher credit rating categories. This effectively provided a "safe harbor" for mutual funds with respect to litigation over fund failures.

Banking regulations enacted under the so-called 'Basel II accords' explicitly rely on NRSRO ratings for determining risk-based capital. In particular, bonds held by banks are assigned risk "weights" based upon their credit ratings, which in turn are used to calculate how much reserve capital should be held.[6] US insurance companies are subject to very similar risk-based capital requirements and European financial companies will follow soon with the implementation of 'Solvency II.' Although there is much discussion about treating bank and insurance assets in the context of their total portfolio that would take into account co-variance rather than security-specific risk, as of mid-2008, a large portion of U.S. institutional portfolios are still subject to regulation tied to ratings by a relatively small number of NRSROs.

In June, 2008, the SEC proposed to eliminate language in many regulations pertaining to NRSROs, and instead allow an alternative decision-making function, perhaps recognizing that reliance on credit ratings agencies had the potential to distort the information gathering and investment decision-

[5] Indeed, some ratings have a point-in-time perspective, whereas others (including the three major CRAs) employ a 'through-the-cycle' vision. Similarly, while some rating agencies aim to reflect cross-sectional variation in default probabilities (like S&P and Fitch), others aim to also incorporate loss given default and reflect dispersion in expected loss (like Moody's).
[6] This is what most smaller banks will use.

making process. The motivation for this change stemmed from the subprime mortgage crisis that began in 2007, and from concerns that the top three CRAs may represent an artificial, effective oligopoly enabled by government regulation. Among other things, the concern is that this oligopoly might not be the optimal mechanism for revealing information related to the risk of fixed income securities, and instead might be used as an artificial safe-harbor to excuse investment managers from exercising business judgment. As such, it could allow the CRAs to extract rents from corporations by virtue of serving as "gate-keepers" to the investment-grade (IG) rating, especially as the CRAs are paid by the corporations whose bonds are rated. Moreover, competition among CRAs could lead to a so called "race to the bottom", i.e. competition over deteriorating standards to attract more customers. This is an often heard concern about the structured finance market in the (subprime) mortgage crisis.

While all of the aforementioned issues are of a regulatory nature, the wider financial industry has also grown increasingly dependent on CRAs. Financial institutions typically center self-regulation around credit ratings, e.g. mutual funds stating in their charter to only invest in investment-grade (IG) quality fixed income securities. Trading and internal risk management models often take credit ratings either as primary or as calibration inputs. Many corporate credit arrangements, like collateral requirements and haircuts are further driven by credit ratings. Moreover, ratings are an important factor in determining whether a bond qualifies for inclusion in prominent corporate bond indices like the Lehman Brothers US Corporate IG Index. Inclusion in such an index may greatly improve the liquidity of an issue, since for example index tracking institutions will trade more in them. Several papers show that a higher liquidity leads to lower credit spreads (see for example Chen, Lesmond and Wei, 2007). Typically, these procedures tend to incorporate all (multiple) rating information available, extending possible certification effects well beyond those resulting from financial regulation.[7]

2.2 Why Multiple Ratings Matter

In this section, we consider different mechanisms that could lead firms to solicit and pay for multiple ratings. We base these hypotheses also on empirical evidence provided by the previous literature. The three hypotheses we consider are (i) the "Information Production" hypothesis, (ii) the "Rating Shopping" hypothesis and (iii) the "Certification" (or clientele or regulation) hypothesis. Below, we will give a short description of each and discuss its testable empirical predictions. Table 1 summarizes their empirical predictions.

To start with, the reason for multiple ratings could be the need for increased information production, with more ratings reducing uncertainty about the credit quality of the rated bonds. Each CRA produces potentially different and new information relative to the other CRAs. If investors appreciate this additional information, it may lead to a reduction in uncertainty and result in lower credit spreads for bonds with more ratings. The natural implication of this hypothesis is that the marginal value of an extra rating will be largest for the bonds that are subject to most uncertainty. However, in a

[7] See for example Lehman Brothers AG Index Factsheet; nowadays this index is called Barclays Global Investor US corporate IG index.

rational asset pricing framework, an information effect will only take place when the rating errors made by, or disagreements amongst, CRAs are systematic. If not, rating errors or disagreements would average out in a well-diversified portfolio of bonds. For example, this can happen when each rating agency fails to incorporate important information from different systematic factors. In this case, ratings can unconditionally be accurate, but not conditional on these factors. Another setting in which an information effect can arise is more behavioral in nature. If investors are averse to even idiosyncratic rating errors, for example if they have utility functions that are averse to Knightian uncertainty (Knight, 1921), they would be willing to pay for bonds with reduced uncertainty caused by more ratings. One would expect that issuers with greater ex-ante uncertainty are more likely to apply for extra ratings since the potential reduction of uncertainty is largest for them.

Second, the "Rating Shopping" effect arises in a setting in which credit rating agencies (CRAs) make rating errors and issuers have better information about their credit quality and try to optimize their average rating. Assuming an unbiased expected rating for each CRA, the optimal strategy for the issuer may be to apply for a rating at the first CRA, and if it is better than the true credit quality, stop, and otherwise apply with the next CRA. Applying for private ratings and making these public if favorable, or deciding which CRA to use based on advice from an investment bank that has knowledge about each CRA's precise rating algorithms leads to similar patterns. For a rating shopping effect, not only the existence of the effect would be of interest. The way this behavior is priced by investors would also be interesting. If aware of this behavior, investors would prefer an average rating given by three CRAs to the same average rating given two, and also to a rating by a single agency. They would thus accept a lower credit spread for multiple ratings, as is the case for an information story. However, in contrast to an information effect, we would expect to see better extra ratings compared to their base rating for issuers with more uncertainty. Uncertainty in ratings over time (time variation in ratings) would reduce the rating shopping effect, because the optimal outcome is more likely to change quickly.

The third explanation for multiple ratings is the "Certification," e.g., whether a bond issue is investment grade (IG) or high yield (HY), which could arise when financial regulation and institutional rules impose frictions on the formation of optimal portfolios. Financial regulation has traditionally relied heavily on credit ratings to determine the suitability and riskiness of fixed income investments. One important purpose of ratings is to determine the reserve capital that banks and insurance companies need to hold for corporate bonds in their portfolio. However, the universe of rules in which credit ratings play a role extends well beyond the corporate bond market. Ratings are also of importance in the structured finance market, the commercial paper market, when determining haircuts on collateral on the discount window of the central bank and when determining whether projects can qualify for government assistance (see for example the Basel Committee on Banking Supervision, 2000). The recent government "rescue" of AIG in 2008 followed a change in the rating of AIG's corporate debt which, in turn, triggered a need for increased collateral in its counterparty arrangements. This event underscores the enormous potential impact of certification, especially for financial firms.

The most prominent distinction based on credit ratings is whether an issue, issuer or structured product is investment grade (IG) or high yield (HY). Much financial regulation is based on this classification and creates strong incentives for issuers to have a rating that will make them IG. In particular, the most prevalent institutional rule used for classifying rated bonds is that, if an issue has two ratings, only the worse rating can be used to classify the issue (e.g. into investment-grade or non-investment grade). However, if an issue has three ratings, the middle rating should be used (see for example the Basel II accord or the NAIC guidelines). Therefore, if e.g. S&P and Moody's ratings are on opposite sides of the investment grade boundary, the Fitch rating (assuming it is the marginal rating) will decide into which class the issue falls.

Under the certification hypothesis, a CRA systematically giving better ratings than the other CRAs could be used to (at least partially) satisfy financial regulation. A rating from this CRA could be requested by issuers for which the extra rating might make them qualify for IG or by issuers that consider themselves likely to experience a downgrade to below IG as some kind of hedge. When investors are aware of this, they may consider this extra rating a bad signal, i.e. that the issue/issuer apparently cannot get a sufficiently good rating from the other CRAs, or is expecting a future downgrade from those. However, if the additional (and potentially upward-biased) rating reduces the probability of experiencing bad effects from a downgrade, this may increase the price of the bond issue. The net effect on the credit spread depends on which of the two effects dominates. For financial firms, their credit rating is one of their most vital business assets, since it is used in so many market practices and regulations. Therefore, under the certification hypothesis, split ratings by Moody's and S&P should give incentives to get a Fitch rating. Moreover, in terms of rating changes, an extra rating may provide a hedge against the regulatory and rule based effects of rating downgrades while also increasing the probability to reap regulatory benefits from upgrades. This effect should be more pronounced for more volatile ratings over time.

Each of the three explanations of multiple ratings (Information Production, Rating Shopping and Certification), have distinct empirical predictions, though different explanations can co-exist. There are potential differences in whether or not we would expect (i) systematic differences across CRAs, (ii) positive association between uncertainty and the level and (iii) the number of ratings, (iv) an impact of the additional rating on credit spreads independent of the information contained therein, (v) the importance of regulatory boundaries and (vi) the association with the time series of rating changes.

Under Information Production, there would be no systematic differences across CRAs, more uncertainty would lead to more ratings but not affect their level; and if the additional rating confirms the other ratings and/or gives better information, credit spreads will be lower. Under Rating Shopping, systematic differences across CRAs are likely to exist, with additional / later ratings being better; more uncertainty would again lead to higher credit spreads and more ratings but now also to better ratings. Finally, under Certification, systematic differences across CRAs again could exist; uncertainty would play no role; unconditionally an additional rating could be a bad signal and thus increase credit spreads if it comes from a CRA that systematically provides better ratings; and strongest effects are expected when the marginal rating matters most for whether the bond issue satisfies the investment grade classification. The various empirical predictions are summarize in the table below, where '–' indicates that the hypothesis is not supported, '+' means it is supported, and '?' means no prediction.

Table 1. Empirical predictions **Reason for multiple ratings**	**Information Production**	**Rating Shopping**	**Certification Effect**
(i) Systematic differences across CRAs	–	+	+
(ii) Extra rating on average better	–	+	+
(iii) Uncertainty increases # of ratings	+	+	?
(iv) Unconditionally, extra rating is bad signal	–	–	+
(v) Regulatory / investment grade boundary crucial	?	?	+
(vi) Extra rating associated with higher time variation in ratings	?	–	+

2.3 Related Research

As asset pricing relies fundamentally on the production and dissemination of information, and this process is endogenously determined, the extent of the related literature is vast. CRAs are only one type of research and information provider to the securities markets. Much of the academic literature about the role of research and information providers has focused on equity analysts rather than debt rating agencies. Studies on the equity markets have addressed a broad range of questions about research providers, ranging from whether analysts' opinions convey value-relevant information, to whether conflicts of interest and personal strategic considerations influence the nature of the information provided. CRAs present a different institutional structure for analysis. While the same basic principals regarding information production apply, CRAs have become integral to regulation pertaining to the credit market (see also the discussion above).

Research about the role of CRAs is more limited, but has provided a useful framework for empirical study. Theory has asked what role CRAs play in the equilibrium pricing process. Boot, Milbourn and Schmeits (2006) highlight CRAs as a valuable coordination device. In a setting in which it is optimal for firms to separately offer informationally-insensitive securities, the investment-grade boundary provides a common signal delineating which securities of the firm can be regarded as such. In this framework, the CRAs provide little value-relevant information at the investment grade boundary other than certification, but some useful valuation information about riskier issues. The further implication of this theory is that firms might specialize at these contrasting tasks.

In contrast to Boot et al., Carlson and Hale (2005) point out that CRAs could also be de-stabilizing, because each investor's optimal strategy becomes highly dependent on the strategy followed by the other investors, once ratings have been issued. Thus, ratings can lead to a multiple-equilibrium problem. In a similar model, Bannier and Tyrell (2006) introduce reputation and competition among rating agencies. Under certain conditions, this will stimulate investors to search for private information and will thus not only restore a unique equilibrium, but could even lead to a more efficient one.

Each of the three potential explanations for multiple ratings has generated empirical research. On the issue of information production, a number of papers have looked at the effects of rating changes on asset prices. For example, Kliger and Sarig (2000) use a refinement in the Moody's ratings system to show that rating changes channel information to the market that changes the value of the debt. However, their results also suggest that this information leaves the aggregate company value intact and thus only influences the value of the debt relative to the value of the equity. Guentay and Hackbarth (2006) investigate the effect of analyst dispersion on credit spreads. They find that higher analyst dispersion is associated with higher credit spreads and conclude that this is probably due to cash flow uncertainty. Becker and Limbourn (2008) consider what happened when Fitch became the third rating agency after Moody's and S&P. They find that that "ratings became friendlier to issuers and less informative as competition increased." Morgan (2002) finds that banks, being inherently more opaque than industrials, are more likely to have rating disagreement between Moody's and S&P.

Jewell and Livingston (1999) investigate whether ratings differ systematically across rating agencies. They find that the average Fitch rating is much better than Moody's and S&P ratings, but that this effect disappears once they restrict their sample to bonds only rated by all three CRAs. They also investigate whether rating shopping takes place, but find no evidence. Covitz and Harrison (2003) look at the trade-off that rating agencies face between income resulting from giving out favorable ratings and expected future fees from customers resulting from reputation. They argue that reputation concerns dominate and prevent CRAs from being "bribed" by wealthy customers. Bannier, Behr and Güttler (2007), like Poon (2003) and Poon and Firth (2005), investigate possible adverse selection and hold-up in the context of CRA and issuer incentives when CRAs issue ratings on an unsolicited basis.[9]

In research most closely related to our own, Cantor and Packer (1997) also look for evidence of the information effect, the shopping effect and the certification effect. They use issuer-level ratings data for the year 1994 to understand the motivation for using a third rating agency, but do not use bond price and yield data to evaluate the market effects and price implications of the third rating. Like our paper, they find that the third CRA rating is systematically higher, however, they fail to find evidence that the

[9] Adverse selection may explain why unsolicited ratings are on average worse than solicited ones. That is, firms that receive a favorable unsolicited rating do not apply for a solicited rating anymore, whereas firms with an unfavorable unsolicited rating pay for another (solicited) opinion. On the other, CRAs could create a holdup problem by underestimating the creditworthiness of companies in their unsolicited ratings to prompt those companies to seek (improved) paid-for solicited rating subsequently. The general conclusion of this literature is that unsolicited ratings are lower than solicited ratings, and that this difference is largely due to adverse selection of debt issuers. There seems to be only weak evidence for holdup by CRAs. Our dataset does not include information on unsolicited ratings for US corporate bonds, so this paper does not address these findings.

use of a third CRA is motivated by information, rating shopping or certification effects. Since the time of their study, bond price data has become more widely available for research. This allows us to conduct more powerful tests of the market response to the additional rating, and to understand in greater detail how market participants interpret ratings.

Brister et al. (1994) find evidence of a "super-premium" in yields of junk bonds due to regulation around the IG boundary. Based on only S&P rating data, they find that yields increase disproportionally from a BBB to BB rating relative to the increase in default risk. Finally, in a recent paper Kisgen and Strahan (2009) find that credit spreads change in the direction of a Dominion bond rating after the accreditation of Dominion as an NRSRO. Moreover, they find that this effect is much stronger around the IG boundary, indicating the importance of certification.

With respect to the nature of the certification effect that we find, our research relates to earlier work on security design. Gorton and Penacchi (1990) set up a model that incentivizes uninformed investors to transform risky assets into information-sensitive and information-insensitive parts, where for the latter category they can avoid losses due to trading with informed investors. Boot and Thakor (1993), on the other hand, develop a model in which security issuers lower funding costs by making informed trading more profitable. Our setup motivating the exploration of the certification hypothesis uses key insights of both papers. In particular, the non-trading region in our setup is the result of the absence of the uninformed investor, whereas the uninformed investor is needed to make trading profitable for the informed investor.

3. Sample Construction and Methodology

3.1 Measures and controls

Section 2.2 derives empirical implications regarding systematic rating differences, the number of ratings and pricing for each of our three hypotheses. These implications originate from relevance of regulation, uncertainty/opaqueness about quality and time series variation in ratings. In our regressions, we measure uncertainty or opaqueness by analyst dispersion of the firm's earnings per share or by rating dispersion of the bond. We measure the importance of regulation by a dummy variable indicating whether a Fitch rating is or can be decisive for satisfying certain regulatory constraints like crossing the IG barrier. To avoid capturing timing mismatches between (multiple) rating transitions, we require that any particular ratings situation has existed for at least a quarter. For the financials, we measure the importance of regulation by the effect of rating dispersion contrasted to that of analyst dispersion. Rating dispersion can also be a measure of uncertainty or opaqueness (like the IG barrier dummies, we also require stability of the difference over at least 1 quarter). But where rating dispersion is also a measure of regulatory relevance, analyst dispersion is not, which will get us the required identification. For financials, we also use dummies similar to those for industrials but focused around the AAA, AA and A boundaries rather than the IG boundary, since financials are typically highly rated. Time variation in ratings is hard to measure, since ratings are rather persistent. Therefore, we do not explicitly include time variation in ratings as a variable in our regressions but analyze the correlation between having a Fitch rating and the likelihood of experiencing rating changes.

To avoid spurious results due to omitted variables in our regressions, we correct for several issue and issuer characteristics as well as for business cycle effects. On the issue level, we correct for callability (using a dummy), size (offering size), and term structure effects (duration and convexity). On issuer level, we correct for credit risk (using the inputs of the Merton (1974) model, leverage and volatility), profitability (ROA), systematic risk (equity beta) and tangibility of assets (PPE/total book assets). Tangibility of assets is important since Moody's as the only CRA also incorporates expected recovery in their ratings. We also include R&D intensity (R&D expenditure over book assets) as an additional control. R&D intensity can be associated with several pricing mechanisms in the corporate bond markets. For example, higher R&D industries may have higher growth opportunities and therefore lower credit spreads. On the other hand, R&D projects tend to be riskier than normal projects, which may increase credit risk. We will control for the aggregate effect. In the pricing regressions, we also include macro-economic variables as controls for business cycle effects, since default probabilities, liquidity and risk premia are likely to vary with the business cycle.[10]

3.2 Data and filters

For our main analysis, we use pricing data from the TRACE database and merge it with bond characteristic and rating data from FISD, equity data from CRSP, financial data from Compustat Industrial Quarterly and analyst data from I/B/E/S. Our time series ranges from July 1st 2002 up to December 31st 2007.[11] The TRACE data contain all trades in TRACE-eligible bonds by NASD members that were disseminated to the public. The dissemination to the public happened in phases, resulting in an expanding universe of bonds. A more comprehensive description of the TRACE database as well as the dissemination process is given in Downing, Underwood and Xing (2005).

We apply several filters to our dataset to remove bonds with special features that we do not want to consider, and to remove seemingly erroneous entries.[12] Next, we use the FISD characteristics to match the trades to bond characteristics using CUSIPs. We only take senior unsecured notes and bonds. We discard all bonds that are exchangeable, putable, convertible or pay-in-kind, that have a non-fixed coupon, that are subordinated, secured or guaranteed or are zero coupon bonds. Removing callable bonds would reduce our sample substantially, so we leave those in, but correct for this feature in our regressions using a dummy variable.

[10] As an alternative, we included month fixed effects, but results were virtually identical.
[11] The TRACE database starts in July 2002.
[12] We remove all trades that include commission, have a settlement period of more than 5 days, and all trades that are canceled. Trades that are corrected, we correct. Moreover, we remove all trades for which we have a negative reported yield, since these will be mainly driven by implicit option premia in the yield. We also found trades with a settlement date later than or equal to the maturity date and removed those bonds. Furthermore, we found several records that we suspect to be duplicates, resulting from both parties involved in a trade reporting to the system. Thus, we filter out duplicate trades that have identical prices, trading time and volume. Moreover, some of the yields changes are extremely high or low. We remove trades with yields of more than 1500 bps. Finally, we deleted all issues with a duration of less than 1 year.

To diminish the impact of remaining data errors, we average all trades in each bond by trading day. To reduce the effect of over-representation of very liquid bonds, we then make monthly observations by only recording for each bond the last daily average credit spread of every month. To avoid issues with severe illiquidity and distressed debt as well as issues relating to non-linearity of credit spreads with respect to rating scales, we remove all issues with an average (based on Moody's, S&P and Fitch ratings, if available) worse than BB- (Ba3). For all bond trades in our sample, we calculate yields and credit spreads. The benchmark rate that is used to construct credit spreads is based on an interpolation of the yields of the two on-the-run government bonds bracketing the corporate bond with respect to duration.

Ratings data is obtained from FISD as provided by Mergent. The credit ratings data provider confirmed that due to changes in their data collecting procedures, the rating data before 2000 is incomplete. This is illustrated by Figure 1, which shows the number of rated bond issues each quarter by Moody's, S&P and Fitch as well as the proportion of all bond issues in the sample rated by each of these CRAs in a given quarter from 1994 – 2007. While the number of rated bond issues is steadily increasing over time for all three CRAs, the sudden jump in the number of issues rated by S&P strongly suggests that too many bond issues before 2000 have missing S&P ratings (i.e., issues had S&P ratings, but these are missing from the database). Specifically, the percentage of all issues rated by S&P equals 58% at the end of 1999 and jumps to 94% in 2000, and remains above 90% until the end of the sample. There is likewise a significant, though smaller, jump in the percentage of bond issues rated by Fitch, from 29% at the end of 1999 to 39% in 2000. As a result, for the analyses that can done without pricing data, we use rating data from the second quarter of 2000 onwards only. For our credit spread regressions the impact of this will be minor, as TRACE only starts in the middle of 2002 and is dominated by data from 2004 onwards (when the number of bond issues contained in TRACE is greatly expanded).[13]

Equity market data is obtained from CRSP. We calculate (rolling window) historical daily volatility and betas to the CRSP value-weighted index based on half a year of historical trading data. An AR(1) filter is used to filter out bid-ask bounces in daily closing prices. For an observation to be included, we need at least 111 return observations in the last half year.

Company data is obtained from Compustat Quarterly. We download data on firm size (total book assets), debt (long and short term debt), profitability (earnings), tangibility of assets (PPE), R&D spending (obtained from Compustat Annual, since usually reported in the annual only) and industry (SIC code). From these data, we construct a leverage variable (total debt over total book assets), a tangibility of assets variable (PPE/total book assets), an R&D spending variable (R&D expenses/total book assets and a dummy for missing values) and a profitability variable (total earnings over total assets). We also construct a 'SIC division' variable that is defined as the division that the 2-digit SIC belongs to.

[13] Another more minor issue is that FISD also confirmed that only from mid 2003 on, they have been using automated rating feeds from the CRAs, whereas before that time these ratings were collected by hand, increasing the potential for data errors in the earlier period.

Monthly analyst forecast data on the one yearly EPS are obtained from I/B/E/S. We download summary data including number of analysts, standard deviation of forecasts, minimum and maximum forecast from the unadjusted file. Following Guentay and Hackbarth (2006) we divide forecast dispersion measured by analyst standard deviation by the share price to end up with dispersion per dollar value invested.

We also include several macro-economic variables. From the Saint Louis FED website, we obtain GDP growth and inflation. From the CBOT website, we get the VIX as a measure of market wide volatility. Following Campbell and Taksler (2001), we include the risk-free rate that was also used to construct the credit spread and the 10 year minus the 3 month yield on government bonds as a measures for the level and the slope of the term structure, respectively. Finally, again following Campbell and Taksler (2001), we include the TED spread, defined as the difference between the yield of 3-month LIBOR versus 3-month treasury debt, as a measure for liquidity and aggregate credit market sentiment capturing flights to quality and liquidity.

Almost all bonds in our final sample are rated by both Moody's and S&P (see also Figure 1). Specifically, about 95% of all bonds in our database with at least 2 ratings are rated by both S&P and Moody's. This lack of cross-sectional variation in having an S&P or Moody's rating means that we can only study the implications for having Fitch as a third rating.

Accordingly, we remove from our sample all bond issues that do not have ratings from both S&P and Moody's.[14] For this sample of bond issues rated by both Moody's and S&P and using quarterly observations for 2000-2007, about 60% of observations have a Fitch rating. As a result, the main focus of our paper will be to consider the 'marginal' role of Fitch ratings, while controlling for S&P and Moody's ratings. Table 2 presents summary statistics for the quarterly ratings sample, and Table 3 for the monthly credit spread sample.

4. Empirical results

4.1 Rating Differences and Rating Information

Following Cantor and Packer (1997), we first test whether Fitch ratings are on average better than Moody's and S&P ratings for the same issue in the same quarter, and present the results in Table 4 and Figure 2. The table presents evidence against an information effect, since the extra Fitch rating is in general significantly better than the Moody's and S&P rating. S&P is also in general more optimistic than Moody's but the difference is much smaller (both for the full sample and for the Fitch-rated sample alone). These differences are potentially explained by differences in philosophies between the two major firms. Moody's rates issues on the expected loss due to default, while S&P focuses on the probability of default. The effect of these philosophical differences is most apparent in the low rating

[14] The only exception is Table 3, which presents differences across ratings and the number of ratings by each of the three CRAs.

categories. Issues with a low rating usually have a high loss given default. Consequently, Moody's systematically gives a worse rating in this category, whereas Fitch and S&P seem to agree, on average. It is mainly in the two middle categories, where regulation is likely to have the most impact, that the optimism of Fitch is largest.

Having established that Fitch is on average more optimistic for IG bonds than Moody's and S&P, we investigate the bond market reaction to the ratings issued by Fitch. Specifically, we are interested in the informational content of a Fitch rating compared to the informational content of a Moody's or S&P rating. To minimize issues relating to selection, we limit ourselves for this test to the sample that is rated by all three CRAs. For this sample, we regress end-of-month credit spreads on dummy variables for the median rating, controls and dummy variables for each of the three CRAs indicating whether the CRA gave a rating above or below the median rating for that bond (we also interact these directional dummies with the distance to the median rating in number of notches). Results can be found in Table 5, using directional differences to the median rating in Panel A and using the size and direction of differences to the median rating in Panel B. All credit spread regressions in the paper use standard errors clustered by issuer, include a large number of controls with time dummies, and are run with and without issuer fixed effects.

The credit spread regressions in Panels A and B of Table 5 indicate that S&P ratings appear to be highly informative. Both directional dummies have highly significant coefficients in the expected directions, with or without issuer fixed effects and in both panels. In the full specifications including directional dummies for all three CRAs (columns 7 and 8 of Panel A, with and without issuer fixed effects, respectively), the results are symmetric, indicating that the credit spread is about 8 to 15 basis points higher (lower) if the S&P rating is worse (better) than the median rating.

Moody's directional dummies also show clear evidence of containing information that is relevant to the bond price. In all specifications, credit spreads are 9 to 14 basis points higher if the Moody's rating is worse than the median rating. For Moody's, the directional variables are only significant for those indicating a worse rating, which may be due to a lack of data on the positive direction (see Panel C of Table 5).

For Fitch ratings, there is no evidence of informational content in the directional dummies. There is no significance with the 'right' sign in any of the four specifications with Fitch directional dummies in Panel A without issuer fixed effects, nor in any of the four specifications also incorporating the size of the difference of the Fitch rating to the median rating in Panel B (with or without issuer fixed effects). The only marginal significance is in columns 4 and 8 of Panel A (with issuer fixed effects). When investigating this further, we find that this effect disappears completely when we restrict our sample to issues with a median rating of BBB or better (column 9). Thus, the only impact Fitch seems to have is around the regulatory IG boundary and this impact does not change with the size of the Fitch rating difference.

As a side note, the frequency of ratings relative to the median (see Panel C of Table 5) confirm the results in Table 4. For both Moody's and Fitch, these are clearly asymmetric and significantly different, with Moody's having a greater frequency of ratings worse (20.9%) than ratings better than the median (4.17%), with the opposite for Fitch (3.6% and 34%, respectively). For S&P, whose ratings are most often the median rating, deviations are more symmetric, with 11.4% worse and 7.3% better than the median.

Table 6 presents another test to investigate the informational content of Fitch ratings on credit spreads. Here, the sample consists of all issue rated by both Moody's and S&P, and thus no longer conditions on also having a Fitch rating as for the sample used for Table 5. While correcting for the average Moody's and S&P rating (using 4 rating group dummies), we look at the informational content of having a Fitch rating and of the Fitch rating dummy (also using 4 rating groups). We also test whether the coefficients on the four Fitch rating dummies are jointly equal to zero. We include all the controls of Table 5, though their coefficients are not reported to save space. Each specification also includes year dummies and is run with and without issuer fixed effects.

The results of Table 6 are broadly consistent with Table 5. Without issuer fixed effects, none of the Fitch rating dummies are significant, while the rating dummies for the average Moody's and S&P ratings are highly significant. With issuer fixed effects, some of the Fitch dummies are significant, but this is mainly due to the fact that the two most extreme rating categories (AAA and BB) are associated with a higher credit spread after taking into account standard controls. There seems to be little distinctive information in Fitch ratings of AA, A and BBB. This point is also clear from column 5 which is identical to column 4, except for the fact that a Fitch A rating is taken as the 'base case' for creating Fitch rating dummies. Jointly, these 'middle ratings' by Fitch seem to differ only marginally, with no evidence of any difference at all if issuer fixed effects are included (p-value of 74%, column 4).

Moreover, the regression with issuer fixed effects provides some evidence that when a Fitch rating is added, this is associated with an increase of credit spreads by at least 6.75 basis points. As we separately control for the Fitch rating group, this increase does not depend on the actual rating Fitch has given. This suggests that the market may consider having a Fitch rating to be a negative signal.

These findings clearly conflict with an information and a rating shopping effect since under both effects one would expect the credit spread to be influenced by the direction of the extra Fitch rating. Neither hypothesis would one expect that having a Fitch rating itself may be a negative signal. This leaves us with a puzzle that we will try to address in the remainder of this paper. Why would an issuer apply for a Fitch rating if there is no informational benefit from doing so, even if such a rating is on average better than the Moody's and S&P ratings? A possible explanation could be certification. Therefore, in later regressions we will specifically consider any certification benefit, which seems most likely to occur for issues whose ratings are close to the investment grade boundary.

4.2 Likelihood for Having a Fitch Rating

In this section, we use logit regressions to consider which factors explain having a Fitch rating. We include in our model variables that may be related to each of the three hypotheses. We employ several proxies for information uncertainty: (i) the dispersion or the absolute difference in number of notches of the Moody's and S&P ratings, (ii) volatility of daily stock returns, (iii) equity analyst dispersion. Further, we include variables that may be related to the relative importance of ratings, such as leverage, firm size and issue offering size. A positive coefficient on the variables relating to information uncertainty could be interpreted as evidence for an information or rating shopping effect.

We investigate the certification effect by including variables pertaining to the possible impact (assuming Fitch as the marginal rater) of an additional Fitch rating on regulatory effects around the IG-HY boundary. As these are greater if the average Moody's and S&P rating is closer to the IG-HY boundary, we include the number of notches the average Moody's and S&P rating is below and above this boundary (columns 2-4). As the number of notches their average rating is away from the IG boundary is by construction positive in both directions, Fitch ratings having a certification effect would imply that these variables have a negative coefficient.

Next, we exploit the regulation feature that if an issue has three ratings, the median rating should be used to determine the issue's rating. We construct a dummy 'Fitch could push IG' which is equal to one if Moody's and S&P ratings are on opposite sides of the IG-HY boundary. In this case, an additional Fitch rating would be decisive about whether or not the issue becomes investment grade. Without a third rating, an issue with Moody's and S&P ratings on opposite sides of the boundary would be below investment grade for regulatory purposes, as in case of two ratings the worse rating should be used. Therefore, if the Fitch rating is above investment grade, the median rating will be above investment grade as well. A positive coefficient on the dummy indicating the condition that Fitch could push the bond over the IG-HY boundary would be evidence for a certification effect. As a robustness check, we also include a dummy variable indicating whether Moody's and S&P ratings are on opposite sides of the A- boundary. The A- boundary obviously does not have the same regulatory importance as the investment grade boundary, such that its coefficient would be expected to be insignificant.

Finally, we add several other controls that influence bond prices, such as rating group dummies based on the average Moody's and S&P ratings, whether the issue is redeemable, the maturity, liquidation values (using proxies for fixed assets and R&D expenses), and always include industry dummies. Standard errors are again clustered by issuer. The marginal effects of the logit regressions are presented in Table 7, where the dependent variable equals 1 if the issue has a Fitch rating, and zero otherwise. The sample consists of all issues that are rated by both Moody's and S&P.

Empirically, we find that all the coefficients on variables related to uncertainty (i.e., analyst dispersion, equity volatility and the dispersion between Moody's and S&P ratings) are either insignificant, or have the wrong (i.e., negative) sign for an information or rating shopping effect. Thus, we find no support in the data for either the information or the rating shopping effects.

On the other hand, column 2 indicates that the closer the average of the Moody's and S&P ratings is to the IG-HY boundary, the more likely it is that the issue has a Fitch rating. Once controls are included in columns 3 and 5, or rating group dummies are added in columns 4 and 5, this effect becomes asymmetric. Therefore, it is especially for issues whose Moody's and S&P rating is above the IG-HY boundary, that being further away from the boundary is associated with a lower likelihood of having a Fitch rating. The marginal effects show an economically large impact, with a Fitch rating likelihood being reduced by about 10% for each notch the average Moody's and S&P rating is above (i.e., better than) the IG-HY boundary. In general, this result suggest that having a Fitch rating is strongly related to certification or the regulation pertaining to ratings.

We consider the importance of the regulation effect more directly in columns 6 and 7 (excluding and including rating group dummies, respectively). The coefficient on the 'Fitch could push IG' dummy is large, positive and strongly statistically significant in both specifications. The coefficient of 0.112 in column 4 means that issues where Moody's and S&P ratings are on opposite sides of the IG-HY boundary are 11.2% more likely to have a Fitch rating. We interpret this as strong evidence in favor of a certification effect: it is precisely in those cases where the marginal rating (i.e., Fitch) is decisive for the critical regulation classification of the bond issue into investment and non-investment grade, that Fitch is most likely to (be asked to) give a rating. Finally, the positive coefficients on leverage and log total assets indicates that issuers for whom the monetary impact of ratings is largest are more likely to have an extra Fitch rating.

The results presented above possibly suffer from endogeneity concerns, as having or getting a Fitch rating is clearly a choice of the firm. For that reason, we next model the time that elapses before an issue gets a Fitch rating, thus only using a sample of issues that start without a Fitch rating. In particular, we estimate a Cox proportional hazard model where a 'failure' is defined as the event of getting a Fitch rating. The Cox model has the convenient property that one can focus on the relative rank of each subject in the cross-section by ignoring the baseline hazard rate and optimizing the partial likelihood function only. The baseline hazard rate can be separated out (as in any proportional hazard model), but also needs no specific parametric form that can influence our results. Estimates of this regression can be found in Table 8, which confirms that 'Fitch could push IG' is strongly associated with getting a Fitch rating, while none of the three main measures of uncertainty provide any evidence for the information production hypothesis.

4.3 Price Effects of Certification

In this section, we consider possible price effects of certification. We previously documented that there is little evidence a Fitch rating provides new information to investors, i.e., we found no association between bond prices and Fitch rating differences with respect to the median rating or the average rating of Moody's and S&P. However, we also found that having a Fitch rating is strongly related to Moody's and S&P ratings being on opposite sides of the investment grade boundary. Therefore, a natural question is how important for credit spreads could a marginal Fitch rating be in this latter case where (assuming it is the marginal or third rating) a Fitch rating would decide whether the issue is investment grade?

Our sample consists of all bonds with both Moody's and S&P ratings. The endogeneity of having a Fitch rating is a major concern, i.e. companies self-selecting on quality or other characteristics in their decision to have a Fitch rating. Table 7 finds that lower Moody's or S&P ratings, lower idiosyncratic volatility, higher leverage and large size are all characteristics associated with a greater likelihood of having a Fitch rating. In the subsequent credit spread regressions, we control for all of these characteristics, and also include rating group, industry and year dummies, as well as dummies for whether the issue has a Fitch rating, and whether any Fitch rating is below or above the average Moody's and S&P rating. The rating group dummies are based on the average Moody's and S&P ratings[15], such that they do not incorporate any effect of the Fitch rating on the mean rating. Directly controlling for whether the issue has a Fitch rating should significantly mitigate selection worries, unless issues where Moody's and Fitch are on opposite sides of the boundary are significantly different in some characteristics that we do not control for. However, as we control for several other measures of uncertainty, including the dispersion of the Moody's and S&P ratings and a dummy for their average rating, we do not think that we have missed any such obvious characteristic. However, our strongest control for self-selection may be the inclusion of issuer fixed effects, for which the estimated certification effects are also strongly reduced.

A robustness check for certification is the coefficient on a dummy variable indicating that the Moody's and S&P ratings are on opposite sides of the relatively innocuous A- boundary. This coefficient would not be expected to be significant under any of the hypotheses considered.

Table 9 presents the pooled panel regressions of credit using monthly credit spreads for the sample of bond issues with both Moody's and S&P ratings, for the time period of 2002-2007. The first three rows show the impact of a Fitch rating when it is better than, equal to or worse than, the average Moody's and S&P rating. Confirming the results of Tables 5 and 6, when the Fitch rating is better, this does not lead to a lower credit spread. Instead, the sign is even opposite, and significantly so with issuer fixed effects. This does not support a rating shopping effect, but would be consistent with an information effect or a certification effect where applying for the third rating is perceived as a signal of bad quality. However, when a Fitch rating confirms the average Moody's/S&P rating, credit spreads are even higher and significantly different from zero. This lends support to a certification effect with bad signaling and goes strongly against an information effect.

[15] We code notched rating categories with consecutive integers that increase as quality declines. However, when one rating notch is odd and the other is even, then the mean rating is not an integer. To avoid too many rating classes, we round up to the nearest integer. This potentially produces a bias towards lower average ratings. To correct for this, we include in the regressions a dummy indicating whether the average rating was rounded or not.

Around the IG-HY boundary, however, we see that Fitch ratings are strongly associated with credit spreads if Moody's and S&P are on opposite sides of the investment grade boundary. If the Fitch rating tips such an issue into investment grade, that issue has a substantially lower credit spread, and the opposite if the Fitch rating is below investment grade. The difference in credit spread is not only statistically but also economically quite large, e.g. equal to 45 basis points in column 2 of Table 9. This would suggest that there are significant certification effects for bond prices associated with a Fitch rating. If issuer fixed effects are used (see column 6), the size of the effects around the IG boundary become much weaker (6.5 basis points) and insignificant. We believe that this is mainly due to a lack of time variation of our specific experiment pertaining to the more general certification effect: cases where Moody's and S&P are on opposite sides of the IG-HY boundary are not very frequent to begin with and changes to these dummy variables occur even more rarely for a given issuer.[16] Alternatively, the lack of robustness with issuer fixed effects could also be due to the endogeneity of the certification estimates, which cannot be ruled out, our many controls for uncertainty notwithstanding. However, the coefficients of the role of the Fitch rating around the A- boundary do not show evidence of any large or significant effects (e.g., they are not statistically different from zero or have the 'wrong' sign).[17]

Interacting the proxies for uncertainty with the dummy for a more positive Fitch rating gives interesting results. Uncertainty measured by analyst dispersion goes in the direction predicted for an information production effect, but with no statistical significance. Uncertainty measured by credit rating dispersion seems to have a statistically and economically significant impact on pricing in the direction predicted by information production. One concern is that this result could be driven by non-linearity in the rounding of the rating scale as described above, especially since A and BBB rated bonds are much more likely to have Fitch rating. Therefore, we do the test excluding all observations where the rating disagreement is only 1 notch, since these observations always lead to rounding and are dominating the sample of split rated bonds, which after their removal will be dominated by disagreement of 2 notches which will not give a rounding effect. In this test, the direction is still the same, but there is no statistical significance anymore. Finally, adding issuer fixed effects removes the effect completely (see column 11).

4.4 Financials

For firms in the financial industry, a strong credit rating is one of their core assets, due to the business they are in as well as due to the high level of regulation that they are subject to. Thus, for financials the question of what drives multiple ratings is most relevant, but also harder to answer than for industrials. One of the reasons is that financials actively manage their credit rating and that several controls like leverage for industrials have a different meaning than for financials. Even within the group of financials, one would expect different controls for different segments. For that reason, we do not

[16] For the variables 'Fitch makes IG' and 'Fitch denies IG' the frequency of *changes* in these variables is only 0.165% and 0.07% of bond/month observations, respectively.

[17] Other unreported robustness checks showed that these findings also hold for credit spreads around the issue date of a bond and when the Fitch rating scale is adjusted by one notch.

conduct credit spread regressions for financials, since they tend to be very sensitive to time-varying firm and sector-specific controls. This issue seems less prevalent in the credit rating regressions for financials, so we focus on those.

Under the certification hypothesis, financials would value an additional opinion very highly if it qualified them for a better rating, that is, in the case of a split rating by Moody's and S&P. However, split ratings can also be an indication of opaqueness. To distinguish between the cases of information production and rating shopping, we also use equity analyst dispersion and stock return standard deviation as proxies for informational uncertainty. The results in Table 10 give the equivalent of the results in Table 7 for financials.

Credit rating dispersion between Moody's and S&P is strongly associated with a higher probability of having a Fitch rating, whereas the other measures of uncertainty are not. This can be seen by looking at the boundaries of the regular rating buckets.[18] Similarly, we present the equivalent of Table 8 for financials in Table 11 (Cox regressions for the time to getting a Fitch rating). In the Cox regressions, the effect of rating dispersion is confirmed (as well as the contrasting, insignificant, result for analyst dispersion). The results on the boundaries are not significant, but this can be due to the smaller sample and most prominently due to the very high proportion of bonds that already have a Fitch rating when they enter the sample.

5. The nature of certification

In this section, we further explore the main empirical finding of our paper, namely strong evidence that multiple ratings are used for certification purposes. The certification effect can be motivated by rules and regulation, but could also have a deeper origin going back to the fundamentals of security design. In this section, we first develop the theoretical intuition for how (multiple) ratings could help resolve market breakdowns in a setting with information-sensitive and insensitive assets and heterogeneous investors. Next, we show that the empirical patterns in the data are in line with the empirical predictions of such a setting.

5.1 Information-sensitive versus Information–insensitive securities

Imagine a bond market with two types of risk averse investors: type I investors with a time-varying natural demand for bonds and high research costs, and type II investors without the natural demand but with low research costs. For simplicity, one could think about type I investors as commercial banks, insurance companies and pension funds, where the natural demand for bonds stems

[18] Notice that we dropped a few controls like leverage, R&D intensity and PPE. As mentioned above, this is due to the fact that these controls have an entirely different impact on financials than on industrials and also differ in impact between the different classes of financials (e.g. leverage for an insurance company may have quite a different effect than leverage for a bank).

from the random flow of deposits and claims, and type II investors as hedge funds and proprietary trading desks. Both types of investors are aware of each other's properties and existence.

Next, suppose that there is a continuum of risky credit assets and that uncertainty about fundamentals increases with decreasing credit quality. Type II investors can purchase information about bond *i* at a cost M_i. With probability p_i this information gives a reduction in uncertainty by a fixed fraction of total uncertainty, where p_i is increasing with declining credit quality and M_i is increasing and convex in credit quality (thus, in terms of expected uncertainty reduction, it has increasing returns to scale).

Since type I investors are at an information disadvantage relative to type II investors, they will invest in securities for which the informational gain of type II investors is small, i.e. in informationally insensitive assets, to avoid losses due to trading with informed investors (see Gorton and Pennacchi, 1990). Type II investors can trade these assets with type I investors without problems. Typically, type II investors will provide liquidity to this market to accommodate aggregate demand shocks.

On the other end of the credit quality spectrum, it is worthwhile for type II investors to generate the information needed, because they do not suffer from the negative effect to utility due to uncertainty; if they need to trade due to liquidity shocks, they trade amongst themselves on an equally informed basis. The region in the middle suffers from a market breakdown. Type II investors could make money if they could profit from informed trading with type I investors (as in Boot and Thakor, 1993). However, for type I investors, the losses due to informed trading prevent them from investing in this region. Credit ratings could give an informative (but potentially noisy) signal about whether or not spending on research will yield information or not. If the conclusion is "no substantial information benefit", then type I investors would invest and type II would not bother to research. If the conclusion is "significant information benefit", then type I investors would not invest and type II investors would invest to hold the security. The IG boundary is the prime candidate for the location on the credit quality spectrum where the unconditionally expected gains from informational trading offset the costs for acquiring information.

5.2 Empirical implications

Several implications follow from the setup described above. First, controlling for systematic risk, HY assets will have a substantially higher yield than IG assets, since the research costs would have to be covered and the type II investors would require some form of rent (assuming capital for these investors is limited and low credit quality firms compete for funding). Moreover, firms whose credit risk is far away from the IG-HY boundary have little incentive to add an extra rating, since the probability that it will change anything is small (p_i is either very small or very large in these regions). Therefore, we expect the most extra ratings in the middle region. Both of these predictions are confirmed by several of the findings in the previously discussed results. Specifically, Tables 6, 7 and 9 document the discontinuity of credit spreads and the importance of the (marginal) Fitch rating around the IG-HY boundary, consistent with the discontinuity between informational-sensitive and insensitive securities. For example, Table 7 indicates that most Fitch ratings are found for firms in the middle of the credit risk spectrum, i.e. for issues with ratings closer to the boundary, and, foremost evidence for the certification effect, that Fitch is significantly more likely to give a rating if Moody's and S&P ratings are on opposite sides of the boundary. These effects are confirmed by Table 8, which models to time to getting a Fitch rating. Both are indications of the importance of the IG-HY boundary.

Second, since type I investors expect to be hit by (idiosyncratic) liquidity shocks, they are not only interested in current information sensitiveness, but also in future information sensitiveness. A future switch from securities being information-insensitive to information-sensitive can be due to changes in firm information-sensitiveness, or higher expected gains resulting from research. By adding a Fitch rating, issuers can try to prevent such transition and to strengthen beliefs about their securities' information-insensitiveness in periods when benefits of research are high. Thus, if firms use (marginal) Fitch ratings to try to qualify their issues as informationally-insensitive securities, then the need to do so will be greater if they expect their other ratings (i.e., Moody's and S&P) to change in the future. Unfortunately, ratings are too persistent to empirically estimate the frequency of rating changes reliably from the rating history. However, we can do the analysis the other way around, i.e. we estimate the association of the probability of undergoing a future rating change with a dummy for having a Fitch rating and several controls for opacity and volatility. The results can be found in Table 12, using only issues rather by both Moody's and S&P, and using the sample of all corporate bonds except financials in Panel A and the sample of financials only in Panel B. Indeed, we find that having future rating changes is positively related to having a Fitch rating for both samples, over and beyond the usual measures of volatility and opacity. For industrials, having a Fitch rating is associated with a quarterly transition probability that is 0.6% to 0.8% higher, which is economically sizable (Moody's and S&P transition probabilities are 5% and 4.6% respectively).

Third, as the market-wide degree of uncertainty varies over time, so will the relative benefit of information trading. Specifically, when market wide uncertainty goes up, the marginal benefit of informational trading goes up as well, such that some credit issues will then move from information-insensitive to information-sensitive. Typically, these will be credit issues close to the IG-HY boundary that ex-ante may have needed more ratings to protect against downgrades. As a result, in times of greater aggregate uncertainty type I investors will, on average, move away from the issues with credit quality close to the IG-HY boundary, to be substituted by type II investors, leading to higher credit spreads in lower quality categories. This leads to two empirical predictions. First, the certification effect of Fitch ratings is more important for firms that are more likely to transition from information-sensitive to insensitive if aggregate uncertainty increases, and such firms should have larger credit spreads. As a result, we would predict a positive coefficient on the interaction between the dummy for having a Fitch rating and our proxy for aggregate uncertainty. Second, changes in aggregate uncertainty should matter most for credit issues around the IG-HY boundary.

Table 13 uses the CBOE VIX-level (i.e., the implied volatility of options on the S&P 500 index) as a time-varying measure of uncertainty, and uses it as an additional control in pooled credit spread regressions for the sample of all issues rated by both Moody's and S&P. In column 1, we find that credit spreads are generally higher when the level of the VIX is higher, even if all the other controls as well as rating and year dummies are included. Therefore, VIX seems an important additional control. Column 2 shows that the major certification result, of significantly lower credit spreads if Fitch pushes the issue into the IG classification, is robust to the addition of the VIX control. In column 3, we find the predicted result that the interaction of VIX and having a Fitch rating has a significant and positive coefficient, such that having a Fitch rating is associated with a larger credit spread during times of greater uncertainty. Importantly, adding this interaction also reverses the (significance of the) unconditional effects of having a Fitch rating in columns 1 and 2 (and see also Table 9).

The larger credit spread for Fitch-rated issues in Table 9 had raised the question of whether a Fitch rating contains a negative signal, and if so, why. These new results suggest that there is no negative signal in having a Fitch rating per se. Rather, Fitch ratings seem to be used for certification purposes, where the need for certification is greater when aggregate uncertainty is larger. In other words, those issues shifting from information-insensitive to sensitive when aggregate uncertainty increases tend to be rated by Fitch. Thus, for certification purposes, they add Fitch, but the effect is not strong enough to put them at par with issues that do not need Fitch when aggregate uncertainty is high. However, when aggregate uncertainty is low, the total effect of having a Fitch rating and the interaction with VIX cancel each other.

Confirming the second prediction, the results in column 4 of Table 13 indicate that changes in VIX matter most for credit issues with BBB and BB ratings. It is exactly for issues that are least informationally-sensitive, that changes in aggregate uncertainty increase the benefit of acquiring additional information the most.

Finally, as trading in informationally-insensitive securities is less costly, the liquidity of IG credit issues would naturally be much larger. This would even hold when the trading demands of all type I investors are perfectly correlated. In a competitive market, Type II investors would provide liquidity and take the other side of the trades in exchange for only a fraction of the utility improvement of the type I investors. In order to show this, we measure monthly bond trading as each issue's aggregated trading volume over the total value of its outstanding bonds, and provide bond turnover regressions results in Table 14. As we include issue fixed effects in this regressions, these results measure the relationship between time series changes in the issue's ratings classification and bond turnover. We find that the investment grade classification has a substantial impact on liquidity, exactly as predicted. Using a sample of all bonds (excluding financials) rated by both Moody's and S&P, we find that having a Fitch rating is not related to bond turnover, but Fitch (as the marginal third rater) giving the issue an investment grade classification significantly increases turnover. The economic magnitude of these effects seems large. The mean monthly turnover is 0.64% (this variable is multiplied by a factor of 1,000 in the regression). Becoming HY is associated with a decrease in turnover by 0.19% points, which is 30% of the mean turnover.

6. Conclusion

Credit ratings play an important role in the capital markets. They are used by regulators and market participants to establish capital requirements and, in a legal setting, to provide safe harbor for fiduciaries. This widespread dependency upon credit ratings has the potential to influence how credit rating agencies (CRAs) are used by issuers and how their ratings are evaluated by the market. A number of theories have been proposed regarding how such dependency will affect the use of multiple CRAs, the type of rating issued by CRAs depending upon their strategic position, and finally about how the market interprets the informational output of rating agencies though the price formation process. Some theory suggests that they may further serve a useful coordination function that allows efficient allocation of information production in the capital markets.

In this paper, we utilize bond issue credit ratings, characteristics and market prices to evaluate some of these proposed theories. We test three hypotheses about three proposed effects: (i) an information effect; i.e. whether the third rater adds value-relevant information, (ii) a rating shopping effect and (iii) a certification effect – in particular whether a third agency plays the role of tie-breaker at the boundary of being classified as an investment-grade – high-yield rating.

Our empirical work contains several results. First, we find that significant differences exist across multiple credit ratings of the same bond issue at the same point of time, with Fitch ratings on average clearly more positive than Moody's and S&P ratings. This is consistent with Fitch playing a strategic role that reduces the threat that the other two CRAs could withhold investment-grade ratings, and extract compensation for certification, i.e., with Fitch being available to push bonds into the investment grade classification when the other two firms may disagree.

Bond price data reveal how the market regards a rating by the third agency. In general, credit rating agencies provide useful information to the market about credit risk. However, we find no robust evidence that Fitch ratings provide additional information incorporated in bond prices, relative to the information contained in the Moody's and S&P ratings. Thus even though Fitch ratings are on average clearly better than Moody's and S&P ratings, there seems little information contained in these ratings that the bond market incorporates. This rules out the information and rating shopping hypotheses.

We find strong evidence that Fitch ratings have a certification effect. The likelihood of having a Fitch rating is strongly associated with Moody's and S&P ratings being on opposite sides of the investment grade boundary. This suggests that in equilibrium, Fitch ratings are sought as a kind of 'tie-breaker' in these cases. However, there is no evidence that Fitch ratings are relatively better if the Fitch rating is decisive for the investment grade classification, as compared to all other Fitch ratings. This is further evidence against ratings shopping or that issuers paying for ratings can significantly influence such ratings when they would, at the margin, benefit most.

In the cross-section of bond prices, we find that the certification effect is strongly associated with credit spreads. Controlling for the average Moody's and S&P rating, for issues where Moody's and S&P ratings are on opposite sides of the investment grade boundary, a Fitch rating pushing the issue into the investment grade category has credit spreads that are about 45 basis points lower than if the Fitch rating would push the issue into the high yield category.

To explain the certification effect, we introduce a setting with bonds having information sensitivity that increases with declining credit quality. With profit-seeking agents on one side using costly information to trade (i.e., 'informed' investors) and agents with fluctuating demand for credit issues but a disadvantage for getting costly information (i.e., 'uninformed' investors) on the other, markets can break down for medium quality bonds, where informed investors can only profit if it is at the expense of the uninformed investors, who thus stay out of that market. Ratings as noisy signals for the potential of trading against informed investors can restore markets again, effectively limiting or erasing this medium quality category (Gorton and Pennacchi, 1990, and Boot and Thakor, 1993).

Empirical results such as higher liquidity for IG bonds, an increase in credit spreads for Fitch rated bonds in times of high uncertainty about fundamentals, as well as a concentration of Fitch ratings in the middle category of the rating spectrum, are all consistent with this setup. Therefore, the reported certification effects seem consistent with an equilibrium outcome in a market with information-sensitive and insensitive bonds, where (Fitch) ratings help to prevent market breakdowns.

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Figure 1. FISD database coverage by CRA

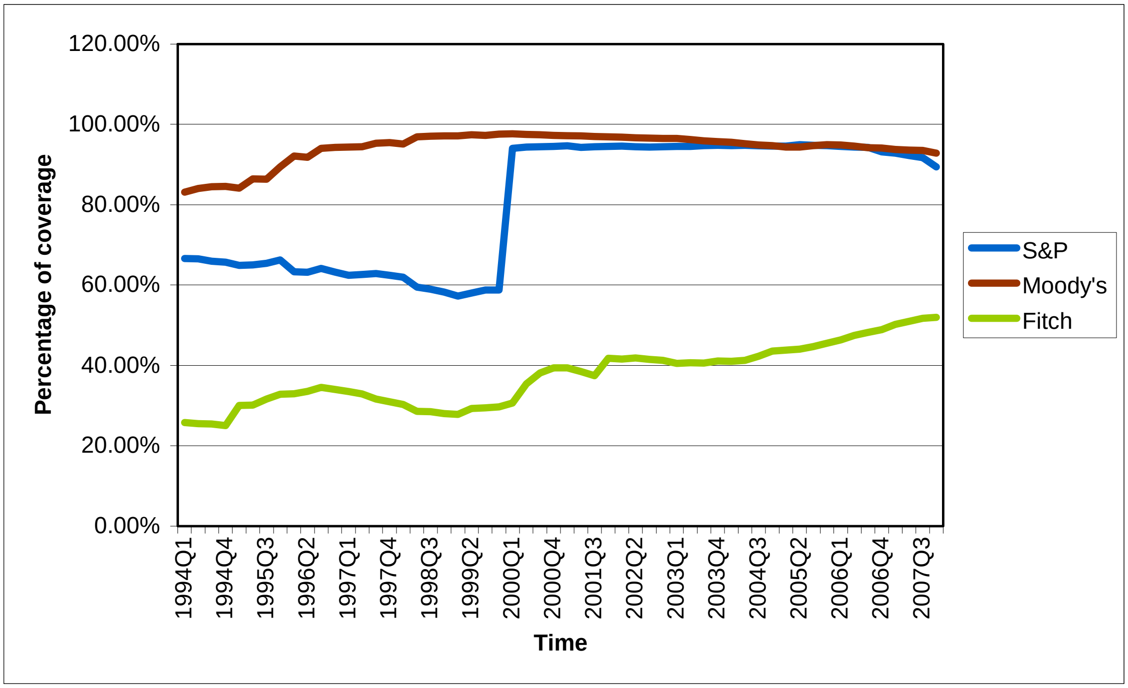

Figure 2. Rating Differences Across CRAs

Table 2. Summary Statistics of Quarterly Ratings Sample

The table presents summary statistics for the sample of bonds issues that have both a Moody's and a S&P rating in the quarterly rating sample for 2000 – 2007.

Variable	Obs	Mean	Std.dev	Min	Max	Description
Stdev	102141	0.017	0.008	0.001	0.12	Daily idiosyncratic equity volatility (past 180 days)
beta	102141	0.91	0.41	-1.01	3.08	Equity beta (past 180 days)
Log Total Assets	102141	10.29	1.62	18.42	26.45	Log of total book value of assets
Log Offering Size	102141	11.06	2.29	7.09	18.42	Log of offering_mat
PPE/assets	101874	0.34	0.23	0.003	0.94	PPE over total book assets
R&D/Assets	102141	0.013	0.021	0	0.20	R&D expenditure over total book assets
R&D missing	102141	0.39	0.49	0	1	R&D expenditure missing
Leverage	102141	0.36	0.15	0	1.74	Book leverage (debt/total assets)
Roa	102141	0.012	0.019	-0.63	0.41	Return on book assets (earnings/total assets)
N_analysts	102141	15.29	6.80	1	42	Number of analyst earning forecasts
Analyst Dispersion	101040	0.003	0.005	0	0.21	Standard deviation of analyst earnings
Analyst Spread	102141	0.009	0.017	0	0.62	Maximum minus minimum analyst earnings
Redeemable	102141	0.52	0.50	0	1	Dummy if the bond is redeemable
Maturity	102141	9.75	10.50	0	98.52	Maturity left (years)
F_rated	102141	0.60	0.49	0	1	Dummy for Fitch rating
N_ratings	102141	2.60	0.49	2	3	Number of ratings
IG_distance_SPM	102141	3.05	2.48	0	8	Distance of avg_SPM_rating to IG boundary
Avg_SPM_rating	102141	6.74	3.17	1	13	Average of S&P and Moody's rating
Fitch push IG	102141	0.03	0.18	0	1	Fitch could push IG
Fitch push A-	102141	0.05	0.22	0	1	Fitch could push A-

Table 3. Summary Statistics for Credit Spreads Sample

The table presents summary statistics for the sample of bonds issues that have both a Moody's and a S&P rating in the monthly credit rating sample for 2002 – 2007.

Variable	Obs	Mean	Std.Dev.	Min	Max	Description
Duration	119514	6.40	3.78	1.00	18.91	Average duration
Convexity	119514	55.29	57.80	1.00	357.47	Convexity
Benchmark Yield	119514	0.043	0.007	0.011	0.055	Risk free benchmark yield
CS	119514	120.72	78.63	-326.75	1496.80	Credit spread
F_rating	78651	7.08	2.47	1	17	Rating Fitch (numeric)
M_rating	119514	6.65	3.27	1	17	Rating Moody's (numeric)
SP_rating	119514	6.50	3.20	1	18	Rating S&P (numeric)
Redeemable	119514	0.64	0.48	0	1	Dummy, 1 if the bond is redeemable
Maturity	119514	10.10	9.77	1.02	98.48	Maturity left (years)
Stdev	119514	0.014	0.005	0.001	0.09	Daily equity volatility (past 180 days)
Beta	119514	0.95	0.37	-0.49	3.12	Equity beta based on 180 day historical data
Mcap	119514	78900	119000	5835.76	505000	Market cap of the equity (in millions of $)
Log Total Assets	119514	10.52	1.57	5.79	13.54	Log of total book value of assets
Log Offering Size	119514	11.82	1.86	4.09	15.42	Log of offering amount
Leverage	119514	0.34	0.15	0.000	1.13	Book leverage (debt/total assets)
Roa	119514	0.014	0.018	-0.45	0.26	Return on book assets (earnings/total assets)
PPE/assets	119142	0.34	0.23	0.004	0.94	PPE over total book assets
R&D/Assets	119514	0.012	0.022	0	0.20	R&D expenditure over total book assets
R&D missing	119514	0.39	0.49	0	1	R&D expenditure missing
N_analysts	119514	16.21	7.06	1	42.00	Number of estimates
Avg_analyst	119514	0.061	0.031	-1.78	0.31	Average analyst earning forecast (per $ share value)
Analyst_disp	118566	0.002	0.006	0	0.47	Standard deviation of analyst earning forecasts
Analyst_spread	119514	0.009	0.019	0	1.28	Max minus min analyst earning forecast
VIX	119514	14.95	4.27	9.89	40.52	VIX implied volatility index (1 day lagged)
Inflation	119514	0.26	0.33	-0.49	1.33	Inflation from CPI index (1 month lagged)
GDP Growth	119514	1.40	0.42	0.58	2.35	GDP growth (1 qtr lagged)
TED Spread	119514	0.55	0.40	0.07	2.13	Yield spread between 3M eurodollar and treasury
Yield Slope	119514	0.98	1.13	-0.53	3.85	Yield spread between 3M and 10-year treasury
SP_rated	119514	1.00	0.00	1	1	Dummy for rating S&P
M_rated	119514	1.00	0.00	1	1	Dummy for rating Moody's
F_rated	119514	0.66	0.47	0	1	Dummy for rating Fitch
N_ratings	119514	2.66	0.47	2	3	Number of ratings
Avg_SPM_rating	113614	6.46	3.21	1	14.33	Average of S&P and Moody's rating
MSP Rating Dispersion	119514	0.44	0.71	0	12	Absolute dispersion between Moody's and S&P rating
Fitch Below Avg MSP Rating	119514	0.37	0.48	0	1	Dummy if Fitch rating worse than avg_SPM_rating
Fitch Above Avg MSP Rating	119514	0.03	0.18	0	1	Dummy if Fitch rating better than avg_SPM_rating
Fitch confirms Avg MSP Rating	119514	0.26	0.44	0	1	Dummy if Fitch rating equal to avg_SPM_rating
F Pushes Above IG	119514	0.015	0.12	0	1	Dummy if Fitch pushes over IG boundary
F pushes below IG	119514	0.009	0.09	0	1	Dummy if Fitch pulls under IG boundary
F Pushes Above A-	119514	0.028	0.16	0	1	Dummy if Fitch pushes over A- boundary
F Pushes Below A-	119514	0.013	0.11	0	1	Dummy if Fitch pulls under A- boundary
Crisis	119514	0.13	0.34	0	1	dummy for crisis period (from Jul 1st 2007)

Table 4. Average Rating Differences

Average rating differences for issues simultaneously rated by multiple CRAs, measured in rating notches, and split up by rating categories. Rating categories are defined by average Moody's and S&P ratings. A negative number means that the first mentioned rating agency gives on average a better rating than the other CRA in that comparison. Quarterly data for 2000-2007 are used. Standard errors are in brackets and clustered by issuer. One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Fitch vs Moody's	Fitch vs S&P	Moody's vs S&P (Fitch rated sample)	Moody's vs S&P (full sample)
All Bonds				
Difference	-0.558***	-0.421***	0.149**	0.157***
	[-5.16]	[-3.83]	[2.45]	[3.55]
N	60989	61121	61136	101947
Number of clusters	397	396	397	667
AAA to AA-				
Difference	-0.124	-0.139	0.011	0.0308
	[-1.57]	[-1.15]	[0.07]	[0.72]
N	3216	3210	3281	19361
Number of clusters	36	36	36	60
A+ to A-				
Difference	-0.787***	-0.651***	0.148	0.172*
	[-5.51]	[-4.90]	[1.41]	[1.94]
N	30893	30968	30954	40175
Number of clusters	137	137	137	219
BBB+ to BBB-				
Difference	-0.310***	-0.241***	0.0725	0.120***
	[-5.03]	[-3.53]	[1.17]	[2.61]
N	21045	21069	21063	33111
Number of clusters	262	263	262	438
BB+ and lower				
Difference	-0.478***	-0.00579	0.507***	0.489***
	[-4.19]	[-0.03]	[3.51]	[4.93]
N	5835	5874	5838	9300
Number of clusters	154	152	154	277

Table 5. Credit Spread Regressions of Rating Differences Relative to the Median Rating

Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds that are rated by all three CRAs on rating directions and sizes for all three CRAs, bond and firm characteristics, and macro-economic variables, with fixed median rating and year effects. Panel A includes dummies indicating whether each of the three CRAs rating was worse or better than the median rating, i.e. the direction in which the rating may be different. Panel B includes the size of the different to the median rating as well, interacting the dummy with the number of notches of the different with the median rating. Panel C gives the frequency of the difference to the median rating. The firm and bond controls include Leverage, liquidation/intrinsic value (PPE/total assets), R&D expenses (divided by total assets and a dummy if not available), ROA (return of assets), Stdev (daily equity volatility), Historical Equity Beta (half year daily corrected for BA-bounces), Log Total Assets (firm size, book value) and Log Offering Size (issue size), Redeemable (dummy for callability), Duration and Convexity. Macro-economic controls include market wide implied volatility (VIX), Inflation, GDP Growth, TED spread, and the level and slope of the term structure. T-statistics are in brackets (using standard errors clustered by issuer).

Panel A: Directional difference of median rating

	1	2	3	4	5	6	7	8	9
crisis	17.12***	19.03***	17.35***	19.30***	17.33***	19.23***	17.07***	19.15***	17.40***
	[7.31]	[8.19]	[7.47]	[8.28]	[7.37]	[8.24]	[7.31]	[8.20]	[10.89]
Moody's worse than median	11.95***	9.656***					13.65***	10.39***	4.854**
	[3.49]	[2.77]					[3.68]	[2.99]	[2.19]
Moody's better than median	-2.683	4.919					-4.102	3.979	4.899
	[-0.45]	[0.76]					[-0.74]	[0.67]	[1.14]
Fitch worse than median			2.957	14.52**			8.172	15.93***	3.813
			[0.50]	[2.25]			[1.35]	[2.63]	[0.49]
Fitch better than median			-0.637	-1.793			-0.961	-0.845	-0.18
			[-0.15]	[-0.49]			[-0.22]	[-0.22]	[-0.06]
S&P worse than median					5.204	10.94***	8.761***	13.07***	6.750**
					[1.61]	[2.72]	[2.88]	[3.32]	[2.47]
S&P better than median					-10.17***	-14.96***	-10.94***	-13.21***	-9.352***
					[-2.87]	[-4.50]	[-3.03]	[-3.80]	[-3.09]
ROA	-335.2***	-187.9***	-346.1***	-188.1***	-335.5***	-184.4***	-320.2***	-190.5***	-215.4***
	[-3.91]	[-2.79]	[-3.94]	[-2.81]	[-3.86]	[-2.75]	[-3.83]	[-2.89]	[-4.27]
Leverage	-15.5	-15.36	-19.2	-20.38	-21.38*	-14.29	-15.2	-17.15	18.36
	[-1.43]	[-0.39]	[-1.46]	[-0.51]	[-1.76]	[-0.37]	[-1.30]	[-0.44]	[0.84]
PPE/total assets	-16.55*	51.92	-18.53**	52.54	-19.94**	45.56	-18.67**	47.59	-40.43
	[-1.78]	[1.33]	[-1.98]	[1.43]	[-2.17]	[1.27]	[-1.99]	[1.23]	[-1.16]
R&D expense/total assets	-153.9**	304.2**	-117.5*	291.0**	-114.5*	289.8**	-145.6**	288.2**	160.3
	[-2.24]	[2.16]	[-1.69]	[2.06]	[-1.67]	[2.34]	[-2.04]	[2.17]	[0.97]
R&D missing	5.4	3.607	7.084	4.582	6.574	2.34	4.671	2.538	9.093*
	[1.11]	[0.70]	[1.39]	[0.92]	[1.28]	[0.50]	[1.01]	[0.51]	[1.67]
Log Total Assets	2.941	-4.587	3.243	-3.939	3.28	-4.429	3.214	-4.906	-6.486
	[1.22]	[-0.61]	[1.33]	[-0.52]	[1.24]	[-0.60]	[1.43]	[-0.68]	[-0.84]
Log Offering Size	-5.688***	-5.526***	-5.519***	-5.336***	-5.436***	-5.584***	-5.590***	-5.716***	-5.142***
	[-7.79]	[-6.29]	[-7.37]	[-5.96]	[-7.35]	[-6.30]	[-7.90]	[-6.50]	[-7.50]
Beta	-23.23***	-26.33***	-24.90***	-26.42***	-25.20***	-26.66***	-23.54***	-25.96***	-16.66***
	[-3.39]	[-4.39]	[-3.55]	[-4.37]	[-3.64]	[-4.43]	[-3.41]	[-4.34]	[-3.73]
Stdev	3698.7***	3595.2***	3778.5***	3578.9***	3773.4***	3559.7***	3691.8***	3542.1***	2415.5***
	[5.04]	[4.64]	[5.08]	[4.61]	[5.08]	[4.62]	[5.03]	[4.62]	[4.74]
VIX	1.519***	1.401***	1.485***	1.385***	1.493***	1.427***	1.524***	1.423***	1.206***
	[7.08]	[7.44]	[6.96]	[7.43]	[7.01]	[7.50]	[7.15]	[7.56]	[9.97]
Inflation	4.036***	4.386***	4.088***	4.292***	4.143***	4.366***	4.039***	4.324***	3.847***
	[4.21]	[4.95]	[4.18]	[4.77]	[4.32]	[4.93]	[4.21]	[4.91]	[5.52]
GdDP Growth	-4.222***	-4.634***	-4.150***	-4.743***	-4.130***	-4.559***	-4.219***	-4.655***	-4.794***
	[-3.12]	[-3.70]	[-3.05]	[-3.81]	[-2.99]	[-3.60]	[-3.13]	[-3.77]	[-4.90]
TED Spread	23.55***	24.47***	23.58***	24.43***	23.81***	24.80***	23.70***	24.70***	24.80***
	[13.03]	[13.51]	[12.77]	[13.26]	[13.09]	[13.73]	[13.26]	[13.75]	[15.99]
Term Structure Slope	-4.427***	-5.690***	-4.554***	-5.695***	-4.562***	-5.780***	-4.401***	-5.651***	-4.340***
	[-3.63]	[-4.44]	[-3.73]	[-4.53]	[-3.64]	[-4.48]	[-3.59]	[-4.37]	[-4.29]
Benchmark Yield	-643.9***	-659.1***	-647.9***	-672.5***	-657.6***	-680.1***	-662.8***	-679.7***	-405.4***
	[-3.55]	[-4.06]	[-3.54]	[-4.11]	[-3.63]	[-4.20]	[-3.69]	[-4.17]	[-3.03]
Duration	15.60***	14.39***	15.77***	14.51***	15.75***	14.44***	15.66***	14.44***	12.36***
	[11.58]	[11.63]	[11.33]	[11.74]	[11.51]	[11.69]	[11.61]	[11.61]	[10.80]
Convexity	-0.574***	-0.492***	-0.586***	-0.497***	-0.584***	-0.494***	-0.576***	-0.493***	-0.394***
	[-7.88]	[-7.86]	[-7.70]	[-7.95]	[-7.80]	[-7.88]	[-7.88]	[-7.84]	[-6.78]
Redeemable	0.319	1.513	0.178	1.352	-0.115	1.469	0.0668	1.502	1.456
	[0.12]	[0.57]	[0.07]	[0.50]	[-0.04]	[0.55]	[0.03]	[0.56]	[0.58]
Issuer FE	no	yes	no	yes	no	yes	no	yes	no
Median Rating Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Only BBB or better MSP	no	no	no	no	no	no	no	no	yes
N	78488	78488	78488	78488	78488	78488	78488	78488	65338
adj. R-sq	0.593	0.686	0.589	0.686	0.591	0.687	0.595	0.689	0.605
Number of clusters	368	368	368	368	368	368	368	368	262

Panel B: Size and Direction of Difference to Median Rating

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cs	cs	cs	cs	cs	cs	cs	cs	cs
crisis	17.07***	19.08***	17.40***	19.32***	17.32***	19.23***	17.08***	19.22***	17.53***
	[7.20]	[8.18]	[7.48]	[8.31]	[7.34]	[8.22]	[7.21]	[8.22]	[10.99]
# of Notches Moody's is worse than median	12.26***	9.001***					13.08***	9.410***	5.582***
	[5.30]	[3.32]					[5.88]	[3.77]	[4.37]
# of Notches Moody's is better than median	2.822	9.001					2.062	8.164	3.613
	[0.40]	[1.29]					[0.32]	[1.38]	[1.11]
# of Notches Fitch is worse than median			0.568	4.345			2.899	4.992	0.517
			[0.19]	[1.37]			[0.88]	[1.60]	[0.18]
# of Notches Fitch is better than median			2.388	1.979			1.552	2.372	1.242
			[0.63]	[0.60]			[0.45]	[0.75]	[0.42]
# of Notches S&P is worse than median					4.411*	9.979***	7.743***	11.57***	6.621***
					[1.68]	[3.39]	[3.26]	[4.32]	[3.15]
# of Notches S&P is better than median					-8.295***	-12.97***	-7.735***	-11.31***	-9.147***
					[-3.09]	[-5.36]	[-3.04]	[-4.28]	[-2.96]
Issuer FE	no	yes	no	yes	no	yes	no	yes	no
Median Rating Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Only BBB or better MSP	no	no	no	no	no	no	no	no	yes

Panel C: Relative Frequencies of Difference to Median Rating within sample rated by all CRAs

	Frequency	Freq. 1 Notch Different
Moody’s worse than median	20.94%	17.67%
Moody’s better than median	4.17%	3.51%
Fitch worse than median	3.55%	2.6%
Fitch better than median	34.00%	30.96%
S&P worse than median	11.36%	10.02%
S&P better than median	7.30%	6.31%

Table 6. Credit Spread Regressions with S&P-Moody's versus Fitch Rating Dummies

Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds on rating dummies for the average of Moody's and S&P as well as for Fitch, bond and firm characteristics, and macro-economic variables, with fixed median rating and year effects. See Table 5 for descriptions of control variables. T-statistics are in brackets (using standard errors clustered by issuer). We also test the joint relevance of the Fitch rating dummies.

	1	2	3	4	5
crisis	16.50***	18.31***	16.66***	18.33***	18.33***
	[9.77]	[12.01]	[9.86]	[11.95]	[11.95]
SPM - AA	-1.258	-2.677	-12.72*	1.04	1.04
	[-0.19]	[-0.35]	[-1.79]	[0.16]	[0.16]
SPM - A	12.07	19.87**	8.79	23.83***	23.83***
	[1.45]	[2.29]	[1.04]	[3.04]	[3.04]
SPM - BBB	46.11***	46.50***	42.16***	50.37***	50.37***
	[6.60]	[4.95]	[5.21]	[6.16]	[6.16]
High Yield S&P – Moody's Rating	144.9***	108.7***	129.4***	102.7***	102.7***
	[15.41]	[8.91]	[11.48]	[8.92]	[8.92]
Fitch Rating			11.31	23.35***	6.741**
			[1.10]	[2.81]	[2.18]
F - AAA					16.61**
					[2.07]
F - AA			6.989	-14.33*	2.277
			[0.66]	[-1.82]	[0.50]
F - A			-10.06	-16.61**	
			[-0.95]	[-2.07]	
F - BBB			-8.5	-14.23	2.381
			[-0.72]	[-1.64]	[0.60]
F - BB			13	10.9	27.50***
			[0.99]	[0.87]	[2.81]
Issuer Fixed effect	no	yes	no	yes	yes
Year FE	yes	yes	yes	yes	yes
N	119571	119571	119571	119571	119571
adj. R-sq	0.581	0.695	0.585	0.697	0.697
Number of clusters	616	616	616	616	616
Test F(AA)=F(A)=F(BBB)(p-val)			0.0735	0.74	0.74

Table 7. Logistic Regressions for Having a Fitch Rating

Logit regressions of having a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P), distance to IG boundary ('MSP Notches Below/Above IG,' both solely based on Moody's and S&P average rating) and whether the Fitch rating 'could push' the issue to IG or A-. 'F could push IG' ('F could push A-') is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG (A-) boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. Only marginal effects are reported, and t-statistics are in brackets (using standard errors clustered by issuer). One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AAA to AA-				0.376***	0.211**		
				[2.81]	[2.39]		
A+to A-	0.426***			0.465***	0.302***		0.425***
	[3.62]			[4.25]	[3.01]		[3.59]
BBB+ to BBB-	0.385***						0.383***
	[3.82]						[3.74]
High Yield (below IG)	0.293***						0.287***
	[5.96]						[5.62]
MSP Notches Below IG		-0.0936***	-0.0185	-0.0382*	0.00427		
		[-2.76]	[-0.90]	[-1.91]	[0.25]		
MSP Notches Above IG		-0.0784***	-0.0741***	-0.147***	-0.128***		
		[-2.67]	[-3.06]	[-3.14]	[-2.97]		
F could push IG						0.116**	0.0989**
						[2.34]	[2.13]
F could push A-						0.031	0.0118
						[0.53]	[0.20]
MSP rating dispersion	0.00333		0.0104		0.00321	0.00805	-0.00454
	[0.11]		[0.34]		[0.11]	[0.21]	[-0.13]
Idiosyncratic volatility	-9.068***		-9.143***		-9.120***	-9.011***	-9.059***
	[-4.68]		[-4.94]		[-4.88]	[-5.11]	[-4.73]
Equity Beta	0.0786***		0.0835***		0.0637**	0.141***	0.0789***
	[2.94]		[2.97]		[2.32]	[4.16]	[2.97]
Analyst Dispersion	0.442		-1.297		0.215	1.219	0.592
	[0.18]		[-0.50]		[0.09]	[0.48]	[0.24]
Leverage	0.355**		0.428***		0.311**	0.599***	0.364**
	[2.31]		[2.86]		[2.15]	[2.97]	[2.36]
PPE/total assets	-0.216		-0.266*		-0.229	-0.304**	-0.214
	[-1.54]		[-1.74]		[-1.55]	[-2.29]	[-1.53]
R&D expense/total assets	0.878		0.719		0.985	-0.251	0.915
	[1.08]		[0.99]		[1.31]	[-0.38]	[1.11]
R&D missing	-0.0465		-0.0287		-0.0213	-0.0464	-0.0452
	[-0.90]		[-0.54]		[-0.42]	[-0.87]	[-0.88]
ROA	0.143		0.342		0.285	-0.707	0.119
	[0.35]		[0.69]		[0.69]	[-1.19]	[0.29]
Log Total Assets	0.166***		0.176***		0.176***	0.135***	0.166***
	[7.90]		[7.98]		[8.98]	[4.38]	[7.86]
Redeemable	-0.0361		-0.0491		-0.0163	-0.0686	-0.0359
	[-0.93]		[-1.13]		[-0.49]	[-1.24]	[-0.92]
Log Offering Size	-0.00352		-0.0113		-0.0157*	0.0142	-0.00313
	[-0.42]		[-1.31]		[-1.94]	[1.09]	[-0.37]
Maturity left (years)	-0.0005		-0.00039		-0.00011	-0.00159	-0.00053
	[-0.31]		[-0.24]		[-0.07]	[-1.01]	[-0.33]
Maturity left squared	1.34E-05		1.95E-05		1.17E-05	0.0000297*	1.34E-05
	[0.71]		[1.06]		[0.67]	[1.70]	[0.72]
Industry FE	yes	yes	yes	yes	yes	yes	yes
N	88484	101947	88484	101947	88484	88484	88484
pseudo R-sq	0.226	0.104	0.221	0.174	0.248	0.177	0.227
Number of clusters	656	667	656	667	656	656	656

Table 8. Cox Regressions for time to getting a Fitch Rating

Cox Proportional Hazard model regressions of time to getting a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P), distance to IG boundary ('MSP Notches Below/Above IG,' both solely based on Moody's and S&P average rating) and whether the Fitch rating 'could push' the issue to IG or A-. 'F could push IG' ('F could push A-') is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG (A-) boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. The coefficients in the partial likelihood are reported, and t-statistics are in brackets (using standard errors clustered by issuer). One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
Redeemable	0.341***	0.167	0.354***
	[4.59]	[1.20]	[4.74]
Log Offering Size	0.0062	0.0222	0.00327
	[0.15]	[0.47]	[0.08]
Log Total Assets	0.321***	0.212**	0.319***
	[5.85]	[2.36]	[5.87]
Leverage	1.695***	1.868***	1.619***
	[4.22]	[3.74]	[4.08]
Analyst Dispersion	-42.94*	-36.15	-46.49*
	[-1.74]	[-1.45]	[-1.78]
Idiosyncratic volatility	-26.83***	-24.72***	-26.29***
	[-3.59]	[-3.46]	[-3.44]
Beta	0.293**	0.389**	0.283**
	[2.31]	[2.28]	[2.18]
F could push IG	0.851**	0.684**	
	[2.48]	[2.01]	
F could push A-	0.143	0.114	
	[0.57]	[0.46]	
MSP rating dispersion	-0.0814	-0.0372	-0.0209
	[-0.44]	[-0.20]	[-0.14]
PPE/total assets	-0.452	-0.756*	-0.431
	[-1.31]	[-1.95]	[-1.24]
R&D expense/total assets	4.047*	1.593	3.732
	[1.74]	[0.70]	[1.60]
R&D missing	-0.183	-0.184	-0.192
	[-1.15]	[-1.28]	[-1.20]
roa	-3.925***	-4.173***	-3.950***
	[-3.12]	[-3.42]	[-3.13]
Maturity left (years)	-0.0001	0.00107	-3.6E-05
	[-0.02]	[0.17]	[-0.01]
Maturity left squared	-5.9E-05	-4.9E-05	-0.00006
	[-1.03]	[-0.82]	[-1.02]
A+to A-	1.489***		1.489***
	[2.84]		[2.87]
BBB+ to BBB-	1.152**		1.172**
	[2.22]		[2.28]
High Yield (below IG)	1.184**		1.336**
	[2.20]		[2.47]
Industry dummies	yes	yes	yes
N	32589	32589	32589
pseudo R-sq	0.032	0.022	0.031
Number of clusters	654	654	654

Table 9. Credit Spread Regressions, Full Sample

Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds on bond and firm characteristics and macro-economic variables, with fixed rating and year effects. Main variables of interest are whether a Fitch rating is better (FR<MSP), equal to (FR=MSP) or worse (FR>MSP) than the average Moody's and S&P rating, as well as variables relating to regulator (IG) and random (A-) boundaries and variables measuring uncertainty (for description see Table 7), also interacted with having a Fitch rating. See Table 5 for other control variable descriptions. T-statistics are in brackets (using standard errors clustered by issuer).

	1	2	3	4	5	6	7	8	9	10	11
crisis	16.90***	17.03***	17.05***	15.31***	10.08***	18.30***	18.70***	18.68***	16.79***	16.80***	18.23***
	[10.47]	[10.43]	[10.53]	[5.42]	[5.84]	[11.97]	[10.48]	[10.44]	[10.46]	[10.45]	[12.14]
FR<MSP	4.78	5.898*	5.166*	5.497	8.909**	10.29***	5.211	5.205	4.135	4.394	10.01***
	[1.48]	[1.81]	[1.66]	[1.35]	[2.05]	[3.09]	[1.63]	[1.63]	[1.31]	[1.40]	[3.04]
FR=MSP	6.747**	6.856**	6.571**	7.545**	12.27***	10.54***	6.811**	7.101**	8.705***	7.663***	10.65***
	[2.43]	[2.50]	[2.41]	[2.11]	[3.34]	[3.27]	[2.52]	[2.56]	[2.95]	[2.79]	[3.06]
FR>MSP	24.46***	20.35***	19.76***	24.02***	22.62**	26.82***	24.53***	24.49***	22.86***	22.30***	28.33***
	[3.18]	[3.03]	[2.93]	[3.53]	[2.46]	[3.90]	[3.11]	[3.09]	[3.12]	[3.06]	[3.77]
F Pushes < IG		-27.95**	-27.46**	-24.82**	-30.03**	-6.419					
		[-2.38]	[-2.36]	[-2.34]	[-2.03]	[-0.74]					
F Pushes > IG		17.14	17.2	12.05	19.14	16.01					
		[1.18]	[1.18]	[0.80]	[0.65]	[0.95]					
F Pushes < A-			11.20*								
			[1.76]								
F Pushes > A-			11.07								
			[1.19]								
Analyst dispersion							1562.0***	1592.2***			
							[5.94]	[5.35]			
Analyst dispersion * FR=MSP								-111.7			
								[-0.32]			
Rating dispersion									4.857**		1.857
									[2.04]		[0.94]
Rating dispersion* FR=MSP									-5.618*		0.333
									[-1.71]		[0.13]
Rating dispersion(>1 notch)										5.414**	
										[2.20]	
Rating dispersion (>1 notch)* FR=MSP										-4.949	
										[-1.30]	
Rounding Dummy	-6.53***	-6.55***	-6.79***	-8.76***	-7.49***	-8.07***	-6.12***	-6.13***	-8.62***	-5.28**	-8.78***
	[-3.07]	[-3.01]	[-3.12]	[-3.38]	[-2.69]	[-4.15]	[-2.89]	[-2.89]	[-3.62]	[-2.46]	[-4.68]
Issuer FE	no	no	no	no	no	yes	no	no	no	no	yes
MSP rating FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Duration > median	no	no	no	no	yes	no	no	no	no	no	no
Rating > median	no	no	no	yes	no	no	yes	no	no	no	no
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	119763	119763	119763	64841	60414	119763	118816	118816	119763	119763	119763
adj. R-sq	0.61	0.611	0.612	0.617	0.583	0.706	0.617	0.617	0.611	0.611	0.706
Number of clusters	617	617	617	551	502	617	608	608	617	617	617

Table 10. Logistic Regressions for Having a Fitch Rating: Financials

Logit regressions of having a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P) and whether the Fitch rating 'could push' the issue to different major rating categories (AAA, AA, A or BBB). 'F could push *' is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the * category boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. Only marginal effects are reported, and t-statistics are in brackets (using standard errors clustered by issuer). One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
A+ to A-	0.00363	-0.0113	-0.0079
	[0.09]	[-0.34]	[-0.20]
BBB+ to BBB-	0.0177	0.0111	0.00798
	[0.36]	[0.23]	[0.14]
BB+ or worse	-0.0381	-0.102	-0.0429
	[-0.38]	[-0.63]	[-0.42]
MSP rating dispersion		0.0989***	
		[2.70]	
F could push AAA			0.0644***
			[3.29]
F could push AA			0.0894***
			[2.82]
F could push A			0.0445*
			[1.88]
Log of total assets	-0.0179	-0.0142	-0.0246
	[-0.84]	[-0.92]	[-1.13]
ROA	-3.36	-2.552	-3.645
	[-1.56]	[-1.42]	[-1.53]
Idiosyncratic volatility	-1.45	-2.228**	-2.471***
	[-1.42]	[-2.49]	[-2.89]
Equity beta	-0.0154	0.0271	0.00965
	[-0.30]	[0.71]	[0.25]
Analyst dispersion	-0.275	0.658	0.219
	[-0.17]	[0.42]	[0.14]
Time to maturity	-0.00305**	-0.00268**	-0.00227**
	[-2.22]	[-2.55]	[-2.12]
Redeemable (d)	-0.00207	0.0208	0.0124
	[-0.04]	[0.57]	[0.26]
SIC 6100-6199	0.0990***	0.116***	0.0967***
	[3.25]	[4.68]	[3.68]
SIC 6200-6299	0.146***	0.135***	0.131***
	[2.93]	[3.93]	[3.15]
SIC 6300-6399	0.0709	0.101**	0.0703
	[1.29]	[2.26]	[1.43]
SIC 6400-6499	0.0672***	0.0607***	0.0538***
	[3.63]	[4.62]	[3.23]
SIC 6700-6799	-0.0258	-0.003	-0.0198
	[-0.24]	[-0.04]	[-0.20]
N	50255	50255	50255
Issuer FE	No	No	No
pseudo R-sq	0.108	0.181	0.148
Number of clusters	150	150	150

Table 11. Cox Regressions for time to getting a Fitch Rating: Financials

Cox Proportional Hazard model regressions of time to getting a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P), distance to IG boundary ('MSP Notches Below/Above IG,' both solely based on Moody's and S&P average rating) and whether the Fitch rating 'could push' the issue to IG or A-. 'F could push IG' ('F could push A-') is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG (A-) boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. The coefficients in the partial likelihood are reported, and t-statistics are in brackets (using standard errors clustered by issuer). One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)
A+ to A-	0.543***	0.551**
	[2.59]	[2.28]
BBB+ to BBB-	-0.367	-0.113
	[-0.91]	[-0.37]
BB+ or worse	-0.417	-0.255
	[-0.85]	[-0.56]
MSP rating dispersion	0.406**	
	[2.19]	
F could push AAA		0.553
		[1.08]
F could push AA		0.489
		[1.51]
F could push A		-0.27
		[-0.52]
Redeemable	0.463**	0.449**
	[2.27]	[2.17]
Log offering amount	0.0119	0.00711
	[0.55]	[0.31]
Log of total assets	-0.0173	-0.0639
	[-0.24]	[-0.77]
Analyst dispersion	-0.653	2.422
	[-0.06]	[0.22]
Idiosyncratic volatility	-47.39***	-44.18***
	[-3.86]	[-3.83]
Equity beta	0.332	0.331
	[1.08]	[1.08]
roa	-31.04*	-32.70**
	[-1.86]	[-2.27]
Time to maturity	-0.0225	-0.0166
	[-1.43]	[-1.16]
Time to maturity squared	0.000114	0.0000795
	[0.64]	[0.49]
SIC 6100-6199	1.225***	1.013***
	[3.07]	[2.69]
SIC 6200-6299	0.825**	0.712*
	[1.99]	[1.73]
SIC 6300-6399	0.607*	0.526
	[1.67]	[1.36]
SIC 6400-6499	0.841**	0.865**
	[2.20]	[2.15]
SIC 6500-6599	-26.84***	-44.35
	[-30.24]	.
SIC 6700-6799	0.761	0.253
	[1.39]	[0.49]
N	9791	9791
pseudo R-sq	0.019	0.018
Number of clusters	151	151

Table 12. Logistic Regressions for Having a Rating Transitions

Logit regressions of having a rating transition on rating category dummies, a dummy indicating whether the issue has a Fitch rating or not, measures for uncertainty as idiosyncratic volatility, beta, Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P). See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. Only marginal effects are reported, and t-statistics are in brackets (using standard errors clustered by issuer). One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A. Samples of all firms except financials.

	1	2
	Moody's rating change	S&P rating change
Fitch Rating	0.00799***	0.00599**
	[2.82]	[2.46]
Idiosyncratic volatility	1.055***	0.732***
	[4.61]	[4.18]
Beta	-0.00436	0.000279
	[-1.03]	[0.07]
Analyst dispersion	0.485	0.373***
	[1.20]	[2.85]
MSP rating dispersion	0.00930***	0.00626***
	[5.52]	[3.43]
Issuer FE	no	no
MSP Rating FE	yes	yes
Year FE	yes	yes
N	94871	94871
pseudo R-sq	0.113	0.096
Number of clusters	650	650

Panel B. Sample of financials only.

	1	2	3
	Moody's rating change	S&P rating change	Moody's or S&P rating change
Fitch Rating	0.00321*	0.0156**	0.0210***
	[1.75]	[2.28]	[3.13]
A+ to A-	0.00118	-0.00168	-0.0011
	[0.56]	[-0.16]	[-0.09]
BBB+ to BBB-	0.0281	-0.0141	0.0308
	[1.64]	[-1.42]	[1.23]
BB+ or worse	-0.00420*	-0.0205***	-0.0289***
	[-1.65]	[-3.91]	[-3.71]
MSP rating dispersion	0.00163	0.0179**	0.0251**
	[1.47]	[2.09]	[2.50]
Idiosyncratic volatility	0.425	1.836**	2.182***
	[1.39]	[2.54]	[3.31]
Beta	-0.0165***	-0.0473***	-0.0755***
	[-2.90]	[-3.78]	[-4.38]
Analyst dispersion	0.360*	0.566	1.281**
	[1.78]	[1.34]	[2.00]
SIC 6100-6199	-0.00518**	-0.009	-0.00726
	[-1.97]	[-0.72]	[-0.41]
SIC 6200-6299	0.0157*	0.0592*	0.0982**
	[1.85]	[1.71]	[2.13]
SIC 6300-6399	-0.00922**	-0.00867	-0.0169
	[-2.35]	[-0.65]	[-1.08]
SIC 6400-6499	-0.00436**	0.0514	-0.00855
	[-2.04]	[1.01]	[-0.83]
SIC 6700-6799		-0.0173	-0.0315***
		[-1.62]	[-4.15]
MSP Rating FE	yes	yes	yes
year FE	yes	yes	yes
N	50031	50255	50255
pseudo R-sq	0.341	0.168	0.202
Number of clusters	139	150	150

Table 13. Credit Spread Regressions, Full Sample

Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds on bond and firm characteristics and macro-economic variables, with fixed rating and year effects. Main variables of interest are whether a Fitch rating is better (FR<MSP), equal to (FR=MSP) or worse (FR>MSP) than the average Moody's and S&P rating, as well as variables relating to regulator (IG) and random (A-) boundaries and the level of the VIX as measure for market wide uncertainty, also interacted with having a Fitch rating and rating categories. See Table 5 for other control variable descriptions. T-statistics are in brackets (using standard errors clustered by issuer).

	1	2	3	4
crisis	16.93***	17.08***	17.13***	16.18***
	[10.54]	[10.55]	[10.85]	[9.85]
FR<MSP	4.786	6.123*	-17.67**	-6.274
	[1.53]	[1.93]	[-2.07]	[-0.96]
FR=MSP	7.481***	7.564***	-16.48*	-5.044
	[2.71]	[2.77]	[-1.93]	[-0.77]
FR>MSP	25.52***	21.34***	-2.388	10.34
	[3.27]	[3.14]	[-0.23]	[1.09]
F Pushes < IG		-27.51***	-27.39***	-27.62***
		[-2.87]	[-2.87]	[-2.97]
F Pushes > IG		17.5	17.98	17.13
		[1.19]	[1.24]	[1.34]
Fitch Rating * VIX			1.602***	0.823**
			[2.91]	[2.02]
(AAA to AA-) * VIX				-0.706*
				[-1.85]
(A+ to A-) * VIX				-0.286
				[-0.60]
(BBB+ to BBB-) * VIX				2.284***
				[4.04]
(BB+ to BB-) * VIX				5.133***
				[6.57]
VIX	1.311***	1.320***	0.293	
	[7.08]	[7.11]	[0.99]	
Controls	yes	yes	yes	yes
MSP rating FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
N	119560	119560	119560	119560
adj. R-sq	0.609	0.611	0.612	0.622
Number of clusters	617	617	617	617

Table 14. Regressions for Liquidity effects of certification

OLS regressions of monthly bond turnover, measured as aggregated trading volume over total value of outstanding bonds on rating category dummies, boundary dummies, a dummy indicating whether the issue has a Fitch rating or not and controls for cross-sectional liquidity (age) as well as time series liquidity (TED spread). All other control variables are dropped due to the use of time and issue fixed effects. Monthly data for July 2002-December 2007 are used; the sample consists of all issues with both Moody's and S&P ratings. t-statistics are in brackets (using standard errors clustered by issuer). One, two and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2	3	4	5
AAA to AA-	-0.505	-0.584	-0.584	-0.577	-0.687
	[-0.84]	[-0.99]	[-0.99]	[-0.97]	[-1.12]
BBB+ to BBB-	0.361	0.37	0.39	0.422	0.372
	[1.27]	[1.30]	[1.36]	[1.42]	[1.30]
BB+ to BB-	-1.922***	-1.934***	-2.042***	-2.021***	-2.066***
	[-3.20]	[-3.22]	[-3.29]	[-3.25]	[-3.31]
TED Spread	-0.589**				
	[-2.44]				
Age	-1.214***	0.157	0.174	0.169	0.184
	[-7.08]	[0.08]	[0.09]	[0.09]	[0.10]
F makes IG			1.783***	1.788***	1.846***
			[2.65]	[2.66]	[2.68]
F denies HY			-1.657*	-1.615*	-1.609*
			[-1.78]	[-1.71]	[-1.77]
F makes A-				0.16	
				[0.48]	
F denies A-				-0.503	
				[-1.40]	
Rated by Fitch					-0.728
					[-1.25]
N	118093	118093	118093	118093	118093
adj. R-sq	0.308	0.31	0.31	0.31	0.31
Year FE	yes	no	no	no	no
Month FE	no	yes	yes	yes	yes
Issue FE	yes	yes	yes	yes	yes
Number of clusters	618	618	618	618	618