Tiebreaker: Certification and Multiple Credit Ratings*

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ABSTRACT

This paper explores the economic role credit rating agencies play in the corporate bond market. We consider three existing theories about multiple ratings: information production, rating shopping and regulatory certification. Using differences in rating composition, default prediction and credit spread changes, our evidence only supports regulatory certification. Marginal, additional credit ratings are more likely to occur because of, and seem to matter primarily for regulatory purposes, but do not seem to provide significant additional information related to credit quality.

Keywords: Credit Ratings, Credit Spreads

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Credit Rating Agencies (CRAs) report information about the credit risk of fixed income securities. 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 regulatory 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. Regulations may mandate insurance companies and banks to keep much higher reserve capital for high yield issues than for investment grade corporate bonds. Other institutions like pension funds and mutual funds are often restricted by their charters in the amount of HY debt they can hold. Taken together, more than half of all corporate bonds are held by institutions that are subject to rating-based restrictions on their holdings of risky credit assets (Campbell and Taksler (2003)). Lower demand for high yield bond can significantly increase the cost of borrowing for those issuers and is related to capital structure decisions (see Ellul, Jotikasthira and Lundblad (2009), Kisgen and Strahan (2009), Kisgen (2006, 2009)). The institutional and regulatory importance of credit ratings to issuers and investors has raised questions about whether the current system provides the proper incentives for issuers to fully disclose value-relevant information, and for investors to invest in research about credit risk.

Using a sample from 2000 - 2008, we document that almost all large, liquid US corporate bond issues are rated by both S&P and Moody's. Fitch typically plays the role of a "third opinion" for large bond issues[1]. During the time period the most prevalent institutional rule used for classifying rated bonds was that, if an issue has two ratings, only the lower rating could be used to classify the issue (e.g. into investment-grade or non-investment grade). However, for issues with three ratings, the middle rating should be used (see, for example, the NAIC guidelines or the Basel II accord).[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) is the 'tie-breaker' and will decide into which class the issue falls. Moreover, this rule directly implies that adding a third rating cannot worsen the regulatory rating classification, but could potentially lead to a higher one. Consistent with this option, we find that in about 25% of Fitch rating additions, the addition leads to a regulatory rating improvement, i.e., the resulting middle rating is higher than the lowest rating before the Fitch rating addition. Ex ante, such an improvement would be particularly important when S&P and Moody's ratings are on opposite sides of the investment grade boundary. Absent the improving third rating, the split between S&P and Moody's would result in a classification of high yield. Thus, the value of the Fitch rating is that it can only push the issue up into the investment grade category, not pull it down into the high yield category.[3]

In this paper, we explore the nature of this tie-breaking role in the context of the broader question of why corporate bonds generally have multiple credit ratings. We consider three hypotheses that could lead to demand for multiple credit ratings, an 'information production' hypothesis, a 'rating shopping' hypothesis and a 'regulatory certification' hypothesis. These are not mutually exclusive but they have some different empirical implications that we exploit to shed light on their relative importance.

Under the information hypothesis, investors are averse to uncertainty, which is reduced by adding extra ratings (see e.g. Güntay and Hackbarth (2010)). Under the rating shopping hypothesis, issuers 'shop' for an additional rating in the hope of improving their rating (see e.g. Poon and Firth (2005), Skreta and Veldkamp (2009), Sangiorgi, Sokobin and Spatt (2009)). Under the regulatory certification hypothesis (see e.g. Brister, Kennedy and Liu (1994)), market and regulatory forces can naturally arise from a need for credibly separating bond issues into two types: informationally sensitive and non-informationally sensitive (Gorton and Pennacchi (1990) and Boot and Thakor (1993)). These correspond to non-investment grade (also called high yield) and investment grade ratings, respectively. If the regulatory certification role of CRA dominates, only the weaker issuers may need a third rating. This leads us to investigate whether the option of a third rating leads to adverse selection effects. As mentioned before, these hypotheses are not mutually exclusive. For example, rating shopping could be more important and thus more prevalent around the HY-IG boundary.

We find the strongest evidence in favor of the regulatory certification hypothesis. First, we consider what happens if a Fitch rating is added for bond issues at the IG/HY boundary, when Fitch could be the tie-breaker and potentially move the bond issue into the IG class. The yield improves if Fitch rates the issue IG, but there is no change following a HY rating, with a 40 basis point difference between an IG and HY classification. This economically large difference suggests that the certification effect can significantly lower the issuer's cost of capital.

Second, Fitch rating additions or changes for issues that are not close to the HY-IG boundary do not seem to be related to changes in yields. We find this not only for Fitch rating additions in a sample of bond issues already rated by both Moody's and S&P, but also for the full sample of all bonds and using quarterly panel regressions of credit spread changes on rating updates made by Moody's, S&P and Fitch. In contrast, credit rating changes (especially downgrades) made by both Moody's and S&P

are significantly associated with credit spread changes across the whole rating spectrum.

Third, Cox proportional hazard model regressions indicate that having and getting a Fitch rating is positively associated with the potential to break the tie between Moody's and S&P ratings, but again only around the IG-HY boundary. Fourth and finally, comparing default predictions on a one year horizon across credit rating agencies for corporate bonds rated by all three agencies over 2000 - 2008, we find that Moody's ratings perform best, immediately followed by S&P and then by Fitch. Ratings by Moody's and S&P add significant forecasting power to those of Fitch, whereas the reverse is not the case. This is consistent with Fitch providing limited additional valuation information relative to that contained in Moody's and S&P ratings.

Thus, the credit spread change regressions provide no support for the information production hypothesis; i.e. that the additional Fitch ratings provide significant information to investors. However, further tests provide some suggestive evidence in support of the rating shopping hypothesis around the HY-IG boundary for possible regulatory arbitrage, but not anywhere else. While the additional Fitch rating tends to be more optimistic than pre-existing Moody's and S&P ratings, investors do not seem to incorporate such increased optimism by lowering credit spreads. This would undermine any rationale to engage in rating shopping. However, we find that the additional Fitch rating is "extra" optimistic for issues rated just below IG or for those issues where Fitch is the tie-breaker around the IG-HY boundary, i.e. more so than elsewhere on the rating spectrum. Those are exactly the issues where we would expect rating shopping incentives to matter most. Specifically, if Moody's and S&P ratings are on opposite sides of the HY-IG boundary, the additional Fitch rating is more likely than otherwise to lead to an improvement in the regulatory rating classification, which in this particular case means an improvement from HY to IG classification (using 'the worst of 2 and median of 3 ratings applies' rule). This evidence is suggestive of rating shopping around the HY-IG boundary, or that the marginal rating is used for regulatory arbitrage.[4]

Endogeneity is a significant concern in our study, as we rely on controlling for confounding variables for identification. We seek to mitigate major selection issues by focusing on credit spread changes and Fitch rating additions. We also directly estimate selection effects using the Cox proportional hazard model to explain the time to add the third rating.

Taken together, our results suggest that a major function of Fitch ratings could be to avoid adverse selection for intermediate quality corporate bonds (Gorton and Pennacchi (1990) and Boot and Thakor

(1993)). Relatively uninformed investors may be reluctant to trade bond issues where they may be at a considerable information disadvantage, i.e. HY or junk issues. Investors specialized at producing information might find it too costly to do so for medium quality issues, unless they can generate profit from trading at an informational advantage with uninformed investors, This could lead to a no-trade region for these intermediate quality bonds. An additional rating that give a clear signal about whether research will yield relevant information (or whether relatively uninformed investors may be at a disadvantage) could resolve such a no-trade region. The generally optimistic Fitch ratings may also be requested as a precautionary measure. For example, issues rated by Fitch ratings are more likely to have subsequent Moody's and S&P rating transitions, suggesting that these issues have relatively less stable ratings.

In the long run, a necessary condition for any 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 rating without research will not serve the certification purpose in the long run. If the regulatory emphasis on credit ratings is reduced or regulation as to which rating should be used is tightened in the aftermath of the recent credit crisis, the certification effect documented in this paper may become less pronounced. In particular, our results suggest that fewer firms may opt for multiple ratings as a result, unless the marginal CRA can convince the market that its ratings are useful not just for regulatory reasons but also provide additional information about credit risk (and particularly about separating information-sensitive from information-insensitive securities). Indeed, less regulatory emphasis on ratings may spur increased competition among CRAs to improve their information production, especially around the IG-HY boundary.

The remainder of the paper is organized as follows. Section I contains our motivation for the empirical tests and the various hypotheses in light of the existing literature. In section II, we discuss the sample construction and methodology. Section III presents the empirical results on the three hypotheses. Section IV concludes.

I Motivation

A Credit Rating Agencies and Regulation

There are currently 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 smaller CRAs that issue credit ratings that qualify for meeting regulatory standards. While the purpose of a credit rating is to reflect the credit-worthiness 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, the SEC requires that money market mutual funds hold instruments with a credit rating in one of the two short-term higher credit rating categories.[6] This effectively provides a "safe harbor" for money market mutual funds with respect to litigation over fund failures. Kisgen (2006) discusses the strong link between short and long term debt ratings and access to the commercial paper market. He concludes that in order to have access to the commercial paper market, typically a rating of BBB is required.

US insurance companies explicitly rely on NRSRO ratings for determining risk-based capital. In particular, bonds held by insurance companies are assigned capital charges based upon their credit ratings. For example, a US life insurance company needs to hold over 3 times as much reserve capital for a BB rated bond compared to a BBB rated bond. At the time of writing, European insurance companies will soon be subject to comparable regulations with the implementation of 'Solvency II.' Banking regulations enacted under the so-called 'Basel II accords' impose very similar risk-based capital requirements.[7] Many pension funds and mutual funds are restricted from investing in non-investment grade corporate bonds by their charter. 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-2010, a large portion of U.S. institutional portfolios are still subject to rules and regulation tied to ratings by a relatively small number of NRSROs. The impact of such rules and regulations on the functioning of the corporate bond market, in particular in determining supply and demand, is almost certainly non-trivial since a vast majority of this market is dominated by institutions that are subject to rating-related restrictions, either through explicit rules and regulations, or through restrictions stated in their charters.[8]

In June, 2008, the SEC proposed eliminating language in many regulations pertaining to NRSROs, and instead to 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-making process. In addition, several other regulations were implemented to try to make rating agencies more accountable and increase the transparency of the rating process. The motivation for these (proposed) changes stemmed from the subprime mortgage crisis that began in 2007, and from concerns that the top three CRAs may represent an 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 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 Barclays Capital (formerly Lehman Brothers) US Corporate IG Index.[9] 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.

B Why Multiple Ratings Matter

In this subsection, we consider three 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, as summarized in the next subsection. The three hypotheses we consider are (i) the "information production" hypothesis, (ii) the "rating shopping" hypothesis and (iii) the "regulatory certification" (or clientele, or regulation) hypothesis. Below, we will give a short description of each and discuss its testable empirical predictions. As these hypotheses could co-exist and are generally not mutually exclusive, we discuss both how they are related and how we can identify some differing empirical predictions that allow us to distinguish which hypothesis may dominate empirically. These empirical predictions are summarized in Table I.

First, the reason to apply for multiple ratings could be the need for increased information production. More ratings can reduce uncertainty about the credit quality of the rated bonds. In a setting in which each CRA relies on different kinds of information to rate bonds, multiple perspectives are advantageous and reduce uncertainty about default probability. CRAs may specialize in evaluating particular drivers of default and thus each may have some advantage that justifies its continued existence in the marketplace. Thus, 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. Moreover, under the information production hypothesis, an extra rating in agreement with the existing ratings would reduce credit quality uncertainty and thereby lower credit spreads.

Second, the "rating shopping" effect can arise in a setting in which CRAs do not perfectly agree or there is considerably uncertainty about credit quality, while issuers may have better information about their own credit quality. In this case, issuers can seek to maximize their average rating by soliciting multiple bids or following a stopping rule that chooses the first rating agency whose rating equals or exceeds the firm's own assessment of quality. Applying for private ratings and making these public only if favorable, or deciding which CRA to use based on advice from an investment bank that has knowledge about (gaming) each CRA's precise rating algorithms leads to similar patterns.

The rating shopping hypothesis thus predicts that issuers will only apply for any additional rating if they think it will be an improvement. Therefore, additional ratings are on average better. Further, if the issuer applies for an additional rating and this additional rating is an improvement, credit spreads should go down. This can be either because the additional rating is actually closer to the firm's true credit quality or because it is not, but the market mistakenly takes the new rating at face value. In the latter case, if the market is not fooled, there would be no incentive to engage in rating shopping.

The third explanation for multiple ratings is "regulatory certification". Financial regulation has traditionally relied heavily on credit ratings to determine the suitability and riskiness of fixed income investments. For instance, bond ratings are used to score the quality of bonds in the investment portfolios of insurance companies and banks and regulatory capital reserve requirements are determined by this score. Ratings are also important in the structured finance market, the commercial paper market, and the overnight repo market. They are used to determine "haircuts" at the discount window of the central bank and for determining whether projects qualify for government assistance (see for example the Basel Committee on Banking Supervision (2000)). They may be the basis for financial contracting between private parties, as the world witnessed in the case of AIG's rating downgrade that triggered a need for increased collateral in its counterparty arrangements. This event underscores the enormous potential impact of certification.

The most prominent distinction made in financial regulation as it pertains to credit ratings is whether an issue, issuer or structured product is "investment grade" (IG) or "high yield" (HY). 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 into investment-grade or non-investment grade. However, if an issue has three ratings, the middle rating is used (see for example the NAIC guidelines or the Basel II accord).[10][11] Therefore, if S&P and Moody's ratings are on opposite sides of the investment grade boundary, the Fitch rating (assuming it is third rater) will decide into which class the issue falls. This classification creates strong incentives for issuers trying to achieve an investment grade rating. Thus, the IG-HY boundary is associated with a clear discontinuity in institutional demand. Assuming a downward sloping demand curve, the lower demand for high yield bond significantly increases the cost of borrowing for those issuers (see Ellul, Jotikasthira and Lundblad (2010) and Kisgen and Strahan (2009)).[12]

Under the regulatory certification hypothesis, the principal value of a CRA which systematically gives better ratings (i.e., in our data Fitch) than the other CRAs (i.e., Moody's and S&P) is simply that it helps satisfy the bright-line requirements of financial regulation. A rating from this CRA could be requested by issuers for whom the extra rating might make them qualify for an IG classification.

In addition, issuers that consider themselves likely to experience a future downgrade from IG to HY could opt for an extra rating for precautionary motives. This could lead to adverse selection effects, as relatively weaker firms with higher credit spreads would then be more likely to apply for a Fitch rating.

Therefore, under the regulatory certification hypothesis, split ratings at the IG boundary by Moody's and S&P should give significant incentives to get an additional rating from Fitch. Moreover, an additional rating may provide a hedge against the regulatory and rule-based effects of possible future rating downgrades, while also increasing the probability to reap regulatory benefits from upgrades. This effect should be more pronounced for issuers expecting to have more volatile ratings over time.

Gorton and Pennacchi (1990) and Boot and Thakor (1993) show that the information and regulatory certification hypotheses can be inherently related in a setting with two types of investors, in which issues with a lower credit quality carry more uncertainty. Type I investors have a time-varying natural demand for bonds and high research costs, and type II investors are without the natural demand but have low research costs.[13] Since type I investors are at an informational disadvantage relative to type II investors, they will only invest in high credit quality 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)). 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.[14] The region in the middle could suffer from a market breakdown if Type II investors only make money if they could profit from informed trading with type I investors (as in Boot and Thakor (1993)).[15]

The importance of regulatory certification could be in preventing a market breakdown for intermediate quality bonds. In this setting, credit ratings can restore trading by reducing the uncertainty about the value of information. Ratings will not only yield information about credit quality, but also about the profitability of research. 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-HY 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. This setting thus explains how a certification effect could arise in equilibrium.

The regulatory certification and rating shopping hypotheses also have some possibly similar features. In particular, while a rating shopping effect could be observed across the whole rating scale, rating shopping incentives are likely strongest around the IG-HY boundary. Therefore, the distinction between these two hypotheses merits discussion. The central prediction of rating shopping is that additional ratings are, on average, optimistic relative to existing ratings. Thus, if rating shopping is most important around the IG-HY boundary, the positive bias of the marginal rating should also be largest there. In contrast, certification would give no reason to expect the additional CRA to be more positive there as compared to other parts of the rating scale. Specifically, certification predicts that if Moody's and S&P ratings are on opposite sides of the IG-HY boundary, it is significantly more likely the issuer pays for the (assumed marginal) Fitch rating. However, in contrast to the rating shopping hypothesis, regulatory certification does not imply that this Fitch rating would be relatively (to Moody's and S&P ratings) more positive than Fitch ratings at other part of the rating scale.

Second, the expectation of future rating changes decreases incentives for rating shopping but increases the importance for regulatory certification. Rating shopping is more worthwhile if investors expect that ratings will remain relatively stable, as in that case credit rating improvements are less likely to be undone or become redundant. Under the regulatory certification hypothesis, (future expected) rating volatility creates a strong precautionary motive, motivating issuers to get an additional rating to hedge against any possible future downgrade below IG.[16] For this reason, additional ratings may be associated with adverse selection, as issuers expecting more negative credit news may be more likely to apply for such precautionary, additional ratings.

Each of the three explanations of multiple ratings (information production, rating shopping and regulatory certification) thus has distinct empirical predictions, though different explanations can coexist. There are potential differences in whether or not we would expect (i) credit spread effects of agreeing ratings, (ii) credit spread effects of relatively optimistic ratings across the rating spectrum, (iii) more uncertainty increasing the number of ratings and (iv) extra ratings when these could push an issue into the IG category, (v) greater optimism of the additional rating around the boundary and (vi) any positive or negative association between additional ratings and the likelihood of future rating changes (see Table I for a summary).

[Table I about here]

Under information production, an additional rating that is in agreement with the prior ratings will reduce uncertainty and thereby lower credit spreads, while more uncertainty would make an additional rating more worthwhile and therefore lead to more ratings.

Under rating shopping, more uncertainty would again lead to more ratings since initial ratings will err more often. Additional ratings are likely to be better and better ratings would lower the credit spread.[17] Time variation in ratings makes shopping less worthwhile since the preferred outcome will be less stable.

Under regulatory certification, a better extra rating would only lead to a lower spread at the boundary but unconditionally an additional rating could be a manifestation of adverse selection (only weaker issuers take an extra rating) and consequently be associated with higher credit spreads. Higher time variation in ratings will give rise to a rating-hedging incentive and thereby increase the probability of having an extra rating even for issues that are not directly at the boundary.

C Related Research

As asset pricing relies fundamentally on the production and dissemination of information, and this process is endogenously determined, 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 CRAs rating corporate debt. 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 principles 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. 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 which CRAs provide little value-relevant information at the investment grade boundary other than regulatory certification, but some useful valuation information about riskier issues. Carlson and Hale (2005) point out that when each investor's optimal strategy is dependent on the strategy followed by other investors, the public rating provided by the rating agency can serve to coordinate investor actions. 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 finds support in the existing academic literature. 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. Güntay and Hackbarth (2010) 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.

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 customers. Bannier, Behr and Güttler (2010), 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.[18]

Inspired by the financial crisis and the allegations addressed at CRAs, several recent theoretical papers put forward models to motivate rating shopping. Skreta and Veldkamp (2009) develop a model where incentives for rating shopping increase as the complexity of the products increases. Bolton, Freixas and Shapiro (2009) show that naive investors in the market may give incentives to CRAs to inflate their ratings and that in a duopoly, this gives extra incentives for rating shopping, which in turn aggravates the problem. Sangiorgi, Sokobin and Spatt (2009) develop a theoretical model of rating shopping and explore biases in ratings conditional upon heterogeneity across issuers in the extent to which different raters agree.

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 more optimistic. However, they fail to find evidence that the 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 and use ratings.

Another closely related paper is Becker and Milbourn (2009), which considers the impact of the major growth in market share of Fitch since 1989. They find that more ”competition leads to lower quality in the ratings market: the incumbent agencies produce more issuer-friendly and less informative ratings when competition is stronger.” They explain this by applying the reputation model of Klein and Leffler (1981), considering CRA incentives to invest in information production in order to improve their reputation. First, such incentives would be weaker if future rents are diminished as a result of increased competition. Second, if demand is more elastic with greater competition, this may force CRAs to spend less on expensive information production or tempt them more responsive to issuer demands, potentially inducing rating shopping.

Brister, Kennedy and Liu (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. Moreover, 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. They also find that this effect is much stronger around the IG boundary, indicating the importance of regulatory certification. Finally, Kisgen (2006) and Kisgen (2009) investigate whether discrete rating boundaries influence capital structure decisions before and after rating changes respectively. Kisgen (2006) finds indeed evidence of reduced debt issuance when ratings are close to an up- or downgrade, suggesting that credit ratings directly affect capital structure decisions in a way not incorporated by traditional capital structure theories. Moreover, this effect is especially pronounced around the IG boundary. Kisgen (2009) finds that managers lower leverage after a rating downgrade, suggesting that managers target credit ratings rather than debt levels or leverage ratios. This effect is again more pronounced around the IG boundary.

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 regulatory 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.

II Sample Construction and Methodology

A Main Measures and Controls

We measure uncertainty or opaqueness by Analyst Dispersion of the firm's earnings per share or by the dispersion between Moody's and S&P ratings (like the IG-HY barrier dummies, we also require stability of the difference over at least 1 quarter).[19] While rating dispersion is also a measure of regulatory relevance, analyst dispersion is not, which will get us the required identification. We consider two measures of rating dispersion: *Notches of MSP Rating Dispersion*, which is the absolute values of the rating difference between Moody's and S&P, and *S&P and Moody's Disagree*, which is a dummy equal to one if their ratings are not the same.

Our main measure for the importance of regulations pertaining to the IG-HY boundary is denoted by *Fitch could push IG*, which is a dummy variable equal to one if Moody's and S&P ratings are on opposite sides of this boundary such that a Fitch rating would be decisive for the IG-HY classification. In some regressions this measure is interacted with the outcome from Fitch.

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 the 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 is the only CRA that 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 credit spread changes regressions, we also include time fixed effects as controls for business cycle effects, since market wide default probabilities, liquidity and risk premia are likely to vary with the business cycle.

B Data and Filters

For our main analysis, we use corporate bond 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 2008.[20] 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.[21] Next, we use the FISD characteristics to match the trades to bond characteristics using CUSIPs.[22] We only use 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.

To diminish the impact of remaining data errors, we average the prices of 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 available daily average credit spread of every month. We then construct quarterly observations by only looking at the last month every quarter. 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 average Moody's, S&P) worse than B- (B3). 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 - 2008. 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 85% 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 do not require pricing data, we use rating data from the second quarter of 2000 onwards. 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).[23]

[Figure 1 about here]

We follow convention and use a numerical rating scale to convert ratings. Therefore, for Fitch and S&P (with Moody's rating between parentheses), the numerical scores corresponding to the rating notches are, respectively, 1 for AAA (Aaa), 2 for AA+ (Aa1), 3 for AA (Aa2), 4 for AA- (Aa3), 5 for A+ (A1), 6 for A (A2), 7 for A- (A3), 8 for BBB+ (Baa1), 9 for BBB (Baa2), 10 for BBB- (Baa3), 11 for BB+ (Ba1), 12 for BB (Ba2), 13 for BB- (Ba3), 14 for B+ (B1), 15 for B (B2) and 16 for B- (B3). However, we will still refer to more optimistic ratings, i.e. implying lower bankruptcy likelihood, as 'higher' or 'better' ratings.

Equity market data is obtained from CRSP. We calculate (rolling window) historical daily idiosyncratic 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. Observations with SIC codes 9100 to 9999 (Public Administration) are excluded because of possible implicit government guarantees.

Analyst forecast data on the annual 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 Güntay and Hackbarth (2010), we divide forecast dispersion measured by analyst standard deviation by the share price to end up with dispersion per dollar invested.

We construct two samples with a quarterly frequency; a credit spread sample and a rating sample. Because the rating sample does not require trade observations, this is a more inclusive panel, especially for the less liquid bonds. Moreover, the period for which we have reliable data is also longer. 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 2000-2008, about 68% 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 II presents summary statistics for the quarterly credit spread sample. For completeness, Internet Appendix Table IA.I presents summary statistics for the quarterly ratings sample. Figure 2 presents the average credit spreads over our sample by rating category. There is very significant variation, especially starting the second half of 2007.

[Table II and Figure 2 about here]

III Empirical Results

A Rating Differences and Rating Information

Following Cantor and Packer (1997), we show that Fitch ratings are on average significantly more optimistic than both Moody's and S&P ratings for the same issue in the same quarter and present the results in Table III and Figure 3. 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).

[Table III and Figure 3 about here]

Next, we investigate the bond market reaction to the rating updates issued. We are most specifically interested in the informational content of Fitch rating changes compared to the informational content of Moody's or S&P rating updates. To minimize issues relating to selection, we limit ourselves for this test to the sample that is rated by all three CRAs. Table IV presents the results of regressing end-of-quarter credit spread changes on dummy variables for these up- and downgrades for each CRA. All regressions on credit spread changes in the paper use standard errors clustered by issuer (unless stated otherwise) and include a large number of controls with time fixed effects.

[Table IV about here]

The credit spread change regressions in columns 1 - 3 of Table IV indicate that all CRAs appear to be highly informative in single CRA specifications. However, in the joint specification in column 7, only S&P and Moody's rating updates seem to contain relevant information associated with credit spread changes. For example, Moody's and S&P downgrades, respectively, are related to credit spread increases of 8 and 17 basis points, respectively. However, Fitch rating updates are not statistically significantly associated with changes in credit spreads. In joint significance tests, we can reject that Fitch rating downgrade coefficients are equal to S&P or Moody's rating downgrade coefficients, though not for the equivalent rating upgrade coefficients. When we restrict ourselves to the upper end of the rating spectrum (see column 5, using only issues with average rating of A- or better), Fitch seems to contain no information even in the single CRA specification. We cannot reject that the reactions to Fitch upgrades and downgrades are statistically different from each other in the presence of the up and downgrades from the other CRAs, while we can for Moody's and S&P (see Internet Appendix Table IA.IX for these tests on Moody's and S&P).

However, rating changes of Fitch at the IG boundary do matter, i.e. when Moody's and S&P ratings are on opposite sides of the IG-HY boundary and Fitch could be the tie-breaker and change the classification of the bond issue into IG versus HY. Economically, the credit spread change associated with Fitch changing the classification to IG rather than HY is about 49 basis points in the full sample (column 4, p-value of 2.82%), about 41 basis points in a sample of bonds rated BBB+ or worse (column 6, p-value of 5.87%), and again about 41 basis points in the full sample controlling for Moody's and S&P rating updates (column 8, p-value of 6.07%). These results are consistent with a regulatory certification effect and inconsistent with an information effect.

Table V presents regressions of price reactions to Fitch additions after the bond has been in our sample for at least one quarter without a Fitch rating but with both Moody's and S&P ratings. Here, the sample consists of all issues 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 V. The subsequent table considers selection directly in modeling the addition of a Fitch rating using Cox proportional hazard model regressions. If selection effects were very strong, one could expect that the event of a Fitch addition by itself would be associated with a change in credit spreads. For example, if adverse selection would lead only firms with poorer prospects to request a (generally more optimistic) Fitch rating, we would expect to see a Fitch rating addition to be associated with an increase in the credit spread. However, column 1 in Table V indicates that a Fitch addition is not related to any change in credit spreads at all (coefficient of -2.28 basis points with a t-statistic of -0.65). This lack of any effect mitigates selection issues, although we do find a mild adverse selection effect in a robustness test in Internet Appendix Table IA.6 where the sample is restricted to the pre-crisis period.

[Table V about here]

Table V also fails to show any evidence in favor of an information production effect. When a Fitch rating is added that confirms the average Moody's and S&P rating, this does not lead to a significantly lower credit spread (see columns 2 - 7). Neither does the interaction of the added Fitch rating with measures of uncertainty show any significant effect (see column 6 with the Analyst Dispersion interaction and column 7 with the 'Notches of MSP Rating Dispersion' interaction). The negative (positive) sign of a Fitch rating added that is better (worse) than the average Moody's and S&P rating is consistent with rating shopping and information production, but is not statistically significant. Likewise, the coefficients on *Fitch Added, Better* and *Fitch Added, Worse* are not statistically different from each other.

However, columns 3 - 5 provide strong evidence in favor of the regulatory certification hypothesis. In the cases for which Moody's and S&P ratings are on opposite sides of the IG-HY boundary, a Fitch rating added that makes the issue qualify for IG is associated with a substantial drop in the credit spread. The difference between Fitch classifying such bond issues as IG rather than HY is associated with a difference in about 41 basis points (p-value of 3.23%) in the credit spread. This result is robust to using either the whole sample or only issues with average Moody's and S&P ratings between BBB+ and BB- (column 3 and 4, respectively) and to double clustering credit spread changes in both issuer and time dimensions.[24]

B Adding a Fitch Rating

This section considers the selection of Fitch as the third rater (all bond issues in our sample are restricted to be rated by both Moody's and S&P). In Table VI, we use Cox proportional Hazard regressions to model getting a Fitch rating, including variables that may be related to each of the three hypotheses. In the Cox model, an 'exit' 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), and therefore needs no specific parametric form that can influence our results.

[Table VI about here]

In our analysis, we employ several proxies for information uncertainty: (i) the absolute difference in number of notches difference between the Moody's and S&P ratings and a dummy equal to one if the S&P and Moody's ratings are different, (ii) idiosyncratic volatility of daily stock returns, (iii) equity analyst dispersion. We further include variables 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 information or rating shopping effects.

We investigate the certification effect by including the *Fitch Could Break Tie* dummy which equals one if Moody's and S&P ratings are on opposite sides of the IG-HY boundary. This approach exploits the fact that regulations typically prescribe that if an issue has three ratings, the median rating should be used to determine the issue's rating, while the worst rating should be used if there are two ratings. Therefore, if Moody's and S&P ratings are on opposite sides of the IG-HY boundary, an additional Fitch rating would be decisive about whether or not the issue becomes investment grade. 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), the maturity left and the square of the maturity left, and always include industry dummies. Standard errors are again clustered by issuer. The sample consists of all issues that are rated by both Moody's and S&P over 2000 - 2008.

Empirically, we find that all the coefficients on variables related to uncertainty (i.e., analyst dispersion, idiosyncratic equity volatility and a dummy indicating Moody's and S&P rating differences as well as a variable measuring the size of the dispersion in notches) are either insignificant, or have the wrong (i.e., negative) sign for an information or rating shopping effect. For example, we find that issues with greater idiosyncratic volatility are less likely to get a Fitch rating, even though further information production may be relatively useful for those issues. Thus, we find no support in the data for either the information or the rating shopping effects.

On the other hand, column 1, 2 and 5 show that if an issue has Moody's and S&P ratings on opposite sides of the IG-HY boundary, the (conditional) likelihood that the issue gets a Fitch rating increases considerably. The economic significance of the coefficient on *Fitch could push IG* is considerable. For example, the coefficient of 0.717 in column 1 implies that issues where Fitch is the tie-breaker have about twice ($2.05 = \exp(0.717)$) the hazard rate, i.e. are about twice as likely to get 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 much more likely to (be asked to) give a rating.

The downside of the Cox regression is that it basically discards any observations that already have a Fitch rating, thereby ignoring some potentially useful information. Therefore, we try to corroborate the results that regulatory certification is an important explanation for having a Fitch rating by directly modeling having a Fitch rating using a logistic regression. Estimates of this regression can be found in Internet Appendix Table IA.VII, which confirms that *Fitch could push IG* is strongly positively associated with having a Fitch rating, while none of the three main measures of uncertainty provide any evidence for the information production hypothesis. With a 12% higher probability to have a Fitch rating if the other two CRAs split at the IG boundary, these results are also economically large. Internet Appendix Table A.VIII shows that these results are robust with double clustering.

C CRA Performance

This subsection investigates the general performance of each CRA in default prediction. The main purpose is to corroborate our previous finding that in general, Fitch rating changes or Fitch rating additions are not associated with credit spread changes, unless Fitch is the tie-breaker around the IG-HY boundary. If so, we would expect that Fitch rating differences to Moody's and S&P ratings are not significantly improving default prediction. We perform two tests. First, we run logistic regressions of issue defaults on one-year lagged credit ratings. Second, we calculate accuracy ratios of the one-year ahead default prediction (i.e., Gini coefficients) to measure rating performance of all three CRAs. This method is also employed by the CRAs themselves for self-evaluation in their annual default study. However, since sample periods and rated populations typically differ among CRAs, the self reported results are not useful for comparative purposes.

The sample we use for this analysis is different from the sample we use for our other analysis. Since defaults are relatively rare events, we maximize the size of our sample by incorporating as many issues as possible. Therefore, we include bonds from issuers for which we have no Compustat, CRSP or IBES data as well as bonds with ratings worse than B-/B3. We still restrict ourselves to only senior unsecured US bonds in US dollars. As before, we exclude bonds that are putable, exchangeable, convertible, perpetual, asset backed or floating rate. We collect ratings for all these bonds in FISD that are rated by all three CRAs between 2000 and 2008 and can be matched with the Moody's Default Risk Services Corporate database containing issuer default events. To avoid over-weighting issuers with many bonds outstanding that are likely to default at the same time, we weight each bond at each point in time with the inverse of the number of bonds outstanding for its issuer. [25]

Table VII shows the results of our default prediction study. Panel A shows that default prediction is best for Moody's and worst for Fitch. This ranking holds true in terms of the pseudo R^2, as well as to how much each CRA adds in default prediction relative to the others. First, we can compare the pseudo R^2 in flexible specifications with dummies for the various notched rating categories (i.e., AAA, AA+, AA, AA-, and up to B-).[26] The pseudo R^2 for Moody's is highest (37%, see column 1), followed by S&P (33%, see column 3) and finally comes Fitch (32%, see column 5). In columns 2, 4 and 6, we instead use a linear rating specification of the CRA ratings in notches, i.e., '1' corresponds to AAA, '2' to AAA-, etc. The resulting pseudo R^2s are quite similar, with pseudo R^2 of 37%, 33% and 31% for Moody's, S&P and Fitch, respectively, which suggests that the linear specification is quite reasonable.

[Table VII about here]

In subsequent columns, we compare different pairs of ratings: Moody's and Fitch ratings in columns 7 - 8, S&P and Fitch ratings in columns 9 - 10 and Moody's and S&P ratings in column 11 - 12. For each comparison, we find pseudo R^2 is not increased by adding the CRA with a lower pseudo R^2 in columns 1 - 6. For example, the pseudo R^2 in columns 7 - 8 combining Moody's and Fitch ratings equals 36.7%, basically identical to the pseudo R^2 of Moody's ratings by themselves of 36.6% in column 2 but higher than the pseudo R^2 of Fitch ratings by themselves of 30.8% in column 6. The difference between Fitch and Moody's ratings is further in insignificant in column 8, while it is significant in column 7. Thus, a Moody's rating adds predictive power to a Fitch rating while the reverse is not the case. We show the same pattern in columns 9 and 10 for the comparison of Fitch with S&P. Taken together, these results suggest that conditional on a Fitch rating, Moody's or S&P ratings provide significant additional information for default prediction one-year ahead, while the reverse is not the case.

Consistent with Panel A, the accuracy ratios (i.e., Gini coefficients) are highest for Moody's and lowest for Fitch. In Figure 4, we plot the cumulative fraction of default over the next year against the cumulative fraction of ratings (from worst to best); this curve is also called a Cumulative Accuracy Power curve (CAP-curve). Here, a smaller area in the upper left-hand corner of the graph implies greater prediction accuracy. The accuracy ratios are the fractions of the areas underneath the plotted lines minus the area under the 45 degree line multiplied by two, such that the accuracy ratio converges to 1 as prediction accuracy improves and is equal to zero if ratings are assigned in a completely random fashion. The graph shows that Fitch line is clearly below (and is thus worse than) the other two over most of the rating spectrum.

[Figure 4 about here]

More formally, we find that accuracy ratio of Moody's (77.9%) and S&P (76.5%) outperform Fitch

(71.8%), and that these differences are statistically significant. There is no statistical significant difference between Moody's and S&P accuracy ratios (with standard errors calculated using a Jackknife with re-sampling based on issuer). We conclude that these confirm the lack of support for the information hypothesis in our data.[27]

D Further Explorations of Regulatory Certification and Rating Shopping

Arguably, rating shopping is more worthwhile around the IG boundary, thus leading to more rating shopping at the boundary. On the other hand, under a certification effect, even for issuers at the boundary that should not qualify for IG and thus expect a worse Fitch rating, the possibility of achieving the IG status by sheer luck may be a motivation to apply for an additional Fitch rating. Thus, at the boundary, one would expect more positive (optimistic) added Fitch ratings than elsewhere in the rating spectrum if there is rating shopping.

As a proxy for the level of optimism in the additional, third Fitch rating, we consider whether or not the additional Fitch rating leads to a regulatory gain, defined as the difference between 'worst of two' to 'medium of 3' ratings.

Table VIII presents results of logistic regressions of regulatory gain on dummies indicating the location of a bond in the rating spectrum. Observations are conditioned to have split ratings from Moody's and S&P as otherwise regulatory gain is impossible. The table provides some suggestive evidence that the (additional) Fitch rating is more optimistic around the HY-IG boundary and thus that some rating shopping might be going on around the IG-HY boundary.[28]

[Table VIII about here]

Moreover, the regulatory gain from the third, additional Fitch rating is largest if that Fitch rating breaks the tie at the HY-IG boundary. If the Moody's and S&P ratings are on opposite sides of the HY-IG boundary, a regulatory gain is about 20% more likely (see columns 1 and 2). Fitch ratings being generally more optimistic, the likelihood of a regulatory gain due to a Fitch rating addition in case of Moody's and S&P ratings disagreement is about 65% on average. As a result, this likelihood of a regulatory gain climbs to about 85% if the Fitch rating could change the HY-IG regulatory classification (controlling for everything else).

Next, one of the predictions in Table I was that of a precautionary extra rating. Given the demand shock of being below the IG boundary, issuers may want to hedge the risk of becoming HY by taking an extra rating due to a precautionary motive. Unfortunately, ratings are too persistent to empirically estimate the frequency of rating changes reliably from the rating history. However, due to data constraints and the forward looking nature of this effect, we can perform the analysis of this precautionary effect 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 IX. Indeed, we find that having future rating changes is positively related to having a Fitch rating, over and beyond the usual measures of volatility and opacity. Having a Fitch rating is associated with a quarterly transition probability that is 1.0% to 1.28% higher, which is economically sizable (Moody's and S&P average transition frequencies are 5.2% and 5.5% respectively).

[Table IX about here]

If the certification effect arises naturally in a setting with information sensitive and insensitive investors, one would expect a very liquid IG market and an illiquid HY market. Moreover, issues around the middle region should have a low liquidity that can be restored if Fitch makes an issue qualify for information insensitive. However, if Fitch gives a HY rating, an issue at the boundary will truly fall into the no-trade region and have an exceptionally low liquidity. Table X confirms these predictions empirically. Bonds that qualify for HY based on their Moody's and S&P rating have a substantially lower turnover than those that qualify for IG. However, if Fitch pulls them into the IG category, this effect is compensated. On the other hand, if Fitch could pull them into the IG category but rather gives a HY rating, liquidity drops dramatically, even after correcting for issue and time fixed effects as well as the on-the-run effect (corrected for by age).

[Table X about here]

IV 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.

In this paper, we utilize bond issue credit ratings, characteristics and market prices to evaluate some of these proposed theories. We test three hypotheses: (i) "Information Production," whether the third rater adds value-relevant information, (ii) "Rating Shopping" and (iii) "Regulatory Certification," in particular whether a third agency plays the role of tie-breaker at the boundary of being classified as investment-grade versus high-yield. The certification effect could arise naturally as an equilibrium outcome in a setting with information-sensitive and insensitive investors and assets along the lines of Gorton and Pennacchi (1990) and Boot and Thakor (1993). An extra rating indicating the potential value to be gained from research could (partially) resolve a no-trade region around the IG-HY boundary.

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 regulatory certification, i.e., 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 already contained in the Moody's and S&P ratings. Thus even though Fitch ratings are on average clearly better (i.e. more optimistic) than Moody's and S&P ratings, there seems little information contained in these ratings that the bond market incorporates. This is inconsistent with both the information and rating shopping hypotheses.

We find strong evidence that Fitch ratings have a regulatory certification effect. The likelihood of getting 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. We find some suggestive 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. In particular, we find evidence that if Moody's and S&P ratings are on opposite sides of the

HY-IG boundary, the additional Fitch rating is more likely than otherwise to lead to an improvement in the regulatory rating classification, i.e., in this particular case to the IG classification. Overall, this provides some evidence of rating shopping around the HY-IG boundary, or the marginal rating being used for regulatory arbitrage.

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 41 basis points lower than if the Fitch rating would push the issue into the high yield category. Moreover, bond issues experiencing relatively many rating changes by Moody's and S&P are more likely to have a Fitch rating, suggesting a precautionary motive of getting a Fitch rating. These results combined with additional results on for example the liquidity of the bonds are consistent with a third CRA arising as a tie-breaker in equilibrium to resolve a no-trade region in a setting with information-sensitive and insensitive investors and assets.

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Notes

[1]For smaller corporate bond issues, Fitch is occasionally one of two raters. However, almost all bonds in our 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. 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 2000-2008, 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. Throughout the paper, we only consider the three major Credit Rating Agencies (CRAs), ignoring all others, as they are much smaller at this point.

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

[3]For firms with split Moody's and S&P ratings, 13% of Fitch additions are such boundary cases.

[4]There is some evidence that regulators are concerned about such 'ratings arbitrage.' See e.g. proposals for the new Basel II accord made in July 2008: "If [an issue] has multiple ratings, the applicable rating would be the lowest rating. This approach for determining the applicable rating differs from the New Accord. In the New Accord, if an exposure has two ratings, a banking organization would apply the lower rating to the exposure to determine the risk weight. If an exposure has three or more ratings, the banking organization would use the second lowest rating to risk weight the exposure. The agencies believe that the proposed approach, which is designed to mitigate the potential for ratings arbitrage, more reliably promotes safe and sound banking practices." Source: `http://www.occ.treas.gov/fr/fedregister/73fr43982.pdf`.

[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 rule is likely to be revised in the future.

[7]See `http://www.occ.treas.gov/law/basel.htm` for an overview of legal and regulatory news pertaining to the Basel accords from the Office of the Comptroller of the Currency (OCC).

[8]Campbell and Taksler (2003) report that about one third of all corporate bonds are held by insurance companies, about 15% by pension and retirement funds, 5% to 10% by mutual funds and 5% by commercial banks; thus, approximately 60% of this market is held by institutions that qualify for ratings based constraints.

[9]The Barclays US corporate IG Index Factsheet is available at `https://ecommerce.barcap.com/indices/index.dxml`.

[10]Quoting the NAIC report: "A security rated and monitored by two NRSROs is assigned the lowest of the two ratings. A security rated by three or more NRSROs is ordered according to their NAIC equivalents and the rating falling second lowest is selected, even if that rating is equal to that of the first lowest." This report can be found at `http://www.naic.org/documents/committees_e_rating_agency_comdoc_naic_staff_report_use_of_ratings.doc`. See also Basel Committee

on Banking Supervision (2000). If an issue has only one rating, that rating will be used. However, several regulations prohibit institutional investors to invest in issues with only one rating.

[11]There have been some time series changes in NAIC regulations, but these changes not significantly affected the validity of our 'tie-breaking' assumption at any point in time, i.e., that the worst of two ratings or the medium of 3 ratings is used for NAIC classifications. First, the NAIC issues its own ratings and 1994 to 2001 the Securities Valuation Office (SVO) of the NAIC would assign an NAIC rating to each security. Anecdotal evidence suggests that the ratings from CRAs were critical, but that the final decision was at the NAIC analyst's discretion. In 2001 a Provisional Exemption rule was introduced under which bonds with standard features would be assigned a NAIC 1 or NAIC2 rating (i.e, allowing smaller capital charges than HY) automatically if at least one CRA would rate it A- or higher at least two CRAs rate it BBB- or higher without the interference of an SVO analyst. Effectively, this came down to a middle rating rule (see `http://www.naic.org/documents/svo_research_SVO_jan01cc.pdf`). Second, on January 1, 2004, the NAIC implemented a Filing Exemption rule, stating that any issue rated by one or more CRAs would be assigned an NAIC rating based on the CRA equivalent rating. In case of split ratings, the 'second best' rating would be taken (see `http://www.naic.org/documents/svo_FE_FAQ.pdf`). Third and finally, this 'second best' rule was changed to a 'second worst' rule in 2007. However, both, the 'second best' as well as the 'second worst' rule effectively boil down to 'worst of 2 if only 2 and medium of 3 ratings' rule in view of the low market share of the other CRAs besides the big three. Our contact within the NAIC SVO argued that these guidelines were in general well adhered to by the individual state regulators.

[12]See further Chernenko and Sunderam (2009) on the effects of the market segmentation due to credit ratings on bond issuance and investments.

[13]For simplicity, one could think about type I investors as commercial banks, insurance companies and pension funds, where the natural demand for bonds stems from the random flow of deposits and claims, and type II investors as hedge funds and proprietary trading desks.

[14]Type II investors 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.

[15]For type I investors, the losses due to informed trading prevent them from investing in this region; they realize that they are at an information disadvantage and thus do not enter this market, while the limited gains for type II investors do not make it worthwhile for them to produce costly information in this intermediate region.

[16]An alternative way to hedge is increasing the average maturity of their debt. However, this is costly since in this region of the rating spectrum, the term structure of credit spreads is typically upward sloping.

[17]This is not necessarily true when a rating agency rates too optimistically, but if credit spreads do not decrease, there seems to be no benefit and thus no reason for rating shopping.

[18]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 for industrials unsolicited ratings are lower than solicited ratings, and that this difference is largely due to adverse selection of debt issuers. There seems to be some evidence for holdup by CRAs, but this is concentrated mainly on financials. Our dataset does not include information on unsolicited ratings for US corporate bonds, so this paper does not address these findings directly. However, several papers report a low incidence rate of unsolicited ratings, like for example Partnoy (2006), who estimates an incidence rate of approximately 1%.

[19]To avoid capturing timing mismatches between (multiple) rating transitions, we require that any particular ratings situation has existed for at least a quarter. This will also mitigate concerns about not correcting for credit watches and credit outlooks (for these variables our data are too sparse to be useful). 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.

[20]The TRACE database starts in July 2002.

[21]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 credit spreads of more than 1000 bps and credit spread changes of more than 500bps. Finally, we deleted all issues with duration of less than 1 year.

[22]CUSIPs of non-exchange traded bonds do not change in case of mergers, acquisitions, etc (see `http://www.cusip.com`).

[23]FISD confirmed that 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.

[24]As suggested by Cantor and Packer (1997), ratings by Fitch could be inflated. To address this issue, we repeat the analysis of Table V where we correct all Fitch ratings by one notch (except for the tie breaking at the boundary). The results can be found in Internet Appendix Table IA.II. These results are consistent with the results reported in Table V. Furthermore, we show similar results in levels in Internet Appendix Table IA.IV, exploiting also observations that already had a Fitch rating when they entered the sample. If anything, results are even stronger since an agreeing Fitch rating is associated with a higher credit spread. The effect of certification is statistically and economically very similar. Finally, one might be concerned that the large movements in credit spreads at the onset of the crisis might drive any of these results. Internet Appendix Tables IA.V and A.VI (showing the results on the sample ending in June 2007) indicate that this is not the case.

[25]That is, the weighting is done in a Weighted Least Squared sense.

[26]For all non-linear regressions in the paper we report McFadden (1973) Pseudo R^2s.

[27]As a robustness check, we also investigate the predictive power of Fitch in case i) Moody's and S&P disagree and ii)

when it breaks a tie at the IG/HY boundary. Results can be found in Internet Appendix Table A.III. For disagreements, the additional predictive power of Fitch has the right sign, but is not significant at conventional levels. Also the tie-breaking role around the IG/HY boundary does not yield any significant effect and has coefficients in the same direction no matter whether Fitch pulls over or under the boundary.

[28] We thank our NBER discussant, Michael Brennan, for suggesting this test.

Table I
Empirical Predictions

The various empirical predictions of the three hypotheses are summarize in the table below, where '−' indicates that the implication is not supported and '+' means it is supported.

Reason for multiple ratings	**Information Production**	**Rating Shopping**	**Regulatory Certification**
(i) Additional agreeing rating lowers credit spreads	+	−	−
(ii) Additional relatively optimistic rating lowers credit spreads (also away from IG-HY boundary)	+	+	Only at IG boundary
(iii) Uncertainty uniformly increases # of ratings	+	+	possible
(iv) Additional rating especially if that could push the issue to an investment grade classification	possible	possible	+
(v) Additional rating more optimistic (especially around IG boundary)	−	+	Only for strategic CRA
(vi) Additional rating associated with higher expected time variation in ratings	+	−	+

Table II
Summary Statistics for Credit Spreads Sample

The table presents summary statistics and a brief description for the sample of bonds issues that have both a Moody's and an S&P rating in the quarterly credit spreads sample for 2002 - 2008.

Variable	N	Mean	Std. Dev.	Min	Max	Explanation
Fitch Could Break Tie	44,366	0.032	0.18	0	1	Moodys and S&P on opposite sides of the IG-HY boundary
Fitch Rated	44,366	0.68	0.47	0	1	Rated by Fitch
Fitch Rating	44,366	5.04	4.17	0	16	Fitch Rating
Moodys Rating	44,366	7.33	3.6	1	18	Moody's Rating
S&P Rating	44,366	7.17	3.55	1	17	S&P Rating
Fitch makes IG	44,366	0.016	0.12	0	1	Fitch pulls IG
Fitch denies IG	44,366	0.0066	0.081	0	1	Fitch denies IG
Notches of MSP Rating Dispersion	44,366	0.43	0.69	0	12	Absolute value of MSP rating difference
Moodys Upgrade	44,366	0.027	0.16	0	1	Moody's upgrade (common sample)
Moodys Downgrade	44,366	0.034	0.18	0	1	Moody's downgrade (common sample)
S&P Upgrade	44,366	0.029	0.17	0	1	S&P upgrade (common sample)
S&P Downgrade	44,366	0.038	0.19	0	1	S&P downgrade (common sample)
Fitch Upgrade	44,366	0.017	0.13	0	1	Fitch upgrade (common sample)
Fitch Downgrade	44,366	0.024	0.15	0	1	Fitch downgrade (common sample)
Fitch Added, Better	44,366	0.0039	0.062	0	1	Fitch added and < MSP
Fitch Added, Equal	44,366	0.005	0.071	0	1	Fitch added and = MSP
Fitch Added, Worse	44,366	0.0003	0.017	0	1	Fitch added and > MSP
Credit Spread	44,366	172.71	141.72	0.12	999.86	Credit spread
Change in Credit Spread	44,366	18.39	68.33	-478.36	498.42	Credit spread change
Redeemable	44,366	0.69	0.46	0	1	callable
Log of Offering Amount	44,366	12.03	1.88	0	15.42	log offering amount
Duration	44,366	6.32	3.72	1	18.91	duration
Idios. Vol.	44,366	0.016	0.0084	0.0012	0.11	idiosyncratic stock volatility
Log of Total Assets	44,366	10.34	1.55	5.34	13.65	log of total assets
Leverage	44,366	0.34	0.17	0	5.77	leverage
ROA	44,366	0.014	0.02	-0.46	0.26	ROA
PPE / Total Assets	44,196	0.36	0.24	0	0.95	PPE/total assets
R&D / Total Assets	44,366	0.012	0.023	0	0.23	R&D/total assets
R&D Missing	44,366	0.43	0.5	0	1	R&D missing
Analyst Dispersion	43,923	0.0033	0.013	0	1.1	analyst dispersion
Beta	44,366	0.95	0.39	-0.25	4.21	equity beta
Convexity	44,366	53.83	56.58	1	357.47	convexity
Turnover	43,292	13.15	15.27	0.018	85.99	trading volume over offering, times 1K

Table III
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. We follow convention and use the numerical rating scale to convert ratings. For Fitch and S&P (with Moody's rating in parentheses), the numerical scores corresponding to the rating notches are, respectively, 1 for AAA (Aaa), 2 for AA+ (Aa1), 3 for AA (Aa2), 4 for AA- (Aa3), 5 for A+ (A1), 6 for A (A2), 7 for A- (A3), 8 for BBB+ (Baa1), 9 for BBB (Baa2), 10 for BBB- (Baa3), 11 for BB+ (Ba1), 12 for BB (Ba2), 13 for BB- (Ba3), 14 for B+ (B1), 15 for B (B2) and 16 for B- (B3). Therefore, 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 2000-2008 are used. t-statistics based on robust standard errors clustered by issuer are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

All Bonds	**Fitch vs. Moody's**	**Fitch vs. S&P**	**Moody's vs. S&P (Fitch rated sample)**	**Moody's vs. S&P (full sample)**
Difference	-0.538***	-0.397***	0.154***	0.185***
	[-5.57]	[-3.99]	[2.79]	[4.41]
N	70,624	70,747	70,738	104,435
N. issuers	450	449	452	818
AAA to AA-				
Difference	-0.111	-0.118	0.0217	0.0415
	[-1.53]	[-0.98]	[0.14]	[0.47]
N	3,557	3,549	3,601	8,619
N. issuers	37	37	37	57
A+ to A-				
Difference	-0.751***	-0.599***	0.165*	0.203***
	[-5.85]	[-4.63]	[1.80]	[2.68]
N	36,461	36,539	36,532	48,905
N. issuers	232	232	233	475
BBB+ to BBB-				
Difference	-0.294***	-0.223***	0.072	0.117**
	[-5.03]	[-3.82]	[1.11]	[2.42]
N	24,177	24,193	24,186	36,841
N. issuers	277	278	276	451
BB+ to BB-				
Difference	-0.492***	-0.0574	0.478***	0.471***
	[-4.76]	[-0.35]	[3.30]	[4.71]
N	6,429	6,466	6,419	10,070
N. issuers	165	163	165	295
B+ to B-				
Difference	-0.800***	-0.457**	0.369*	0.430***
	[-6.80]	[-2.46]	[1.82]	[3.20]
N	3,279	3,272	3,282	6,200
N. issuers	98	98	99	268

Table IV

Change in Credit Spreads and Rating Changes

Using quarterly panel data between 2002 and 2008, we regress changes in credit spreads for AAA to B- rated bonds that are rated by all three CRAs on rating up- and downgrades for all three CRAs, changes in bond and firm characteristics, dummies for boundary effects and time fixed effects. Up- and downgrades are coded as dummies indicating whether each of the three CRAs upgraded or downgraded its rating. The following firm and bond controls are included but not shown (all in changes): Leverage, liquidation/intrinsic value (PPE/total assets), R&D expenses (divided by total assets), ROA (return on assets), daily idiosyncratic equity volatility, Historical Equity Beta (half year daily corrected for Bid-Ask-bounces), Log Total Assets (firm size, book value) and Log Offering Size (issue size), Redeemable (dummy for callability), Duration and Convexity. *Fitch Upgrade, Breaks Tie* is a dummy indicating that a Fitch upgrade made the issue qualify for IG, while *Fitch Downgrade, Breaks Tie* is a dummy indicating that a Fitch downgrade made the issue lose its IG qualification. *Fitch Could Break Tie* is a dummy indicating that the S&P and Moody's ratings are on opposite sides of the IG-HY boundary. Column (5) is restricted to issues rated A- or better by Moody's and S&P, whereas column (6) is restricted to issues rated BBB+ or worse by Moody's and S&P. t-statistics are in brackets (using robust standard errors clustered by issuer; N. issuer gives the number of issuers). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. 'F-test *Fup=Fdown* (p-value)' gives the p-value for the coefficients on *Fitch Upgrade* and *Fitch Downgrade* being equal, while 'F-test *Fup,tie=Fdown,tie* (p-value)' gives the p-value for the F-test of the coefficients on *Fitch Upgraded, Breaks Tie* and *Fitch Downgraded, Breaks Tie* being equal.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Moody's Upgrade	-4.501**						-2.369	-3.125
	[-1.97]						[-1.11]	[-1.47]
Moody's Downgrade	14.19***						7.385*	7.575**
	[4.00]						[1.96]	[2.10]
S&P Upgrade		-5.594**					-4.312	-4.423
		[-2.07]					[-1.62]	[-1.59]
S&P Downgrade		22.34***					18.75***	17.32***
		[5.25]					[4.26]	[4.43]
Fitch Upgrade			-6.463**	-5.612*	6.975	-8.209***	-4.807	-3.892
			[-2.10]	[-1.83]	[0.59]	[-2.70]	[-1.59]	[-1.30]
Fitch Downgrade			12.98**	10.52**	-0.595	22.30***	4.596	2.875
			[2.46]	[1.99]	[-0.26]	[4.00]	[0.80]	[0.49]
Fitch Upgrade, Breaks Tie				-17.59		-16.26		-14.94
				[-1.18]		[-1.11]		[-1.03]
Fitch Downgrade, Breaks Tie				31.53*		24.67		26.65
				[1.76]		[1.45]		[1.49]

Continued on next page

Table IV – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fitch Could Break Tie				13.81**		9.475*		13.33**
				[2.39]		[1.75]		[2.48]
Lagged Credit Spread	-0.253***	-0.258***	-0.251***	-0.253***	-0.400***	-0.255***	-0.259***	-0.261***
Change	[-11.07]	[-11.71]	[-11.08]	[-11.48]	[-15.02]	[-10.72]	[-11.72]	[-12.01]
Sample	All	All	All	All	≤A-	≥BBB+	All	All
N	24,282	24,282	24,282	24,282	11,330	12,952	24,282	24,282
Adj. R^2	0.531	0.533	0.531	0.533	0.45	0.605	0.534	0.536
N. issuers	380	380	380	380	117	313	380	380
F-test Fup=$Fdown$			0.15%	0.80%	56.30%	0.00%	15.00%	30.80%
(p-value)								
F-test Fup,tie=$Fdown,tie$				2.82%		5.87%		6.07%
(p-value)								

Table V

Credit Spread Regressions on Fitch Rating Additions

Using quarterly panel data between 2002 and 2008, we regress changes in credit spreads for AAA to B- rated bonds that are rated by Moody's and S&P on rating additions from Fitch, the relative ranking of those additions and whether additions happened at the IG boundary, interactions with uncertainty measures and changes in bond and firm characteristics plus time fixed effects. *Fitch Added, Better*, *Fitch Added, Equal* and *Fitch Added, Worse* are dummies indicating whether a Fitch rating has been added that is respectively better than, equal to and worse than the average rating by Moody's and S&P. *Fitch Added, Makes IG* and *Fitch Added, Denies IG* are dummies that indicate whether the added Fitch rating makes the issue qualify for IG or not, conditional on Moody's and S&P ratings being on opposite sides of the boundary. See Table IV for descriptions of bond and firm level control variables. t-statistics are in brackets (using robust standard errors clustered by issuer in all columns except column 5, which uses double clustering by both issuer and time). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. 'F-test *Fadded,IG=Fadded,HY* (p-value)' is the p-value of the F-test of *Fitch Added, Makes IG* and *Fitch Added, Makes HY* being equal. The sample is all issues rated by both Moody's and S&P with their average rating better or equal to B-, except in column 4, where their average rating is between BBB+ and BB-.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fitch Added	-2.28						
	[-0.65]						
Fitch Added, Better		-5.832	-5.254	-8.644	-5.254	-7.243	-6.197
		[-0.83]	[-0.75]	[-1.16]	[-0.66]	[-1.00]	[-0.88]
Fitch Added, Equal		-0.205	0.0847	3.238	0.0847	2.14	1.598
		[-0.06]	[0.03]	[0.46]	[0.02]	[0.59]	[0.51]
Fitch Added, Worse		4.422	5.089	6.347	5.089	3.063	5.383
		[0.84]	[0.94]	[0.81]	[0.98]	[0.40]	[0.97]
Fitch Added, Makes IG			-30.47**	-23.00**	-30.47***		
			[-2.54]	[-1.98]	[-2.76]		
Fitch Added, Makes HY			10.8	22.93	10.8		
			[0.65]	[1.04]	[0.57]		
At IG boundary			15.32***	10.93**	15.32**		
			[3.22]	[2.56]	[2.23]		
*Fitch Added, Equal * Analyst Dispersion*						-949.1	
						[-0.90]	
Analyst Dispersion						700.4***	
						[6.24]	

Continued on next page

Table V – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*Fitch Added, Equal **							-4.755
Rating Dispersion							[-0.82]
S&P and Moodys Disagree							2.417**
							[2.02]
Lagged Credit Spread	-0.257***	-0.257***	-0.258***	-0.277***	-0.258***	-0.265***	-0.258***
Change	[-14.39]	[-14.40]	[-14.81]	[-12.78]	[-5.78]	[-14.96]	[-14.67]
Sample	All	All	All	BBB+ to BB-	All	All	All
Double Clustering	No	No	No	No	Yes	No	No
N	34,568	34,568	34,568	15,058	34,568	34,671	34,568
Adj. R^2	0.531	0.531	0.532	0.626	0.532	0.535	0.531
N. issuers	668	668	668	463	668	669	668
F-test			3.23%	5.58%	9.35%		
Fadded,IG=Fadded,HY							
(p-value)							

Table VI
Cox Regressions for Time to Adding Fitch Rating

Cox Proportional Hazard model regressions of the time to adding a Fitch rating on rating category dummies based on average Moody's and S&P (MSP) ratings, 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 IG or A-. *F could push IG* and *F could push A-* are dummies indicating whether the Moody's and S&P ratings are on opposite sides of the IG or A- boundary respectively. Other controls that are included but not shown are the firm Beta, Leverage, PPE / Assets, R&D Expenses / Assets, ROA, Log of Offering Amount, Maturity Left and Maturity Left Squared and Redeemable (see Table IV for descriptions). Quarterly data for 2000-2008 are used, and the sample consists of all issues with both Moody's and S&P ratings that are on average rated B- or better. Coefficients on the covariates in the partial hazard function are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Pseudo R^2 refers to McFadden (1973) pseudo R^2.

	(1)	(2)	(3)	(4)	(5)
MSP A+ to A- Rating	1.553***		1.548***	1.568***	1.524***
	[3.04]		[3.06]	[3.08]	[3.06]
MSP BBB+ to BBB- Rating	1.146**		1.156**	1.119**	1.071**
	[2.28]		[2.32]	[2.22]	[2.19]
MSP BB+ to BB- Rating	1.346**		1.481***	1.408***	1.292**
	[2.53]		[2.79]	[2.60]	[2.49]
MSP B+ to B- Rating	1.131**		1.114**	1.159**	1.073**
	[2.06]		[2.06]	[2.12]	[2.00]
Fitch could pull IG	0.717***	0.693***			0.702**
	[2.83]	[2.83]			[2.44]
Fitch could pull A	0.248	0.221			0.231
	[1.23]	[1.13]			[1.00]
Avg MSP BB+				0.292	
				[1.27]	
Avg MSP BBB-				0.235	
				[1.41]	
Notches of MSP					-0.128
Rating Dispersion					[-0.72]
S&P and Moodys Disagree	-0.307	-0.267	-0.254	-0.251	
	[-1.16]	[-0.90]	[-1.03]	[-1.02]	
Analyst Dispersion	-4.988	-4.262	-6.275	-6.479	-5.979
	[-0.58]	[-0.53]	[-0.69]	[-0.70]	[-0.64]
Idiosyncratic Volatility	-26.11***	-23.85***	-25.62***	-26.08***	-26.61***
	[-3.95]	[-3.86]	[-3.86]	[-3.93]	[-3.88]
Log of Total Assets	0.296***	0.200**	0.290***	0.299***	0.289***
	[5.53]	[2.57]	[5.39]	[5.67]	[5.26]
N	38,351	38,351	38,351	38,351	38,351
Pseudo R^2	0.029	0.019	0.029	0.029	0.028
N. issuers	813	813	813	813	813

Table VII
CRA Default Prediction

Using yearly panel data between 2000 and 2008, we compare CRA performance with respect to default prediction on a one year horizon. Panel A shows results from a logit regression of issuer default events on rating scales, rating scale dummies and rating differences for the complete universe of bonds that are rated by all three CRAs. The rating variables are in notches where '1' corresponds to AAA, '2' to AAA-, etc. The difference variables measure the difference between the first minus the second CRA in notches. Only marginal effects are reported (multiplied by 10,000), and t-statistics are in brackets (using robust standard errors clustered by issuer). Panel B shows Accuracy Ratios and their differences for all three CRAs for a one and two year forecasting horizon. Standard errors are constructed using the Jackknife method with re-sampling at issuer level (equivalent to clustering by issuer). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Default prediction logit regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Moody's Rating		4.23***						04.25***				4.22***
		[4.60]						[4.59]				[4.55]
S&P Rating				5.02***						5.08***	4.22***	
				[4.98]						[4.97]	[4.55]	
Fitch Rating						5.98***	4.25***		05.08***			
						[5.30]	[4.59]		[4.97]			
Difference Moodys and Fitch Ratings							3.94***	-0.306				
							[4.27]	[-0.75]				
Difference S&P and Fitch Ratings									3.84***	-1.24		
									[3.72]	[-1.49]		
Difference Moodys and S&P Ratings											3.57***	-0.646
											[4.06]	[-1.40]
Moodys Rat. FE	Yes	No	No	No	No	No	No	No	No	No	No	No
Fitch Rat. FE	No	No	No	No	Yes	No	No	No	No	No	No	No
S&P Rat. FE	No	No	Yes	No	No	No	No	No	No	No	No	No
N	104,966	112,329	97,371	112,329	103,803	112,329	112,329	112,329	112,329	112,329	112,329	112,329
pseudo R^2	0.371	0.366	0.333	0.333	0.323	0.308	0.367	0.367	0.337	0.337	0.367	0.367
N. Issuers	1,994	2,066	1,949	2,066	1,984	2,066	2,066	2,066	2,066	2,066	2,066	2,066

Table VII – continued from previous page

Panel B: Accuracy ratios

	1 year horizon		2 year horizon	
	Value	t-stat	Value	t-stat
Moody's Rating	0.779***	25.38	0.713***	21.05
Fitch Rating	0.718***	18.5	0.657***	15.97
S&P Rating	0.765***	24.12	0.704***	20.15
Moodys − Fitch Rating	0.062**	2.46	0.057**	2.25
S&P − Fitch Rating	0.047*	1.83	0.047**	1.97
Moodys − S&P Rating	0.015	1.31	0.009	0.8

Table VIII
Relative Rating Levels

The table shows logit regressions of achieving a regulatory gain on rating category dummies, Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) as a measure for uncertainty and whether the Fitch rating 'could push' the issue to IG. *F could push IG* is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG boundary. Other controls that are included but not shown are the firm Beta, Leverage, PPE / Assets, R&D Expenses / Assets, ROA, Log of Offering Amount, Maturity Left and Maturity Left Squared and Redeemable (see Table IV for descriptions). Quarterly data for 2000-2008 are used, and the sample consists of all issues rated by Moody's, S&P and Fitch that are on average rated B- or better. Marginal effects are reported for the regressions and all t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
A+ to A-	0.0691		0.0698
	[0.43]		[0.42]
BBB+ to BBB-	-0.155		-0.155
	[-0.76]		[-0.75]
BB+ to BB-	-0.0823		-0.016
	[-0.34]		[-0.08]
B+ to B-	-0.0516		-0.052
	[-0.19]		[-0.19]
Fitch could push IG	0.187***	0.196***	
	[3.73]	[3.62]	
Analyst Dispersion	5.461	5.366	5.192
	[1.44]	[1.60]	[1.41]
Idiosyncratic Volatility	-1.432	-2.132	-1.735
	[-0.34]	[-0.44]	[-0.40]
Log of Total Assets	0.0351	0.0476	0.0316
	[0.90]	[1.41]	[0.80]
Other Controls Included	Yes	Yes	Yes
Only with MSP disagreement	Yes	Yes	Yes
Fitch added	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	569	569	569
pseudo R^2	0.15	0.114	0.131
N. issuers	170	170	170

Table IX

Logistic Regressions for Having a Rating Transitions

Logit regressions of having a rating transition next quarter on rating category dummies (AAA and AA+ are merged to avoid singularities), 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 IV for descriptions of bond and firm level control variables. Quarterly data for 2000-2008 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 robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Moody's rating change	S&P rating change
Fitch Rated	0.0128***	0.0102***
	[3.68]	[2.94]
Idiosyncratic volatility	1.509***	0.712***
	[5.95]	[3.17]
Beta	-0.00562	0.00528
	[-1.21]	[0.96]
Analyst Dispersion	0.0459	0.0549
	[1.27]	[1.51]
Notches of MSP	0.0128***	0.00611**
Rating Dispersion	[4.55]	[2.16]
MSP Rating FE	Yes	Yes
Year FE	Yes	Yes
N	104,629	104,629
Pseudo R^2	0.082	0.067
N. issuers	818	818

Table X

Turnover Regressions

OLS regressions of quarterly bond turnover, measured as aggregated trading volume over total value of outstanding bonds on rating category dummies, a dummy indicating whether the issue has a Fitch rating or not and controls for off-the-run vs on-the-run effects (age). *F makes (denies) IG* is a dummy equal to 1 if Moody's and S&P ratings are on opposite sides of the IG-HY boundary and the Fitch rating is IG (HY). All other control variables are dropped due to the use of both time and issue fixed effects. Monthly data for July 2002-December 2008 are used; the sample consists of all issues with both Moody's and S&P ratings. t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)
MSP AAA to AA- Rating	-2.889***	-2.887***	-2.891***
	[-2.92]	[-2.91]	[-2.91]
MSP BBB+ to BBB- Rating	0.722	0.749	0.745
	[0.97]	[1.00]	[0.94]
MSP BB+ to BB- Rating	-2.434*	-2.543*	-2.554*
	[-1.83]	[-1.78]	[-1.77]
MSP B+ to B- Rating	-5.368***	-5.270***	-5.280***
	[-3.51]	[-3.40]	[-3.38]
Age	-4.035***	-4.033***	-4.022***
	[-6.91]	[-6.92]	[-6.91]
F makes IG		4.208***	4.213***
		[2.67]	[2.67]
F denies IG		-5.801**	-5.767**
		[-2.18]	[-2.16]
Fitch Rated			0.952
			[1.40]
Time FE	Yes	Yes	Yes
Issue FE	Yes	Yes	Yes
N	43,292	43,292	43,292
adj. R^2	0.278	0.279	0.279
N. issuers	739	739	739

Figure 1
FISD database coverage by CRA

The figure plots the percentage of bonds in FISD covered by S&P, Moody's and Fitch. While FISD starts earlier, we use ratings starting in 2000, as S&P data seems incomplete before, as this figure suggests.

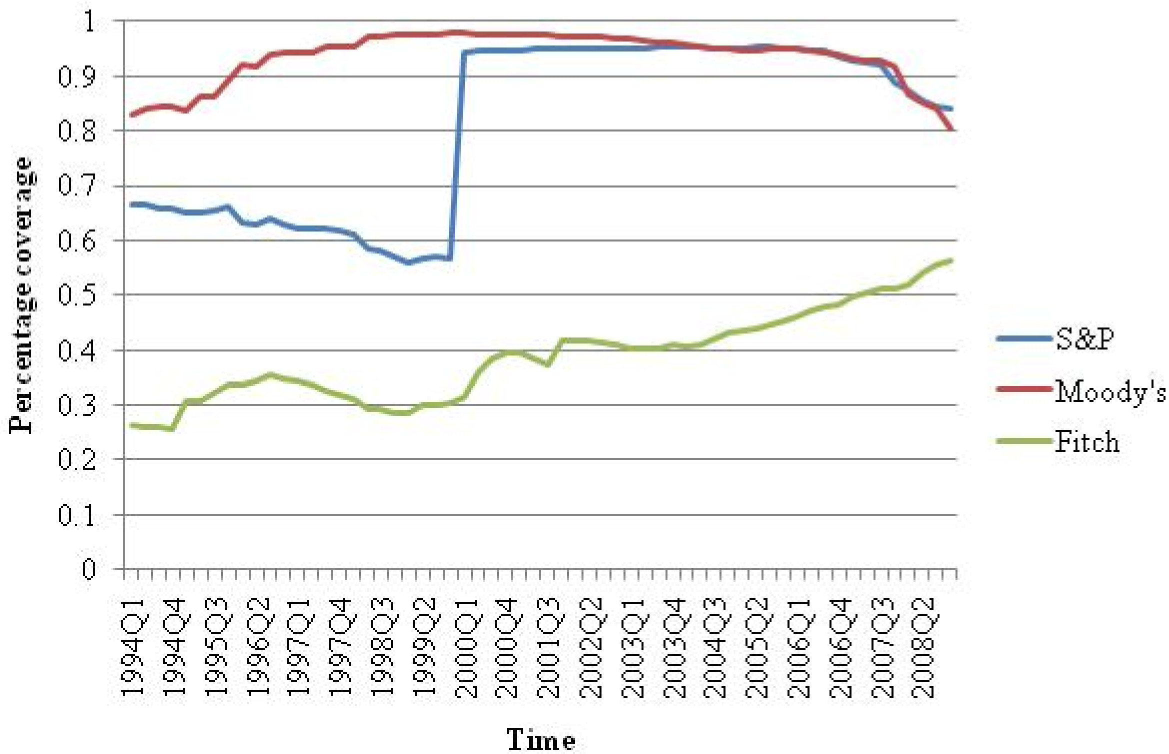


Figure 2
Average Credit Spreads by Rating Category

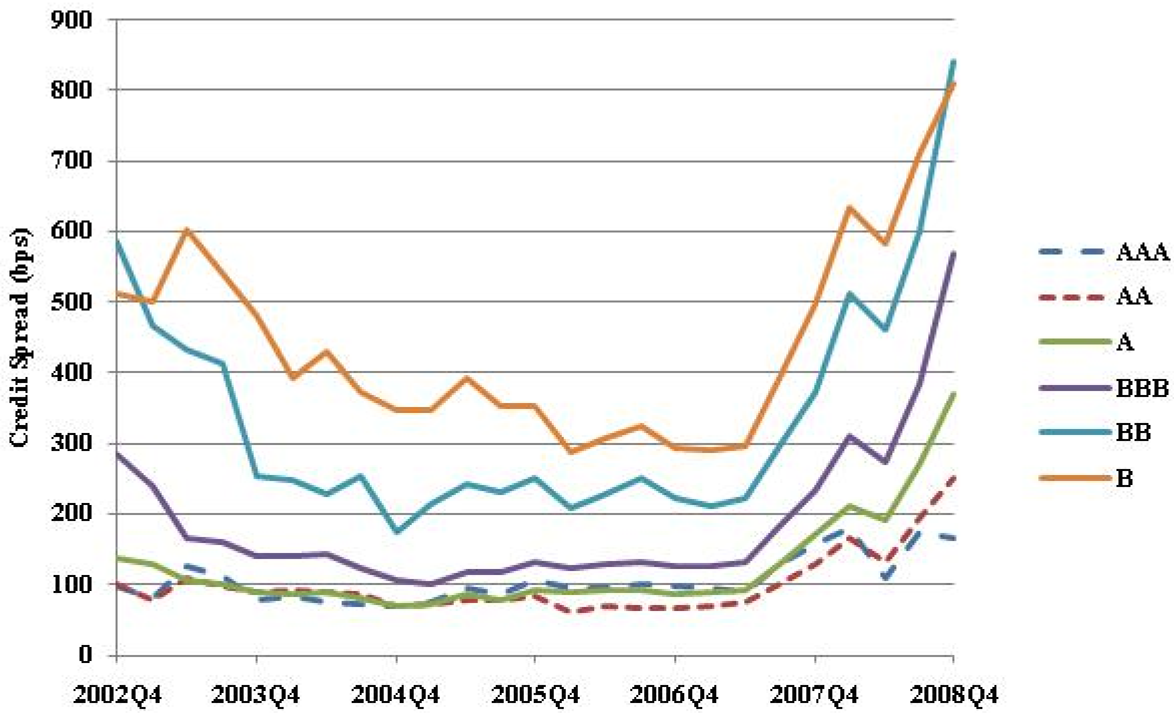


Figure 3
Rating Differences Across CRAs

The figure plots rating differences for different pairs of credit rating agencies (CRAs). We use a numerical scale for ratings, where a lower rating score means a better (more optimistic or lower bankruptcy likelihood) rating (see Table III for the full rating scale). In the figure, a negative number thus means that the first mentioned rating agency gives on average a better rating than the other CRA in that comparison.

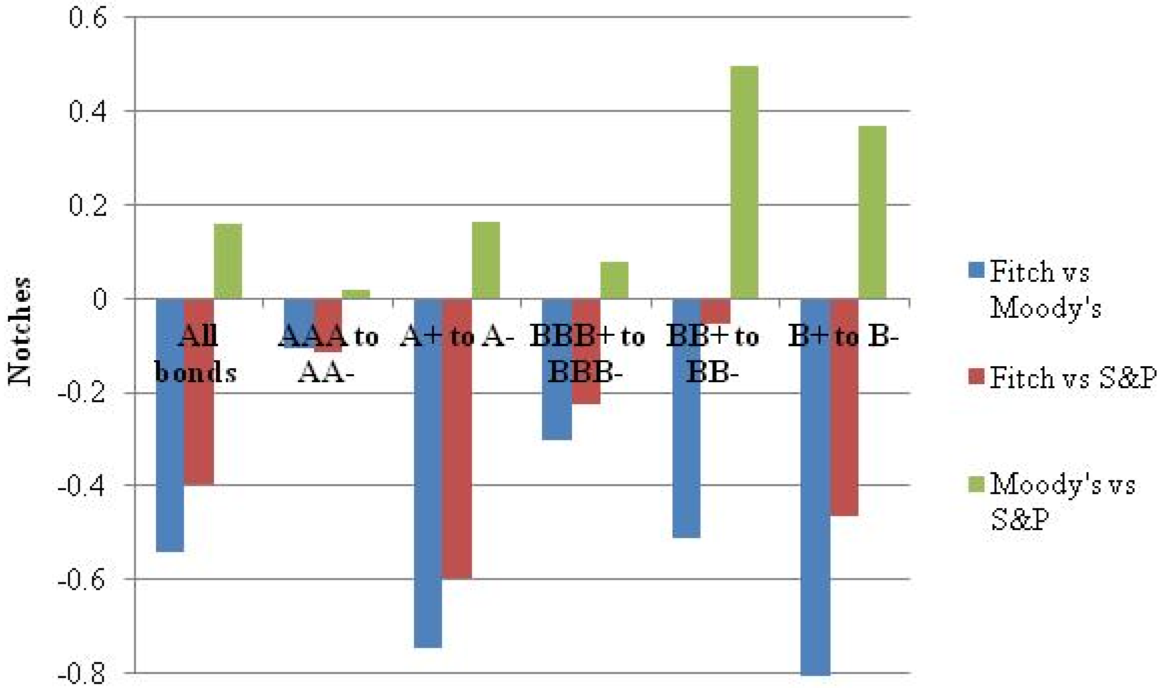
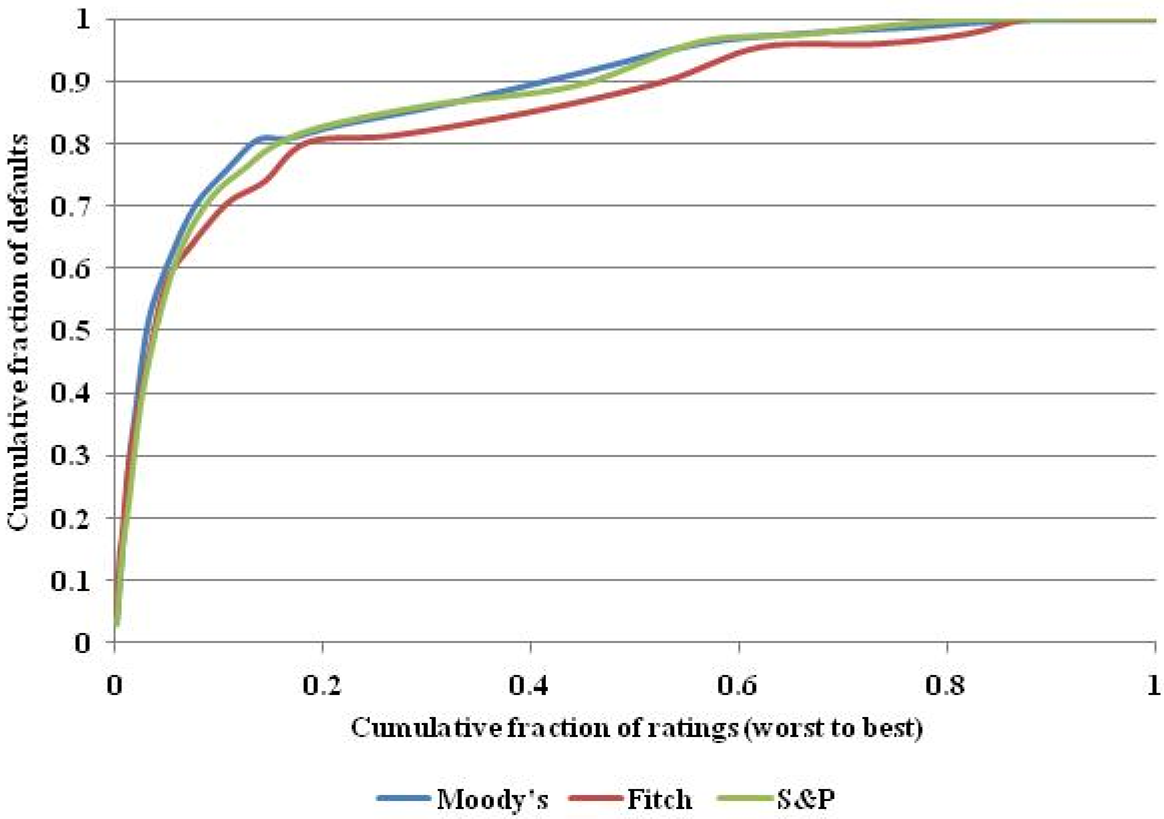


Figure 4

Default Prediction Accuracy

The figure plots the cumulative fraction of defaults on US corporate bonds over a one year horizon against the cumulative fraction of ratings (from worst to best), for Moody's, S&P and Fitch based on data from 2000 to 2008. The accuracy ratios that rating agencies use for self-evaluation and that we report in Table VII Panel B are based on the areas under the graphs. A larger area under the graph corresponds to a better accuracy. This type of graph is also known as a Cumulative Accuracy Power (CAP) curve.



Internet Appendix for "Tiebreaker: Certification and Multiple Credit Ratings"

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

This Internet Appendix contains 9 supplementary tables to the main article.

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Table IA.I
Summary Statistics of Quarterly Ratings Sample

The table presents summary statistics and a brief description for the sample of bond issues that have both a Moody's and an S&P rating in the quarterly rating sample for 2000 - 2008.

Variable	Obs	Mean	Std. Dev.	Min	Max	Explanation
Fitch Rated	104,629	0.68	0.47	0	1	Dummy for Fitch rating
Fitch Rating	70,863	7.27	2.84	1	19	Fitch rating
Moodys Rating	104,629	7.85	3.07	1	18	Moody's Rating
S&P Rating	104,629	7.66	2.99	1	20	S&P rating
Fitch could push IG	104,629	0.04	0.19	0	1	Fitch could push IG
Fitch could push A-	104,629	0.05	0.22	0	1	Fitch could push A-
S&P and Moodys Disagree	104,629	0.37	0.48	0	1	Dummy for MSP disagreement
Notches of MSP Rating Dispersion	104,629	0.47	0.73	0	12	Notches of MSP rating dispersion
Analyst Dispersion	104,629	0	0.02	0	1.66	Analyst dispersion
Stdev	104,629	0.02	0.01	0.0012	0.13	Daily idiosyncratic equity volatility (past 180 days)
Beta	104,629	0.94	0.44	-1.01	4.39	Equity beta (past 180 days)
Log Total Assets	104,629	9.85	1.25	5.32	12.59	Log of total book value of assets
PPE / Total Assets	104,629	0.38	0.23	0	0.96	PPE over total book assets
R&D / Total Assets	104,629	0.01	0.02	0	0.23	R&D expenditure over total book assets
R&D missing	104,629	0.45	0.5	0	1	R&D expenditure missing
Leverage	104,629	0.35	0.15	0	6.04	Book leverage (debt/total assets)
ROA	104,629	0.01	0.02	-0.63	0.41	Return on book assets (earnings/total assets)
Log of Offering Amount	104,629	11.42	2.2	0	15.07	Log of offering amount
Maturity Left	104,629	9.61	10.71	0	98.52	Maturity left (years)
Redeemable	104,629	0.56	0.5	0	1	Dummy if the bond is redeemable

Table IA.II

Fitch Inflated Credit Spread Regressions on Fitch Rating Additions

This table is equivalent to Table V of the main article except that for determining whether Fitch is better, equal or worse than the average of Moody's and S&P rating, the Fitch rating is corrected with one notch. Thus, an original AAA rating by Fitch would in this table correspond to a AA+ rating. The column with only a dummy for a Fitch rating added in Table V is not replicated here since it is invariant to this correction.

	(1)	(2)	(3)	(4)	(5)
Fitch added and better	-0.726	0.132	-5.533	-2.973	-1.09
	[-0.09]	[0.02]	[-0.73]	[-0.35]	[-0.15]
Fitch added and equal	-6.747	-6.22	-10.37	1.624	-1.683
	[-0.84]	[-0.77]	[-0.95]	[0.32]	[-0.13]
Fitch added and worse	2.645	2.953	9.538	2.909	3.203
	[0.64]	[0.71]	[1.06]	[0.70]	[0.77]
Fitch added and makes IG		-30.71***	-22.98**		
		[-2.86]	[-2.15]		
Fitch added and denies IG		11.16	22.99		
		[0.60]	[0.89]		
At IG boundary		15.57***	11.10***		
		[3.26]	[2.60]		
*Fitch added and equal**				-2036.8	
analyst dispersion				[-1.10]	
analyst dispersion				588.2***	
				[4.13]	
*Fitch added and equal**					-8.636
rating dispersion					[-1.11]
rating dispersion					2.399**
					[2.00]
Controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Segment	All	All	BBB+ to BB-	All	All
N	34,621	34,621	15,100	34,724	34,621
adj. R^2	0.531	0.532	0.626	0.534	0.531
N. issuers	671	671	465	672	671

Table IA.III

CRA Default Prediction with MSP Disagreement

Using yearly panel data between 2000 and 2008, we compare CRA performance with respect to default prediction on a one year horizon. The table shows results from a logit regression of issuer default events on Moody's and S&P rating scales, rating differences between Moody's and Fitch, dummies for the effect of Fitch as a tiebreaker when Moody's and S&P are at different sides of the IG boundary and time fixed effects for the complete universe of bonds that are rated by all three CRAs. The rating variables are in notches where 1 corresponds to AAA. The difference variables measure the difference between the First minus the second CRA in notches. Column 1 is restricted to cases where Moody's and S&P disagree. Only marginal effects are reported (multiplied by 10,000 for readability), and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)
Moody's Rating	5.00***	3.91***
	[3.28]	[4.00]
S&P Rating	0.403	0.37
	[0.54]	[0.65]
Difference Fitch vs Moody's	5.00***	
	[3.28]	
Fitch makes IG		-5.63
		[-1.52]
Fitch denies IG		-4.08
		[-0.96]
Year FE	Yes	Yes
Moody's and S&P disagree only	Yes	No
N	56,376	112,329
pseudo R^2	0.372	0.369
N. issuers	1693	2066

Table IA.IV

Credit Spread Regressions, Full Sample

Using quarterly panel data between 2002 and 2008, we regress credit spread levels for AAA to B- rated bonds on bond and firm characteristics, with rating and time fixed 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 regulation (IG). See Table IA.V for descriptions of other control variable descriptions. However, levels instead of changes are used for the controls. Time fixed effects are estimated for the IG and HY category separately to accommodate the sharp widening of the IG/HY spread during the crisis. t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Fitch<MSP	4.314	5.487	3.771	4.1
	[1.14]	[1.42]	[1.00]	[1.12]
Fitch=MSP	7.151**	7.184**	6.594*	7.678**
	[2.12]	[2.15]	[1.94]	[2.27]
Fitch>MSP	16.37**	13.16**	16.68**	15.71**
	[2.28]	[2.04]	[2.30]	[2.18]
Fitch makes IG		-26.35***		
		[-2.62]		
Fitch denies IG		18.22		
		[1.17]		
*analyst dispersion**			207.4	
Fitch=MSP			[1.40]	
analyst dispersion			252.2	
			[0.95]	
*Rating dispersion**				-1.356
Fitch=MSP				[-0.35]
Rating dispersion				2.083
				[0.64]
Controls	Yes	Yes	Yes	Yes
Time FE by IG/HY	yes	yes	yes	yes
MSP Rating FE	yes	yes	yes	yes
N	44,139	44,139	43,711	44,139
adj. R^2	0.814	0.815	0.815	0.814
N. issuers	739	739	716	739

Table IA.V

Change in Credit Spreads and Rating Changes, Pre-Crisis Sample

Using quarterly panel data between 2002 and 2007Q2, we regress changes in credit spreads for AAA to B- rated bonds that are rated by all three CRAs on rating up- and downgrades for all three CRAs, changes in bond and firm characteristics, dummies for boundary effects and time fixed effects. Up- and downgrades are coded as dummies indicating whether each of the three CRAs upgraded or downgraded its rating. These firm and bond controls are included but not shown (all in changes): Leverage, liquidation/intrinsic value (PPE/total assets), R&D expenses (divided by total assets), ROA (return on assets), Stdev (daily idiosyncratic equity volatility), Historical Equity Beta (half year daily corrected for Bid-Ask-bounces), Log Total Assets (firm size, book value) and Log Offering Size (issue size), Redeemable (dummy for callability), Duration and Convexity. *Fitch Upgrade, Breaks Tie* is a dummy indicating that a Fitch upgrade made the issue qualify for IG, while *Fitch Downgrade, Breaks Tie* is a dummy indicating that a Fitch downgrade made the issue lose its IG qualification. *Fitch Could Break Tie* is a dummy indicating that the S&P and Moody's ratings are on opposite sides of the IG-HY boundary. Column (5) is restricted to issues rated A- or better by Moody's and S&P, whereas column (6) is restricted to issues rated BBB+ or worse by Moody's and S&P. t-statistics are in brackets (using robust standard errors clustered by issuer; N. issuer gives the number of issuers). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. 'F-test *Fup=Fdown* (p-value)' gives the p-value for the coefficients on *Fitch Upgrade* and *Fitch Downgrade* being equal, while 'F-test *Fup,tie=Fdown,tie* (p-value)' gives the p-value for the coefficients on *Fitch Upgraded, Breaks Tie* and *Fitch Downgraded, Breaks Tie* being equal.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Moody's Upgrade	-5.546**						-2.794	-2.472
	[-2.44]						[-1.41]	[-1.28]
Moody's Downgrade	14.59***						9.905**	9.704***
	[4.42]						[2.56]	[2.66]
S&P Upgrade		-9.268***					-8.036***	-7.805***
		[-3.20]					[-3.20]	[-3.13]
S&P Downgrade		16.31***					11.66***	11.38***
		[4.49]					[3.47]	[3.53]
Fitch Upgrade			-6.228*	-6.134*	-0.435	-6.175	-4.103	-4.227
			[-1.86]	[-1.79]	[-0.13]	[-1.65]	[-1.40]	[-1.41]
Fitch Downgrade			13.97***	10.31***	0.662	14.95***	6.467	3.32
			[3.04]	[2.63]	[0.26]	[2.89]	[1.44]	[0.82]
Fitch Upgrade, Breaks Tie				-3.222		-5.122		-0.185
				[-0.38]		[-0.65]		[-0.02]
Fitch Downgrade, Breaks Tie				44.20**		38.69*		40.55**
				[2.16]		[1.92]		[1.98]

Continued on next page

Table IA.V – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fitch Could Break Tie				-4.869*		-3.611		-5.081*
				[-1.85]		[-1.42]		[-1.94]
Lagged Credit Spread	-0.266***	-0.268***	-0.264***	-0.263***	-0.419***	-0.223***	-0.271***	-0.270***
Change	[-9.24]	[-9.14]	[-8.95]	[-8.91]	[-22.09]	[-6.67]	[-9.38]	[-9.32]
Sample	All	All	All	All	≤A-	≥BBB+	All	All
N	16,889	16,889	16,889	16,889	8,535	8,354	16,889	16,889
Adj. R^2	0.204	0.207	0.202	0.206	0.269	0.23	0.212	0.214
N. issuers	343	343	343	343	107	276	343	343
F-test Fup=$Fdown$			0.05%	0.16%	79.00%	0.09%	5.19%	14.00%
(p-value)								
F-test Fup,tie=$Fdown,tie$				3.25%		4.44%		
(p-value)								

Table IA.VI

Credit Spread Regressions on Fitch Rating Additions, Pre-Crisis Sample

Using quarterly panel data between 2002 and 2007Q2, we regress changes in credit spreads for AAA to B- rated bonds that are rated by Moody's and S&P on rating additions from Fitch, the relative ranking of those additions and whether additions happened at the IG boundary, interactions with uncertainty measures and changes in bond and firm characteristics plus time fixed effects. *Fitch Added, Better*, *Fitch Added, Equal* and *Fitch Added, Worse* are dummies indicating whether a Fitch rating has been added that is respectively better than, equal to and worse than the average rating by Moody's and S&P. *Fitch Added, Makes IG* and *Fitch Added, Denies IG* are dummies that indicate whether the added Fitch rating makes the issue qualify for IG or not, conditional on Moody's and S&P ratings being on opposite sides of the boundary. See Table IA.V for descriptions of bond and firm level control variables. t-statistics are in brackets (using robust standard errors clustered by issuer in all columns except column 5, which uses double clustering by both issuer and time). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. 'F-test *FAdded,IG=FAdded,HY* (p-value)' is the p-value of the F-test of *Fitch Added, Makes IG* and *Fitch Added, Makes HY* being equal. The sample is all issues rated by both Moody's and S&P with their average rating better or equal to B-, except in column 4, where their average rating is between BBB+ and BB-.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fitch Added	0.0133						
	[0.00]						
Fitch Added, Better		-7.003	-6.641	-2.535	-6.641	-7.365	-6.903
		[-0.97]	[-0.91]	[-0.39]	[-0.83]	[-1.01]	[-0.95]
Fitch Added, Equal		5.256*	5.021*	11.94**	5.021**	2.798	4.947*
		[1.84]	[1.76]	[2.11]	[2.03]	[0.94]	[1.80]
Fitch Added, Worse		-0.00141	-0.0856	17.21	-0.0856	-0.466	-0.187
		[-0.00]	[-0.01]	[0.86]	[-0.01]	[-0.04]	[-0.02]
Fitch Added, Makes IG			-20.28*	-20.13*	-20.28*		
			[-1.65]	[-1.70]	[-1.70]		
Fitch Added, Makes HY			30.46	27.03	30.46		
			[1.45]	[1.28]	[1.35]		
At IG boundary			-1.259	-1.149	-1.259		
			[-0.46]	[-0.45]	[-0.46]		
*Fitch Added, Equal **						1280.3	
Analyst Dispersion						[0.99]	

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Table IA.VI – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Analyst Dispersion						184.8	
						[1.51]	
*Fitch Added, Equal **							0.602
Rating Dispersion							[0.10]
S&P and Moodys Disagree							-0.686
							[-1.24]
Lagged Credit Spread	-0.276***	-0.277***	-0.277***	-0.243***	-0.277***	-0.279***	-0.277***
Change	[-11.99]	[-12.02]	[-12.01]	[-7.62]	[-6.84]	[-12.18]	[-11.99]
Sample	All	All	All	BBB+ to BB-	All	All	All
Double Clustering	No	No	No	No	Yes	No	No
N	24,557	24,557	24,557	9,751	24,557	24,650	24,557
Adj. R^2	0.205	0.206	0.206	0.224	0.206	0.207	0.206
N. issuers	605	605	605	404		608	605
F-test			3.24%	4.59%	8.93%		
FAdded,IG=FAdded,HY							
(p-value)							

Table IA.VII

Logistic Regressions for Having a Fitch Rating

Logit regressions of having a Fitch rating on rating category dummies based on average Moody's and S&P (MSP) ratings, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value), Dummy S&P and Moody's Disagree or *Notches of MSP Rating Dispersion* (absolute value of the notches difference between Moody's and S&P), and *F Could Break Tie* and *F Could Push A-* are dummies indicating whether the Moody's and S&P ratings are on opposite sides of the IG-HY and A- boundaries respectively. All specifications further include industry fixed effects. In column (6) and (7) issues are removed after, respectively, their first year and first quarter after being rated by Fitch. Other controls that are included but not shown are the firm Beta, Leverage, PPE / Assets, R&D Expenses / Assets, ROA, Log of Offering Amount, Maturity Left and Maturity Left Squared and Redeemable (see Table IA.V for descriptions). Quarterly data for 2000-2008 are used, and the sample consists of all issues with both Moody's and S&P ratings that are on average rated B- or better. Marginal effects are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Pseudo R^2 refers to McFadden (1973) pseudo R^2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MSP Rating A+ to A-	0.418***		0.417***	0.420***	0.414***	0.216**	0.0985**
	[3.97]		[3.93]	[3.98]	[3.95]	[2.36]	[2.02]
MSP Rating BBB+ to BBB-	0.401***		0.397***	0.386***	0.395***	0.191***	0.0726**
	[4.31]		[4.21]	[4.08]	[4.24]	[2.69]	[2.26]
MSP Rating BB+ to BB-	0.299***		0.291***	0.290***	0.289***	0.243*	0.123
	[6.70]		[6.25]	[6.12]	[6.23]	[1.96]	[1.60]
MSP Rating B+ to B-	0.266***		0.266***	0.267***	0.263***	0.223	0.111
	[6.13]		[6.09]	[6.19]	[5.96]	[1.60]	[1.30]
Fitch Could Break Tie		0.144***	0.117***		0.103**	0.092	0.0369
		[3.99]	[3.18]		[2.51]	[1.60]	[1.17]
Fitch Could Pull A		0.0649	0.0328		0.00998	0.0282	0.0226
		[1.31]	[0.60]		[0.17]	[0.63]	[0.96]
Avg MSP BB+				0.0952**			
				[2.39]			
Avg MSP BBB-				0.0790**			
				[2.24]			
Notches of MSP Rating Dispersion					-0.00204		
					[-0.07]		

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Table IA.VII – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
S&P and Moodys Disagree	-0.0305	-0.0309	-0.0426	-0.0333		-0.0347	-0.022
	[-0.69]	[-0.62]	[-0.87]	[-0.74]		[-1.10]	[-1.60]
Analyst Dispersion	0.835	0.728	0.855	0.816	0.903	0.337	0.0652
	[0.96]	[0.84]	[0.96]	[0.98]	[0.97]	[1.21]	[1.29]
Idiosyncratic Volatility	-5.432***	-5.334***	-5.397***	-5.513***	-5.388***	-2.103**	-0.182
	[-4.67]	[-4.80]	[-4.70]	[-4.75]	[-4.68]	[-1.98]	[-0.56]
Log of Total Assets	0.177***	0.151***	0.177***	0.179***	0.178***	0.0766***	0.0195***
	[8.86]	[5.64]	[8.82]	[8.90]	[8.87]	[5.87]	[5.36]
Time Limit after Fitch Addition	No	No	No	No	No	1 Year	1 Quarter
N	104,435	104,435	104,435	104,435	104,435	27,550	32,135
Pseudo R^2	0.223	0.174	0.224	0.225	0.223	0.163	0.098
N. issuers	818	818	818	818	818	639	683

Table IA.VIII

Logistic Regressions for Having a Fitch Rating with Double Clustering

Logit regressions of having a Fitch rating on rating category dummies based on average Moody's and S&P (MSP) ratings, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value), Dummy S&P and Moody's Disagree or *Notches of MSP Rating Dispersion* (absolute value of the notches difference between Moody's and S&P), and *F Could Break Tie* and *F Could Push A-* are dummies indicating whether the Moody's and S&P ratings are on opposite sides of the IG-HY and A- boundaries respectively. All specifications further include industry fixed effects. Other controls that are included but not shown are the firm Beta, Leverage, PPE / Assets, R&D Expenses / Assets, ROA, Log of Offering Amount, Maturity Left and Maturity Left Squared and Redeemable (see Table IA.V for descriptions). Quarterly data for 2000-2008 are used, and the sample consists of all issues with both Moody's and S&P ratings that are on average rated B- or better. Only coefficient estimates are reported, and *t*-statistics are in brackets using robust standard errors clustered by issuer in Column (1) and standard errors clustered by issuer and time in Column (2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Double clustered standard errors are calculated using the Stata code available on Mitchel Petersen's website.

	(1)	(2)
MSP Rating A+ to A-	2.411***	2.411***
	[3.76]	[3.69]
MSP Rating BBB+ to BBB-	2.440***	2.440***
	[3.84]	[3.74]
MSP Rating BB+ to BB-	2.645***	2.645***
	[4.00]	[3.92]
MSP Rating B+ to B-	2.472***	2.472***
	[3.45]	[3.39]
Fitch Could Break Tie	0.705***	0.705***
	[2.61]	[2.66]
Fitch Could Pull A	0.172	0.172
	[0.58]	[0.59]
Notches of MSP Rating Dispersion	-0.213	-0.213
	[-0.87]	[-0.89]
Analyst Dispersion	4.331	4.331
	[0.96]	[0.82]
Industry FE	yes	yes
Double clustering	no	yes
N	104,435	104,435
pseudo R^2	0.224	
N. issuers	818	

Table IA.IX

Change in Credit Spreads and Rating Changes, verification tests

Using quarterly panel data between 2002 and 2008, we regress changes in credit spreads for AAA to B- rated bonds that are rated by all three CRAs on rating up- and downgrades for all three CRAs, changes in bond and firm characteristics, dummies for boundary effects and time fixed effects. Up- and downgrades are coded as dummies indicating whether each of the three CRAs upgraded or downgraded its rating. These firm and bond controls are included but not shown (all in changes): Leverage, liquidation/intrinsic value (PPE/total assets), R&D expenses (divided by total assets), ROA (return on assets), Stdev (daily idiosyncratic equity volatility), Historical Equity Beta (half year daily corrected for Bid-Ask-bounces), Log Total Assets (firm size, book value) and Log Offering Size (issue size), Redeemable (dummy for callability), Duration and Convexity. *Fitch Upgrade, Breaks Tie, Moody's Upgrade, Breaks Tie* and *S&P Upgrade, Breaks Tie* are a dummies indicating that the respective CRA upgrade made the issue qualify for IG, while *Fitch Downgrade, breaks no tie anymore, Moody's Downgrade, breaks no tie anymore* and *S&P Downgrade, breaks no tie anymore* are dummies indicating that a downgrade by the respective CRA made the issue lose its IG qualification. *Fitch Could Break Tie, Moody's Could Break Tie* and *S&P Could Break Tie* are a dummies indicating that the ratings by the other CRAs are on opposite sides of the IG-HY boundary. Columns (3) and (4) are restricted to issues rated A- or better by Moody's and S&P, whereas columns (5) and (6) are restricted to issues rated BBB+ or worse by Moody's and S&P. t-statistics are in brackets (using robust standard errors clustered by issuer; N. issuer gives the number of issuers). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. 'F-test $Mup{=}Mdown$ (p-value)' and 'F-test $SPup{=}SPdown$ (p-value)' give the p-values for the test on the coefficients on *Moody's Upgrade* and *Moody's Downgrade* being equal and the test on the coefficients on *S&P Upgrade* and *S&P Downgrade* being equal respectively. Similarly 'F-test $Mup,tie{=}Mdown,tie$ (p-value)' and 'F-test $SPup,tie{=}SPdown,tie$ (p-value)' give the p-values for the test of the coefficients on *Moody's Upgraded, Breaks Tie* and *Moody's Downgraded, Breaks Tie* being equal and the test of the coefficients on *S&P Upgraded, Breaks Tie* and *S&P Downgraded, Breaks Tie* being equal respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moody's upgrade	-4.463*		-5.414**		-8.704***		-2.493	-2.418	-2.587
	[-1.90]		[-2.34]		[-3.18]		[-1.13]	[-1.13]	[-1.17]
Moody's downgrade	14.06***		9.149**		18.55***		7.378**	7.032*	8.239**
	[4.09]		[2.22]		[3.97]		[2.07]	[1.89]	[2.41]
S&P upgrade		-4.977*		-10.41***		-4.846	-4.321	-3.701	-3.833
		[-1.84]		[-2.64]		[-1.65]	[-1.62]	[-1.37]	[-1.40]
S&P downgrade		16.63***		4.094		20.43***	18.70***	13.13***	12.95***
		[4.39]		[1.06]		[4.76]	[4.21]	[3.52]	[3.50]
Fitch upgrade							-4.948	-5.207*	-4.086
							[-1.64]	[-1.72]	[-1.36]
Fitch downgrade							4.631	4.779	4.2
							[0.80]	[0.84]	[0.71]

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fitch upgraded and breaks tie									-8.796
									[-0.62]
Fitch downgraded and breaks no tie anymore									4.181
									[0.21]
Fitch could break tie									10.27**
									[2.08]
Moody's upgraded and breaks tie	-2.479				3.764		-0.728		1.183
	[-0.37]				[0.58]		[-0.12]		[0.21]
Moody's downgraded and breaks no tie anymore	1.052				-2.068		-1.156		-18.97
	[0.04]				[-0.08]		[-0.04]		[-0.70]
Moody's could break tie	2.818				-0.792		2.661		-6.331
	[0.74]				[-0.26]		[0.71]		[-1.38]
S&P upgraded and breaks tie		-14.25*				-10.03		-13.21*	-12.1
		[-1.82]				[-1.57]		[-1.73]	[-1.58]
S&P downgraded and breaks no tie anymore		40.15***				36.08***		39.51***	40.53***
		[2.98]				[2.92]		[2.84]	[2.61]
S&P could break tie		11.87***				8.468**		12.14***	7.797*
		[2.61]				[2.13]		[2.64]	[1.66]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rated by All 3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Range	All	All	≤A-	≤A-	≥BBB+	≥BBB+	All	All	All
N	24282	24282	11330	11330	12952	12952	24282	24282	24282
adj. R^2	0.531	0.537	0.451	0.451	0.602	0.608	0.534	0.537	0.538
N. issuer	380	380	117	117	313	313	380	380	380
F-test *Mup=Mdown* (p-val)	0		0.008		0		0.015		
F-test *Mup,tie=Mdown,tie* (p-val)	0.897				0.833		0.987		
F-test *SPup=SPdown* (p-val)		0		0.008		0		0	

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Table IA.IX – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
F-test		0				0.001		0.001	
$SPup,tie$=$SPdown,tie$									
(p-val)									