The Credit Rating Game: Evidence from a Strategic Game Model

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Abstract

This paper empirically analyzes the effect of competition on rating quality under the "issuer-pay" compensation scheme. Using hand-collected data of collateralized debt obligations (CDOs), we specify the competition among credit rating agencies with a discrete game framework and test its influence on the rating quality. We find that competition raised the probability of choosing lenient rating by 31% for Moody's and 27% for S&P in the sample period of 2007-2008. We further demonstrate that the propensity for selecting lenient rating increases with the bargaining power of the underwriters and the complexity of the CDOs. Overall, we find evidence suggests that competition among CRAs reduces their rating quality under the "issuer-pay" scheme.

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"Oh God, are you kidding? All the time. I mean, that's routine. I mean, they would threaten you all of the time. ... It's like, 'Well, next time, we're just going to go with Fitch and S&P.' "

— Gary Witt, a former Moody's team managing director told the Financial Crisis Inquiry Commission when asked if the investment banks frequently threatened to withdraw their business if they did not get their desired rating[1].

1 Introduction

Credit ratings provides a cost-efficient assessment of a security's default risk, reduces the investor's duplication of effort, and therefore, plays a crucial role in the financial market. It also serves as an explicit measure of risk that both regulation and private contracts rely on. However, the collapse of structured finance products with "AAA" ratings during the 2007 - 2008 financial crisis have drawn the public attention to the reliability of credit ratings. The unprecedented scale of malfunctioning of credit ratings has spurred a series of discussions on the possible factors distorting the rating quality.

Among all the discussions, one possible contributor is the conflict of interests arising from the "issuer-pay" business model. From the public perspective, the media has been criticizing the CRAs for competing to cater for favorable ratings to attract business. Mr. Witt's statement also underlines the enormous competition pressure faced by the CRAs. From the theoretical perspective, several recent studies have provided appealing models explaining the economic relation between CRAs' competition and the rating quality of structured finance products. For instance, Bolton, Freixas, and Shapiro (2012) offer a model in which the competition among CRAs facilitates issuers to shop for favorable ratings, leading to lenient ratings when the CRAs are less likely to be punished for inaccurate ratings in the booming market. Camanho, Deb, and Liu (2012) also find that the CRAs are more liable to inflate their scores under competition compared to monopoly.

While both public media and theoretical studies agree that the competition pressure generated by the "issuer-pay" business model leads to upward bias in ratings, the empirical evaluation faces three primary challenges. First, oligopolistic competition among CRAs can generate a broad range

[1] The Financial Crisis Inquiry Report. National Commission on the Causes of the Financial and Economic Crisis in the United States. 2011. p. 210.

of outcomes depending on the parameters of the market structure. Interpreting empirically, CRAs could behave differently in alternative rating markets regarding the number of incumbent CRAs, the relative reputation of CRAs, the complexity of the security, the fee structure, etc. Thus, it is not feasible to generalize empirical findings from the quasi-experiment in one particular rating market to others. In other words, the rating outcome is sensitive to the structure of the rating market.

The second challenge is to measure the competition among CRAs. In the most of the history, the credit rating industry features the competition among three major CRAs: Moody's, Standard & Poor's, and Fitch. Therefore, traditional measures of market competition, such as the Herfindahl index and the concentration ratio index, are improper. Without an explicit measure of the competition among CRAs, we cannot quantify its impact on their rating quality.

The third challenge is the lack of benchmark in evaluating the quality of observed letter scores. On one hand, we can only observe the discrete letter grades in the data while the underlying credit risk is unobservable. On the other hand, the input information used to generate the ratings, especially the key default correlation parameter, is unavailable. Consequently, it is hard to find a precise quantitative measure to evaluate the quality of the observed ratings.

Given these challenges, we depart from the traditional literature by modeling the CRA's competition in a discrete game model. Abstract from the discussion of Skreta and Veldkamp (2009) and Bolton, Freixas, and Shapiro (2012), the credit rating game starts with an issuer proposing a deal structure to multiple CRAs and asks for an initial evaluation. Then, each CRA provides an initial rating, either lenient or strict, to the issuer privately. In the third step, the issuer compares all the initial ratings from all the CRAs. Since it is hard to sell a structured finance product with low ratings, the issuer chooses the highest rating among all initial ones and pays the CRA with the highest rating to publish. Given the structure of the game, a CRA takes its rivals' rating actions into consideration when selecting its initial ratings. Under this circumstance, we model the competition among CRAs through their strategic interaction in posting initial credit ratings.

We then impose the structure of the game to a hand-collected dataset of CDOs and empirically back out model parameters from the observed rating scores. The choice of credit market for CDOs yields three benefits. First, there are only two dominating CRAs: Moody's and S&P, in the CDOs rating market. Therefore, the structure naturally fits into the discrete game framework. Second, the strategic interaction among CRAs is especially prominent for CDOs due to the lucrative profit margin. For example, Morgenson and Rosner (2010) document that Moody's could charge as much as five times the fee to rate a mortgage pool compared to the municipal bond with a similar size. Third, the uncertainty in risk assessments for CDOs gives CRAs substantial leeway in choosing their rating standards. For example, there is a significant surge of additional layers of repackaging in the CDO contracts after 2005 while the risk models failed to catch up. This observation is also supported by Coval, Jurek, and Stafford (2009), who find that an increase in the default correlation from 20% to 40% could bring an initially "AAA" -rated CDO to a "B+" rating.

We aim to answer three questions in this paper. First, does competition among CRAs lead to more lenient ratings in the CDO market? Second, to what extend can CRA's competition explain the observed lenient ratings? Finally, when does competition among CRAs has the strongest impact on choosing lenient credit ratings? With the modeling and empirical strategies, we analyze the effect of competition among CRAs in the CDO market and confirm the significant role competition plays in rating CDO products. First, we find that CRAs do coordinate their lenient ratings, i.e., a CRA's probability of choosing lenient ratings increases when it expects a higher propensity for its rival to choose lenient ratings. In other words, competition indeed reduces rating quality. Second, we evaluate the impact of competition by shutting down the strategic interaction in the model. At the aggregate level, if the strategic interaction between CRAs is muted, the predicted odd of Moody's choosing lenient ratings decreases by 31%, and 27% for S&P. Last, we find the competition effect be stronger for CDOs organized by stronger underwriters and with more complex structures. Possible explanations include higher bargaining power and information asymmetry. We also conduct a series of robustness checks with various model specifications and find similar results.

This paper makes both substantive and methodological contributions to the growing body of literature that improves our understanding of problems in the credit rating industry. On the substantive side, this paper contributes to the literature on the role of CRAs competition in the collapse of structure products market. Griffin and Tang (2012) finds that ratings are upward adjusted. Griffin, Nickerson, and Tang (2013) shows that CDOs rated by both Moody's and S&P are more likely to default than those rated by one of them, and they also find descriptive evidence that CRAs consider the influence of it rival's actions. By using the discrete game model, this paper provides novel quantitative evidence that establish a direct link between CRAs competition and ratings quality in the CDOs market, which is consistent with several claims in the theoretical literature (Bolton, Freixas, and Shapiro (2012)) .

This paper also adds to the strand of literature understanding the general relation between competition and information quality. In the related literature of analyst forecasts, Hong and Kacperczyk (2010) document a causal link between the decrease in analyst coverage and an increase in optimism bias, suggesting that competition reduces reporting bias. They also note that their results can be applied to credit ratings market as suppliers of reports in the two markets face similar trade-off between long-term reputation and short-term profits. In the context of corporate bond market Becker and Milbourn (2011) find that competition reduces ratings quality, whereas Doherty, Kartasheva, and Phillips (2012) show that the intensified competition when S&P entered into the insurance ratings market led to more stringent rating standards. These opposing conclusions, as also noted by Doherty, Kartasheva, and Phillips (2012), may stem from the fact CRAs compete along different dimensions in different market environments. In our empirical setting, the CDOs market boomed during 2005-07 when the short-term profits far outweighed reputation concern (Bolton, Freixas, and Shapiro (2012); Bar-Isaac and Shapiro (2013)). Our results show that competition reduces ratings quality under this environment, highlighting the importance of long-term reputation for ratings quality.

Another contribution of this paper is the introduction of a new empirical framework to quantitatively analyze the competitive effects in the rating industry. White (2002) stresses the oligopolistic competition in rating industry and call for an "industrial organization" paradigm to investigate the rating industry. The econometric implementation specified in this paper provides the first step towards this direction. Traditional empirical approaches rely on quasi-experimental settings, usually variations in market structure, to evaluate the effect of CRAs competition. But these strategy faces three difficulties: (1) such settings are rare in the credit rating industry, and (2) as has long been noticed in the industry organization literature, the market structure itself cannot be considered as an exogenous variable (e.g., Bresnahan and Reiss (1991); Berry (1992)), and (2) it is hard to generalize such results to other ratings markets. The econometric implementation in this paper circumvents these difficulties and can provide a versatile tool to examine the effect of competition in the credit rating industry. With proper extensions it is possible to incorporate different market characteristics into the CRA strategic game, helping us understand the effect of CRAs competition in different rating markets.

Understanding the economic mechanisms behind the collapse of the 2007-2008 "AAA"-rated CDOs market could provide helpful policy implications for the prevention of such events. The rating industry is highly regulated. Especially after the 2007-08 crisis, there have been growing discussions over regulatory measures that can improve ratings quality by encouraging competition in credit rating industry. However, these exists little empirical analysis that can offer quantitative guideline for policy decisions[2]. This paper fills this void, and shows that given the current "issuer-pay" business model, competition along is no guarantee for high ratings quality.

The rest of the paper is organized as follows. Section 2 presents the empirical design. Section 3 describes the data set. Section 4 describe our econometric implementation. Section 5 provides our empirical results and their implications. Section 6 concludes.

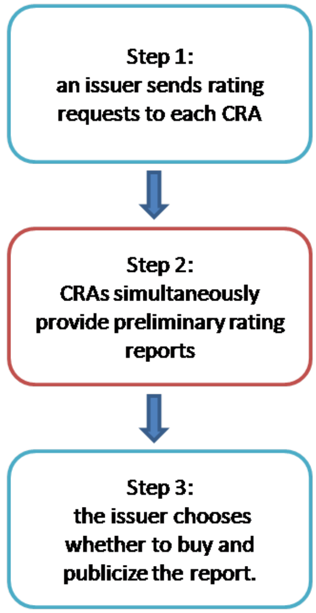
2 Econometric Design

2.1 Credit Rating as a Simultaneous-Move Game

In this paper, we model CRA's credit rating process as a simultaneous-move discrete game with incomplete information. Under the current "issuer-pay" business model, the underwriter of an CDO security first obtains an initial rating from a CRA and only pays the CRA if it is satisfied with the rating and requests the CRA to make the rating public. If we assume an issuer acquires credit ratings simultaneously, the entire process can be sketched with three steps as shown in Figure 1,

[2]In fact, the U.S. Department of Justice's Antitrust Division has adopted similar methods in evaluating the competitive effects of proposed mergers and acquisitions.

Figure 1: Time horizon of credit rating process.



The strategic game between CRAs is played in Step 2 when they provide initial ratings for CDOs. we model CRAs' initial ratings for CDOs as the equilibrium outcomes in the play of a game with the same structure. Formulating a strategic game involves specifying several elements: a set of players, a set of actions, the relevant time horizon and information set of each player, and the payoff preferences over the set of action profiles. In the discrete game model of credit ratings, the players involve a finite number of CRAs, $i \in \{1, ...n\}$, which for the most part consists of two or three dominating CRAs in the CDO market.

For each CDO, a CRA has two possible actions, adopting a lenient rating that lies at the lower bound of the underlying credit risk of the CDO, or a strict rating that is at the higher bound of the underlying credit risk. We denote the set of a CRA's strategic actions as $A = (0, 1)$, where element action $a = 1$ corresponds to choosing a lenient rating and $a = 0$ denotes choosing a strict rating. We restrict all CRAs to have the same set of strategic actions. To distinguish action of different CRAs, let a_i be the action chosen by CRA i, and a_{-i} be the actions of other CRAs.

When specifying CRAs' relevant time horizon, there are two main alternatives: a one-shot static game or a dynamic game that is played several rounds. In this paper, we assume all CRAs play a one-shot static game, issuing their credit reports simultaneously for each CDO. Indeed, an issuer typically solicit ratings reports from several CRAs, and all CRA report their initial ratings assessments before the issuance. We also assume each CRA does not have exact information regarding other CRAs' ratings.

We assume that the competition takes place at each CDO. A CDO has a vector of characteristics $x_i = (z_{i1}, ..., z_{im}, w_{i1}, ..., w_{in})$ with z_i and w_i representing CDO-specific and CRA-specific characteristics respectively. All characteristics are common knowledge to every CRA in the game and in our econometric analysis. After a CRA provides the rating report, it realizes the deterministic part of its expected payoff (For a detailed discussion of the payoff function see Appendix A),

$$\pi_i(x, a_i, a_{-i}; \theta) = \begin{cases} \beta x_i + \delta \sum_{j \neq i} p(a_j = 1) & if\ a_i = 1 \\ 0 & if\ a_i = 0 \end{cases} \tag{1}$$

The deterministic part of the expected payoff contains characteristics specific to both the CDO and the CRA, as well as the CRA's beliefs regarding its rival CRA's action $p(a_j = 1)$. $\theta = \{\beta, \delta\}$ is a finite-dimensional parameter vector. The parameters β captures the effects of the CDO- and CRA-specific characteristics on the payoff. The coefficient to the strategic term δ captures the *competitive effect* that CRA j exerts on CRA i's rating action. The strategic coefficient captures the effect of competition and has a very intuitive interpretation: if a CRA's odds of choosing lenient ratings go up as it believes that other CRAs will have higher odds of choosing lenient ratings, then the strategic coefficient is positive, $\delta > 0$, and the CRAs competition lowers ratings quality.

Each CRA also has privately observed information about each CDO which we label as ε_{ij}. ε_{ij} is not known to other CRAs and our econometricians. This idiosyncratic CDO-specific shock captures unobservable factors that vary among CRAs and could enter CRA's payoff function of choosing rating actions (see Rust (1994)). We assume these shocks are drawn from an i.i.d distribution $F(\varepsilon_{ij})$. Then the payoff function of CRA i for CDO j is given by

$$\Pi_i(x, a, \varepsilon_{ij}; \theta) = \pi_i(x, a_i, a_{-i}; \theta) + \varepsilon_i \tag{2}$$

The utility function in our model is similar to a standard discrete choice model except that CRA i's payoff also depends on its beliefs regarding its rivals' actions. The stochastic term ε_i represents private information to CRA j, and CRA i cannot predict its rival CRA j actions a_{-i} with certainty. Similar to discrete choice models, the underlying latent payoffs are not observable, and I can only observe the revealed bested responses of CRAs. A CRA i's best response function is based on its expected payoff that includes its beliefs regarding its rivals' actions,

$$a_i = \begin{cases} 1 & if\ \beta x_i + \delta \sum_{j \neq i} p(a_j = 1) + \varepsilon_{ij} \geq 0 \\ 0 & if\ \beta x_i + \delta \sum_{j \neq i} p(a_j = 1) + \varepsilon_{ij} < 0 \end{cases} \tag{3}$$

In which the probability $p(a_j = 1)$ is CRA i's beliefs regarding its rival CRA j actions. The probability of CRA i choosing action a_i conditional on the parameter vector θ can be written as the following

$$\begin{aligned} p(a_i = 1) &= \int 1\{\varepsilon_{ij} \geq -(\beta x_i + \delta \sum_{j \neq i} p(a_j = 1))\} f(\varepsilon_{ij}) d\varepsilon_{ij} \\ &= F(\beta x_i + \delta \sum_{j \neq i} p(a_j = 1)) \end{aligned} \tag{4}$$

Where $1\{\varepsilon_{ij} \geq -(\beta x_i + \delta \sum_{j \neq i} p(a_j = 1))\}$ is an indicator function that equals to 1 if the inequality is satisfied and 0 otherwise. F and f are the probability distribution function and density function of the error terms ε_{ij}.

Typically, if there are more than three players, it is hard to formulate a likelihood for the game and one has to adopt a GMM approach to solve the game. Fortunately, the credit ratings game examined in this study only includes two major players, Moody's and S&P. While there were three major nationally recognized statistical rating organization (NRSRO)[3] in our sample period of 2005-07, the bond credit rating market was largely dominated by Moody's and S&P . Their combined total market shares are estimated to more than 80 %, and the smaller player, Fitch, only takes around 15 percent (White (2010)) of the total market shares. Further, even these figures understate the dominance of Moody and S&P as it is well documented that there exists a norm for bond issuers to seek ratings from both Moody's and S&P, and Fitch only provides a role of "third opinion"(Bongaerts, Cremers, and Goetzmann (2012)). Thus it is reasonable to specify that the

[3] NRSRO is a CRA whose credit ratings have been endorsed by U.S. Securities and Exchange Commission (SEC) to be used by other financial firms for certain regulatory purposes. Originally, seven rating agencies were recognized as NRSROs, the number reduced to three as a result of mergers by 2003. After the financial crisis, a number of CRAs were designated as NRSROs by the SEC. As of November 2011, there were nine NRSROs.

competition in the rating market mainly occurs between S&P and Moody's.

With only two major CRAs in our setting, denote Moody's and S&P with subscripts 1, 2 respectively, equations 3 and 4 can be written as

$$\begin{aligned} a_{1j} = &\quad 1[x_1\beta_1 + \delta p_2 + \varepsilon_{1j} \geq 0] \\ a_{2j} = &\quad 1[x_2\beta_2 + \delta p_1 + \varepsilon_{2j} \geq 0] \end{aligned} \tag{5}$$

CRAs' conditional choice probabilities (CCPs) of choosing lenient ratings can be described by the following system of simultaneous equations,

$$\begin{aligned} p_1(a_1 = 1) = &\quad F(x_1\beta_1 + \delta p_2) \\ p_2(a_2 = 1) = &\quad F(x_2\beta_2 + \delta p_1) \end{aligned} \tag{6}$$

The system of simultaneous equations characterizes the Bayesian Nash equilibrium of the game. The solution to the system of simultaneous equations 6 characterize every CRA's best response in the Bayesian Nash equilibrium. δ captures the magnitude of strategic interaction between the two CRAs. If $\delta > 0$ then it is easy to see that a CRA tends to take the action $a = 1$ if it believes its rival is likely to take action $a = 1$.

Once we obtain the CCPs, we then plug them into the likelihood function to obtain parameter estimates from the revealed choice data,

$$\begin{aligned} \Theta &= \underset{\Theta}{\text{argmax}}\, \mathscr{L}(Y, X, \Theta) \\ &= \underset{\Theta}{\text{argmax}} \prod_{i \in \{1,2\}} p(a_i = 1|X_i)^{Y_i}[1 - p(a_i|X_i)]^{1-Y_i} \end{aligned} \tag{7}$$

Where $p(a_i = 1|X_i)$ is the CCPs of player i choosing action $a = 1$, and Y_i are the observed actions in the data. In the similar spirit of maximized likelihood estimation, the parameter estimates are obtained by finding a unique set of parameters that maximized the likelihood function Equation 7 based on the revealed choice data.

2.2 Properties of Bayesian Nash Equilibria

One complexity in solving the system of simultaneous equations is the existence of multiple equilibria. Specifically, the underlying latent payoffs could be consistent with more than one equilibrium outcomes of CCPs. The existence of equilibrium is theoretically guaranteed by Brouwer's fixed-point theorem as long as the error term εs are drawn from a continuous distribution. However, the number of equilibrium can vary with the parameters. If there exist multiple equilibria, for a give parameter vector θ, more than one set of CCPs satisfies the system of simultaneous equations 4 that characterizes the BNE of the game. In this case, we can no longer get a well defined likelihood function, which is the key for the identification of the maximum likelihood estimation.

Fortunately, the CRAs ratings game can be modeled as a two player-two action game, in which we can prove the uniqueness of equilibrium when the strategic interaction is moderate. In Appendix D, we provide a detailed mathematical proof which shows that if the magnitude of strategic interaction is smaller than 4, there is one unique equilibrium in the 2×2 game. As an illustration, Figure 4 plot the best response functions (CCPs) for six different cases of Equations 6, where player 1(2)'s CCP is on the vertical(horizontal) axis. We parameterize δ and $x\beta$, and there is an equilibrium wherever best response functions cross.

Insert Figure 4 Here

In Panels (a)(c)(e) $|\delta| = 0.5 < 4$, so there is always only one equilibrium in the game, regardless of the deterministic part of a CRA's the payoff $x\beta$. By contrast, when the magnitude of strategic interaction is very strong $|\delta| = 6 > 4$, there may exist three equilibria in the game for some values of $x\beta$ as in panels (d)(f).

3 Empirical Implementation

3.1 Data and Descriptive Statistics

3.1.1 Data Construction

We construct the data set from two sources: (1) the Bloomberg database and (2) the Pershing Square's Open Source Research data[4]. We begin our data collection process from the CDOs information assembled in the Pershing Square's Open Source Research data. These data was collected by Pershing Square Capital Management in its attempt to improve the level of disclosure in the bond insurance market. The data universe is comprised of 534 deals of CDOs of ABS and CDO-Squareds (CDO^2) that were insured by Ambac and MBIA. All the CDOs were issued during 2005-2007. The data provide extensive description of 30499 underlying collateral assets identified by CUSIP, including the collateral type, original and current (as of January 2008) credit ratings, amount outstanding, tranche sizes, and tranche priority. There are 4145 CDO tranches in total.

We supplement the Pershing Square data with information from the Bloomberg database. For each CDO tranche, we look up their CUSIP in the bloomberg database. If the CUSIP is not available, we use the tranche name instead. From the Bloomberg database, we collect information including issuer name, underwriter name, current follow-up ratings (as of August 2013), CDO type, interest rate, payment method, and final maturity, when available. In this study, to reduce the influence of new information generated between the initial ratings and follow-up ratings. we only focus on ratings for long-term investments and exclude CDOs with maturity earlier than year 2025. The final data set consists of 3072 CDO tranches from 495 deals.

Insert Table 2 Here

Insert Table 3 Here

Insert Figure 2 Here

Insert Figure 3 Here

[4]The same dataset was also used by Efraim and Jennifer (2010).

Table 2 shows the number of CDOs at each rating grade in the combined data universe. The initial ratings are apparently much high that the current follow-up ratings. More than one third of the initial ratings are “AAA”-rated and less than one tenth are speculative grades. In contrast, only around 10 CDOs maintain investment grades in their current ratings. Table3 reports the amount of CDOs at each rating grade, and the contrast is even larger. Both Moody’s and S&P issue the highest rating “AAA” to more than 83% of all CDO issued, while more than 99% of all CDOs fall below investment grades in their current ratings. Figures 2 and 3 illustrate the distribution of initial ratings and current ratings.

There is one potential concern with the sample. Certain CDOs might be more likely to get insurance and thus show up in the data. However, there are two counterbalancing sample selection processes in the sample. On the one hand, buyers of low quality CDOs tend to be more inclined to buy additional insurance and thus the sample may involve more low quality CDOs. On the other hand, the two insurers would be very selective and carefully screen the bonds within the CDOs they agree to wrap, leading to higher CDO quality compared to the overall market. The two selection processes may offset each other and mitigate the concern over the sample selection issue.

3.1.2 Factors Related to Ratings Action

In the strategic game of CRAs competition, A CRA’s strategic rating action depends on its expected payoff function. We need to specify the state variables that are associated to a CRA’s payoff. We include two sets of state variables, CRA-specific characteristics and CDO-specific characteristics. All characteristics are common knowledge for all CRAs in the game and in the econometric analysis.

The first set of state variables are CRA-specific characteristics, which include underwriter-CRA and issuer-CRA relations. The underwriter and the issuer are the two major participants on the sell side in a CDO transaction. The issuer of a CDO deal is usually a special purpose entity that is constructed to purchase and manage a portfolio of underlying assets. The underwriter of a CDO is typically an investment bank, and acts as the organizer that work closely with the issuer in every step of the issuance of a new CDO deal. One of the underwriter’s responsibilities is to work with the CRA to gain the desired ratings for each tranche. Therefore the relation between a underwriter (issuer) could influence the credit ratings. Intuitively, the underwriter and issuer relations could affect a CRA's ratings decisions in two aspects. First, underwriters with strong relation with a CRA could have stronger bargaining power in obtaining their favorable ratings by threating to seek ratings elsewhere. Second, as the underwriter-CRA relation builds up, a underwriter could gain trust from a CRA, which could also help it obtain favorable ratings.

Insert Table 4 Here

Insert Table 5 Here

Table 4 lists the top 20 underwriter in terms of market share in the sample by market share – Merrill Lynch, UBS, Citigroup, Goldman Sachs, Wachovia Securities, Deutsche Bank Securities, Calyon Financial, RBS Greenwich Capital, Credit Suisse, Bank of America, Lehman Brothers, ICP Asset Securities, Bear Stearns, Fortis Securities LLC, Morgan Stanley Wells Fargo Bank, Barclays Capital, Societe Generale, Dresdner Kleinwort Wasserstein, and Credit Suisse First Boston. Almost all major investment banks on Wall Street before the financial crisis have substantial presence in the CDOs market, and the top four underwriters, Merrill Lynch, UBS, Citigroup, and Goldman Sachs, account for more than half of the total market share.

We quantify underwriter- and issuer-CRA relations using two measures, the number of CDOs and the amount of CDOs (Billion $) that are organized (issued) by an underwriter (issuer) and rated by Moody's/S&P. Table 5 reports the two measures for top 20 underwriters. Since the two CRAs Moody's and S&P are involved in almost all CDO deals, the figures for Moody's and S&P are very similar.

Another set of state variables are CDO-specific characteristics. Table 3 reports the summary statistics for these variables.

Insert Table 3 Here

Tranche seniority specifies a CDO tranche's priority on the collateral and coupon in the waterfall payment structure of the entire deal, thus is closely related to the default risk of a CDO tranche. In the data, lower value of tranche seniority corresponds to more senior tranche. The highest tranche number is 15. The next two variables are the CDO tranche's tranche size, and the size of the entire deal. Since the rating fees charged by CRAs are generally proportional to the size of a CDO, the tranche size of a CDO tranche and the entire CDO deal ought to enter a CRA's payoff for ratings. We also include a Fitch dummy to control for the effect of the presence of Fitch ratings. Fitch dummy equals one if the CDO tranche is also rated by Fitch, and zero if not. In the sample only 19% of CDO tranches are rated by Fitch. Weighted average rating factor (WARF) measures the credit quality of the underlying collateral, and lower value corresponds to higher credit quality[5]. The dummy for *WARF* equals 1 if the WARF is lower than 180 (investment grade), and zero if the WARF is higher than 180 (speculative grade). In the sample, only 38% of all CDOs have WARF of investment grade (< 180).

CDO^2s are CDOs that are backed by other CDOs. In fact, the underlying collateral can consist of any higher level of repackaged CDOs and the corresponding can be CDO^3 or CDO^n. In the sample, we can only identify whether the underlying collateral is CDOs. The CDO^2 Dummy equals 1 if the underlying collateral of a CDO consists of other CDOs , and zero if not. In the sample 42% of all CDOs tranches are CDO^2.

CDOs can be categorized into cash CDOs and synthetic CDOs based on the underlying assets. Cash CDOs own actual assets such as mortgage-backed securities (MBS) and asset-backed securities (ABS). Synthetic CDOs contain no actual assets, and use credit default swaps to generate periodic premiums by agreeing to insure for default risk of other CDOs. Hybrid CDOs mix cash CDOs and synthetic CDOs. *Synthetic Dummy* equals 1 if the CDO is a synthetic CDO. *Hybrid Dummy* equals 1 if the CDO portfolio includes both cash assets and synthetic assets. In the sample, 41% of all CDO tranches are synthetic, and 2% are hybrid.

There are generally two coupon payment methods, floating rate FLT and fixed rate FIX. Floating rate coupons adjust periodicaly based on an index and may have a upper or lower cap. The coupons can also adjust inversely with a index, denoted INV. In the sample the majority of CDOs use floating rate, and they generally use the Bank of America Merrill Lynch U.S. Corporate Index as the benchmark. The dummy for floating rate equals 1 if the coupon is based on an index, and 0 if fixed.

[5] The WARF on a CDO is calculated by first evaluating the rating factor for each asset underlying the CDO and then taking the value-weighted average the factors. The WARF allows CRAs to treat the collateral portfolio underlying a CDO as a single security, and assign the CDO a single rating.

3.2 Classification of CRA actions

The focus of this paper is the effect of CRAs competition on ratings quality. CRAs competition is captured as the strategic interaction between the two CRAs in which a CRA's ratings decisions influence and are influenced by the rival CRA's rating decisions. In addition to the state variables that are relevant a CRA's payoffs, the empirical implementation of the discrete framework requires a proper classification to identify CRAs' ratings actions.

Credit ratings are discretized and it is hard to find a continuous measure of a CRA's rating quality. Instead of trying to look for a continuous measure of rating quality, however, we discretize a CRA's rating quality into a binary classification. For each CRA I consider two actions, lenient ratings ($a = 1$) and strict ratings ($a = 0$). The binary classification of ratings quality could accommodate the discretized nature of credit ratings and enable a better inference of the qualitative differences in ratings quality.

We classify a CRA's rating action on a CDO tranche according to the *ex post* performance of the CDO. Ideally one would use the actual adjustments beyond a CRA's objective risk assessments from its main rating model to measure a CRA's rating action. Unfortunately, CRAs' objective risk assessments are in general not observable to econometricians[6], and even if the original ratings were available, there is no way to identify whether the input parameters have been adjusted. In this paper, we classify whether a CRA has chosen a lenient rating or a strict rating for a CDO depends on the difference between initial ratings and current follow-up ratings.

We use two criteria for classifying lenient initial rating actions. The first criterion is the initial rating. In the baseline estimation, the initial rating needs to be above “A-” to be classified as lenient. This criterion is based on the following consideration. First, due to a series of regulatory restrictions, financial products that cannot obtain high enough ratings will loss access to a large pool of institutional investors[7]. Therefore issuers would exert competitive pressure on CRAs to

[6]Griffin and Tang (2012) managed to obtain a private data set of credit ratings by the surveillance team in a major CRA, but there was no information about whether the input parameters used by the surveillance team were adjusted already.

[7]For example, the US Department of Labor restricts ERISA-regulated pension fund investments to securities rated A or higher. Section 106 of the Secondary Mortgage Market Enhancement Act of 1984 permits federal- and state-chartered financial institutions to invest in mortgage-related securities if the securities are rated in one of the two highest rating categories. In an attempt to steer banks' investments into 'safe' assets, in 2001 the Fed, FDIC and the OTS issued the "Recourse Rule" that directly linked the credit ratings of asset-backed securities to banks' capital reserve requirements âĂŤ those requirements being a major cost to banks. For example, securities rated AAA or AA required one tenth the capital that anything rated BB required.

obtain high initial ratings. Second, lenient standards bias the ratings upward, and are more likely to locate at high initial ratings.

The second criterion is the number of notches downgraded from initial ratings to follow-up ratings. we require the downgraded notches to be larger than 10 for the initial ratings to be classified as lenient. The reason is the following. First, relative to follow-up ratings, initial ratings are more susceptible to competitive pressure as a CRA's payoffs hinge on whether it can attract initial rating business[8]. Second, since lenient (strict) ratings lie at the lower (upper) end of the underlying credit risk, lenient initial ratings are more likely to be downgraded.

If all the two criteria are satisfied, the CRA has chosen a lenient rating for this CDO, $a = 1$. Otherwise, the CRA has chosen a strict initial rating for this CDO, $a = 0$. It is also possible that one CRA did not provide initial rating for a CDO, the CRA has chosen a strict rating. In the robustness check section, I provide detailed analysis on how the results vary to changes in the criteria.

One concern about this classification strategy is that it may bring in measurement errors. In particular, the new information generated between the initial rating date and the follow-up rating date may have material influence on the rating of a CDO tranche. We use two strategy to mitigate this concern. The first strategy is to focus on ratings of long-term investments. As credit ratings are forward-looking opinions for credit risk, a strict rating on longer-term investments should be less likely affected by such short-term information. If short-term information does lead to dramatic downgrades on a large scale, such as what happened for "AAA"-rated CDOs in the 2007-08 crisis, it is hard not to question the initial ratings. In constructing the sample, we exclude CDOs with maturity dates earlier than year 2025. The second strategy is to use aggressive classification criteria to accommodate the possible influence of new information. In fact, It is very rare for an initial rating to be downgraded by more than 10 notches in the corporate bond arena. We have also done a series of robustness checks for the likely impacts of the classification criteria. We repeat the estimation in subsamples with longer maturities, and they all yield similar results. We also reestimate the model using more aggressive classification criteria, and the estimated competition strength are stronger.

Insert Table 7 Here

[8] Upon obtaining an initial rating, an issuer pays upfront a considerable amount of initial fees, and only needs to pay a small amount of fees to maintain the follow-up service. Once a rating service is purchased from a CRA, an issuer is effectively held up by this CRA because losing rating is widely perceived as negative information by investors

Table 7 presents the percent of CRAs' ratings actions in different CDO subsamples divided by CDO characteristics. First, based on the classification, S&P are slightly more likely to adopt lenient ratings standards relative to Moody's in all subsamples. In the full sample, S&P's has adopted lenient ratings standards in 71% of all CDOs, where only 69% of Moody's initial ratings are lenient. Second, Both Moody's and S&P are less likely to issue lenient ratings in the subsample with Fitch ratings than in the subsample without Fitch ratings.

We also examine the two subsamples of CDOs split by their funding type, synthetic CDOs and cash CDOs. Cash CDOs still involve a portfolio of cash assets, while synthetic CDOs do not own real assets, but use credit default swaps and other derivatives to bet on the performance of other assets. The extra complexity of synthetic CDOs facilitate CRAs to adopt different rating standards. The weight average rating factor (WARF) is used by CRAs to determine the credit risk of a portfolio. This factor is typically calculated as the weighted value of all the underlying assets in the portfolio. Higher value of WARF corresponds to higher credit risk, thus CDOs with low WARFs are more likely to obtain high ratings. The value of 180 is the dividing line between a rating of "A-" and "BBB+". Tranche seniority specifies the priority of the payment goes. Generally, the more senior rated tranches have higher credit ratings than the lower rated tranches.

3.3 Estimation Methods

Econometrically, strategic game models rely on the consistent estimation of CRAs' beliefs regarding the CCPs of its rivals. However, the system of simultaneous equations 6 poses a challenge for the estimation of discrete games and there are active on-going studies in this field (see for example Su and Judd (2012), Aguirregabiria and Mira (2013)). Generally, the entire estimation of the discrete game involves two procedures: a procedure that estimates the CCPs of other CRAs' actions in equation 6, and a maximum likelihood procedure that solves the discrete choice problem in Equation 7[9]. Depending on the procedure used to estimate the probabilities of other CRAs' actions, there are two types of estimation approaches, two-step approaches and full-solution approaches.

Two-step estimation Two-step approaches are relatively straightforward and can exemplify the basic idea behind the estimation of discrete game models. As you can tell from the name, two-step

[9] Su and Judd (2012) recently propose a new estimation strategy in which the simultaneous equations are used as constraints in the maximum likelihood procedure

methods simplify the entire estimation into two steps: a first step that estimates the CCPs using parametric or non-parametric estimators, and a second step that solves a discrete choice problem with the estimated CCPs from the first step as an additional variable. We use the Logistic model as the first-step estimator.

NFXP estimation We use the nested fixed point method (NXFP) to obtain a consistent full-solution for the BNE specified in Equation 6. Here we only provide an overview of this method, and the algorithm is detailed in Appendix B. The NXFP procedure consists of two loops: an inner fix-point loop that consistently solves the CCPs specified in Equations 6 using sequential approximation, and an outer loop that maximizes the likelihood function (Equation 7) to obtain the parameters.

The two estimation approaches have different strengths. Two-step approaches are computationally light(it can be done in standard software packages (Bajari, Hong, Krainer, and Nekipelov (2010))) and relatively flexible. However the computational convenience does come with drawback: the reliability of two-step estimations hinges on the consistency of the reduced-form estimator in the first step. Full-solution approaches can solve the consistency issue in two-step approaches, but meanwhile it brings in tremendous computational burden. In addition, full-solution approaches face the problem of complexity that the underlying game may have multiple equilibria and the system of simultaneous equations 6 may have more than one solution. This multiplicity problem can make hard to converge in solving the fixed point problem. Fortunately, in this paper the CRAs competition can be modeled as a two player-two action game. This game promises the uniqueness of equilibrium as long as the competition strength is not too strong (I provide a mathematical proof in Appendix C).

3.4 Unobserved Heterogeneity

While the data set contains a large number of covariates upon which CRAs may condition their actions, there may be common information about the choices that is commonly observable to the CRAs but unobserved by econometricians. Ignoring the common information about the choices will lead to a simultaneity bias in estimating the effect of the strategic interaction between CRAs on their payoffs from the revealed choice data. In other words, how can we be sure that CRAs are actually reacting to the actions of their rivals, rather than simply optimizing over some common but unobserved variables. Dealing with common unobservables is still a continuing work and the treatment remains limited. Following Seim (2006), We handle this problem by incorporating a random effect at the level of the rating grade within the nested fixed point problem. Our main results are robust to this treatment.

The strategy we used is to add a common unobservable, denoted η_k to the payoff function of each CRA. The payoff function then can now be written as

$$\Pi_i(x,a,\varepsilon_{ij};\theta) = \pi_i(x,a_i,a_{-i};\theta) + \xi_k + \varepsilon_i \tag{8}$$

Where ξ_k is assumed to be orthogonal to the covariates, and follow a pre-specified density $g(\xi)$. The unconditional probability of the BNE can be solved by integrating out the unobserved variable ξ_k,

$$\begin{aligned} p_1(a_1 = 1) = & \int F(x_1\beta_1 + \delta p_2 + \xi_k) g(\xi_k) d\xi_k \\ p_2(a_2 = 1) = & \int F(x_2\beta_2 + \delta p_1 + \xi_k) g(\xi_k) d\xi_k \end{aligned} \tag{9}$$

We use a simulated maximum likelihood procedure to integrate out the unobserved variable ξ_k. We assume the unobservable ξ_k follows a normal distribution $\mathcal{N}(\mu_k, \sigma)$ within each cluster. We draw a set of values from the normal distribution. We find the BNE for each random draw. Then the unconditional probability is approximated by

$$\begin{aligned} p_1(a_1 = 1) = & \tfrac{1}{M} \sum_{m=1}^{M} F^m(x_1\beta_1 + \delta p_2 + \xi_k^m) \\ p_2(a_2 = 1) = & \tfrac{1}{M} \sum_{m=1}^{M} F^m(x_2\beta_2 + \delta p_1 + \xi_k^m) \end{aligned} \tag{10}$$

3.5 Identification

The identification of the discrete game approach with incomplete information rests on four assumptions. The first assumption is inherit from the standard identification problem in multinomial choice model, which normalizes the expected payoffs of actions relative to one benchmark action. This is satisfied by choosing the payoff of strict ratings as the benchmark. The second assumption is that the error terms ε follow i.i.d. distribution across all CDOs and are drawn from a known distribution, e.g., type I extreme value. The third assumption is the uniqueness of equilibrium, which is required in the maximum likelihood procedure. As discussed above, this assumption is satisfied if the competition strength is moderate when there is one unique equilibrium in the 2×2 game.

The last assumption is an exclusive restriction. Bajari, Hong, Krainer, and Nekipelov (2010) establish exclusive restrictions as one way to identify the system of simultaneous equations that characterize discrete games of incomplete information. The exclusive restrictions require one or more state variables that enter player i's payoffs, but not the payoff of any of its rivals. The need for the exclusive restriction creating a collinearity problem[10]. Strictly speaking, the exclusion restriction are not necessary because the inherent nonlinearity of the functional form of CCPs. However, in practice the functional form of the conditional choice problem may be roughly linear in some parameter region. Therefore, it is recommended to include one or more exclusive variables that only enter player i's payoffs.

In the two CRA-two action game, the exclusive restriction requires to include variables that enter the payoffs of CRA i only, but not the payoffs of its rival CRA. In this paper, the exclusive restriction is satisfied by including the underwriter- and issuer-CRA relations. This would imply that, for instance, the relation between Goldman Sachs and Moody's should only affect Moody's initial rating for a CDO organized by Goldman Sachs, but should not directly influence S&P's initial rating for the same CDO.

4 Empirical Results

The questions that I ask are whether CRAs competition influences ratings quality, and if the answer is yes, the extent to which ratings quality is affected by CRAs competition. We evaluate two specifications and estimate them using both two-step and NFXP methods. In both specifications, we include underwriter- and issuer-CRA relations, and we use two measures, number of CDOs and amount of CDOs, to quantify the underwriter- and issuer-CRA relations.

[10] A similar problem also crops up in self-selection models when the selection equation and the outcome equation share the same set of state variables.

The basic specification (Model 1) include four basic CDO-specific characteristics, tranche seniority, log of tranche size, log of deal size, dummy for whether there is Fitch rating, and dummy for whether the weighted average rating factor is investment grade ($WARF < 180$). In the full specification (Model 2), we include four additional dummy variables of CDO-specific characteristics, a dummy variable for CDO^2, a dummy for hybrid CDOs, a dummy for synthetic CDOs, and a dummy for floating coupons.

4.1 Strategic Interaction

By modeling CRAs competition as a discrete strategic game, we am able to address the central question in this paper: what is the impact of competitive expectations on the choice of ratings. The strategic coefficients to the CCPs in Equation 6 provide a quantitative evaluation of the impact of CRAs competition.

Insert Table 8 Here

Table 8 reports the estimates using the two-step method. Columns (1)(2) present estimates using the number of CDOs as the measure for underwriter- and issuer-CRA relations, and columns (3)(4) show estimates using the amount of CDOs. We find that the CCP of the other CRA is a strong determinant of a CRA' rating action: the strategic coefficient to the CCP δ is positive and statistically significant across all specifications. The results using the two-step method are quite different in the two specifications, $\delta = 1.54$ in the basic specification and $\delta = 1.15$ in the full specification. This large variation arises from the inconsistency of the first step estimator.

Insert Table 9 Here

Table 9 reports the NFXP results. Again columns (1)(2) present estimates using the number of CDOs as the measure for underwriter- and issuer-CRA relations, and columns (3)(4) use the amount of CDOs as the measure.

The estimates of δ are significantly positive for both of the measures in all specifications, suggesting that a CRA is more likely to adopt lenient ratings when it expects its rival has higher chance of adopt the same rating standard. In agreement with the inconsistency affecting the two-step estimates, the coefficients using the NFXP method are larger and more stable than those from two-step method in Table 8.

The coefficient on tranche seniority is significantly negative. Give that the higher value of tranche seniority corresponds to junior trnaches, this result implies that senior tranches are less likely to receive lenient ratings. Intuitively, senior tranches are relatively safe in the waterfall payment structure, and they would get high ratings even using strict ratings standards.

The two variables log(tranche size) and log(deal size) are both significantly positive. The rating fees charged by CRAs are usually propotional to the size of the transaction. Thus, when a CDO's principal value is large or it belongs to a large deal, a CRA has higher incentive to solicit this business, thus is more likely to adopt lenient standards to cater to the issuer.

Interestingly the coefficients on Fitch is significantly negative in all specifications, around -0.5 in the two-step estimation and -0.3 in the NFXP estimation. This result implies that the presence of Fitch rating is associated with lower probability of other CRAs adopting lenient ratings. Hence if one assumes the presence of Fitch is associated with intensified competition in the ratings market it appears competition reduces rating quality, which would be in contradiction to the main result of this paper. A plausible explanation for this puzzling result is that the presence of Fitch ratings is not exogenous, but endogenous to the rating decisions by Moody's and S&P's. An underwriter is more likely to turn to Fitch when if it cannot obtain the initial ratings by Moody's and S&P disagree or one of them chooses not to give favorable ratings. On the other hand, if both Moody's and S&P give favorable ratings, the incentive for an issuer to seek addition rating would be greatly reduced. Therefore the presence of Fitch rating should be negatively correlated with the odds of adopting lenient ratings by Moody's and S&P.

4.2 Counterfactuals

We now use the model estimations to construct counterfactuals. We conduct a policy experiment highlighting the mechanism through which competition effect influences CRAs actions. To infer competition effect in ratings quality, we simply shut off the strategic effect and compare the odds of CRAs choosing lenient ratings under this conterfactual scenario to what we observe in the data:

$$y_{i,m} - E\left[p_{i,m}|\delta = 0\right] \tag{11}$$

The first term $y_{i,m}$ is the observed action of CRA i for CDO m, and the second term $E\left[p_{i,m}|\delta = 0\right]$ is the imputed odds that a CRA would adopt lenient ratings if there is no strategic interaction.

Insert Table 10 Here

The results are shown in Table 10. Again we use two measures for underwriter- and issuer-CRA relations. The two types of measures give very similar results, and I only discuss the results from using number of CDOs. At the aggregate level, the observed odd for Moody's is 69.08%. Once the strategic interaction is muted, the odd drops to 37.49%, 31.59% lower than the true odd. For S&P, the decrease is a little mild. while the observed initial decrease is 71.13%, higher than Moody's, the decrease in odd is only 28.63%. This exercise shows that more than a third of the observed lenient ratings can be ascribed to the strategic interaction between Moody's and S&P.

4.3 Subsample

The previous two sections established that CRAs coordinate their lenient ratings, i.e., a CRA would be more likely to adopt lenient ratings if it expects its rival would do so. The natural question is: When is the strategic competition effect more pronounced? We attempt to address this question by repeat the NFXP estimation in subsamples divided by different exogenous characteristics.

Insert Table 11 Here

Table 11 reports parameter estimates for the subsamples divided by underwriter market share and asset complexity. Strong underwriters consists of the four biggest underwriters–Merrill Lynch, UBCS, Citigroup, and Goldman Sachs –whose jointly take more than 50% of the total market share. The rest underwriters are classified as weak underwriters. Using both measures, the strategic coefficients in subsample of strong underwriters are higher than those in subsample of weak underwriters. One plausible interpretation is that strong underwriters have more bargaining power and can exert higher competitive pressure on CRAs which is consistent with the results in He, Qian, and Strahan (2011, 2012),

We also split the sample by the complexity of the CDOs products. Complex assets include synthetic CDOs, hybrid CDOs, and CDO^2. Less Complex assets mainly include cash-flow CDOs. CDO^2 is backed primarily by the tranches issued by other CDOs. Synthetic CDOs do not own cash assets like bonds or loans, but generate periodic premiums by the use of credit default swaps. Hybrid CDOs mix both synthetic CDOs and cash CDOs. Due to the additional complexity, it is even more difficulty to have accurate assessments of the underlying credit risk for complex CDOs than less complex cash CDOs. Table 11 shows the strategic coefficients estimated in subsamples by asset complexity. The coefficients in subsample of complex assets are higher than those in subsample of less complex assets.

Admittedly, because of the difficulty in the NFXP estimation, there is no statistical procedure that can formally test the above results. Yet, estimations using different measures both generate qualitatively similar results.

5 Robustness

All the results presented so far depend on the specifications of our estimation framework. This section examines how results vary with different specifications. We estimate the model using more aggressive classifications for CRAs' actions, subsamples with longer maturities, and fixed effects to deal with unobserved heterogeneity. In the main results, the two measures for underwriter-CRA and issuer-CRA relation, the number of CDOs and amount of CDOs, generate quantitatively very similar results. In this section we only report results using the number of CDOs for brevity. Results using the amount of CDOs as the measure for relations are available upon request.

5.1 Alternative Classifications for CRAs' Actions

Although the binary classification for CRAs' actions can accommodate the discretized nature of credit ratings and enable a better inference of the qualitative differences in ratings quality, the model estimates could also depend on the specific criteria of classification. In this subsection we examine sensitivity of the results to different classification strategy.

5.1.1 Different Classification Criteria

In the main specification we use the following criteria for classifying a CRA's action as lenient: (1) the follow-up rating must be more than 10 notches lower than the initial rating, (2) the initial rating must be above "BBB+". If both criteria are satisfied, we classify the CRA's action for this CDO as lenient ratings $a = 1$. Otherwise, the CRA has chosen strict ratings $a = 0$. In this section, we examine how the results changes as the two criteria vary.

Insert Table 13 Here

First we examine the sensitivity of our results to the first criterion, number of notches downgraded from the initial rating to the follow-up rating, ceteris paribus. Table 13 reports the estimated competitive strength δ as a function of downgraded notches. As the required number of downgraded notches is increased from 7 notches to more than 13 notches, the results are not sensitive in both the two-step and NFXP estimations. This result is not surprising as in the data as the CDO market collapsed, most the initially highly rated CDOs are downgraded to speculative grades or even lost their ratings.

Insert Figure 5 Here

We next examine the sensitivity to both of the criteria for initial rating and downgraded notches. In our baseline results, the competition strength is moderate, $\delta \approx 2.7$, which guarantees the unique fixed point for NFXP method as the competition strength δ is below 4. However, as the criterion for initial ratings is higher, the competition strength becomes too strong to estimate using the NFXP method. We use the two-step method instead. Although the two-step method is not consistent, the two-step method tends to bias downward the competition strength in the main results. Thus if the two-step method yields significant results, the true competition strength should be greater.

The results are shown in Figure 5. In each plot, the vertical axis is the estimated competition strength, we vary the number of downgraded notches required to be classified as lenient ratings from 5 notches to 17 notches. From plot (a) to plot (f),the criterion for initial ratings to be classified as lenient increases from above "A-" to above "AA+". Estimates of the competition strength δ in all criteria are consistently above 2.5. Recall that in our baseline model the criterion for initial ratings is above “BBB+”, and the estimated competition strength is only around 1.5. As the criterion for initial ratings is increased, the competition effect becomes stronger, $\delta \approx 7.8$ in plots (d)(e)(f).

To sum up, as we use more aggressive criteria to classify lenient CRA actions, the estimated competition strength using both NFXP and two-step methods becomes stronger. In the extreme case, if only initially AAA-rated ratings are classified as lenient, the competition strength in the two-step estimation reaches the highest value. This result suggests the results are robust to different classification criteria.

In addition, as the criteria become more aggressive, the classification for CRAs' actions can accommodate more variation not related to the initial ratings quality. In particular, new information generated between initial ratings and current ratings may bring in substantial rating changes that are not related to the initial rating quality. The robustness check results can partially mitigate this concern as the competition strength reaches maximum with the most aggressive classification criteria, which can likely accommodate large impact from new information.

5.1.2 Classification Based on Collateral Quality

Instead of using ex post performance of a CDO, we also try classifying a CRA's rating decisions based on the difference between the initial rating and the weighted average rating factor of the underlying collaterals. If the weighted average rating factor is below investment grade ($WARF > 180$) and the initial rating is in the three highest categories (above A-), the initial rating is is classified as lenient. Otherwise the initial rating is strict.

Insert Table 14 Here

Table 14 reports the estimates of the full model using the NFXP mehtod. The coefficient to the strategic term δ is significantly positive.

5.2 Subsamples with longer Maturities

In our framework, we classify a CRA's initial ratings actions based on the performance of each CDOs, comparing initial ratings with their current follow-up ratings. One concern with this classification strategy is that new information generated between initial ratings and current ratings could brings in substantial variation in ratings that is not related with the initial ratings. This concern is partially mitigated by using more aggression classification criteria in the above subsection. To further reduce the influence of new information, this paper only focuses on long-term investments using sample with maturities after year 2025 in the baseline results since credit ratings are forward-looking in nature and short-term information is likely to have less impact on ratings for long-term investments. In this subsection, we repeat the estimation in subsamples with longer maturities.

Insert Table 12 Here

Table 12 reports the estimated competition strength and the corresponding counterfacturals in subsamples with maturities longer than year 2030, 2035, 2040, and 2045. As the maturity increases from 2030 to 2045, the subsample size shrinks dramatically from 3067 to 2001 observations. However the estimated competition coefficient remains positively significant and only reduces slightly from 2.69 to 2.44, suggesting the competition strength is robust in long-term investments.

5.3 Unobserved Heterogeneity

Finally, while the dataset includes a large number of CDO and CRA-specific characteristics, the CRAs may have common information about the discrete choices that are not observable to our econometricians. In other words, how can we be sure that CRAs are actually reacting to the actions of their rivals, rather than simply optimizing over some common but unobserved variables. Such common unobservables raise concerns over the effect of strategic interaction.

It is difficult to deal with common unobservables as no parametric or nonparametric methods can provide consistent estimates of CCPs in the presence of common unobservables. More specifically, we cannot recover the beliefs of CRAs from the data in the first step. Following Seim (2006), we handle this problem by incorporating a random effect at the level of the rating grade within the nested fixed point problem.

6 Discussions and Future Research

Using a discrete game framework that accounts for the strategic interaction between CRAs in the oligopolistic credit rating industry, this paper examines CRAs competition effect on the quality of CDO ratings. We find that, ceteris paribus, the stronger the competition, the higher the odds that

CRAs adopt lenient ratings. Controlling for CRA- and CDO-specific characteristics, we predict that, at the aggregate level, the probabilities of choosing lenient rating would be 31% lower for Moody's and 28% lower for S&P if the competition between them is muted. Therefore, our framework takes the first attempt towards providing a quantitative model to evaluate the effect of CRAs competition.

However, at the current stage, our model is silent about alternative mechanism contributing to the collapse of the structured products during the 2007-2008 crisis. The episode could be just due to "honest mistakes" or reputation incentives. In our empirical setting, we find that both Moody's and S&P have established their reputation in the CDO market before the crisis. Also, the boom in the CDO market during 2005-2007 lowers the probability of CRAs publishing questionable ratings (Bolton, Freixas, and Shapiro (2012)). Hence, these two issues won't overturn the primary results in our paper.

Besides, the discrete game framework is versatile and has the potential to accommodate other features of CRAs competition in the credit rating industry. One interesting extension is to quantitatively distinguish the impacts of "rating shopping" and "rating catering" on the observed inflation in CDO ratings. Griffin, Nickerson, and Tang (2013) find empirical evidence that "rating catering" inflates CDO ratings significantly before the credit crisis. Along with their argument, we would like to extend our model to include both incentives. As long as the mechanism that generates the observed CDO ratings is clear, our model has an immediate advantage. We back out magnitudes of alternative mechanisms from the perceived rating scores, instead of imposing assumptions on the sample.

One important implication of the extension is to evaluate government policies on CRAs. A telling example is the Credit Rating Agency Reform Act of 2006, requiring the SEC to increase competition among CRAs. **?** recently document that new entrants cater to issuers by issuing higher ratings than incumbents, and therefore, amplify the rating inflation through the catering mechanism. However, an alternative scenario is that new entrants choose to enter into the markets where issuers found it hard to shop ratings in the past. In the future, we will contribute to the discussion by quantitatively tracing out the sources of rating inflation using our discrete game model, and therefore, evaluate the effectiveness of regulations on CRAs.

Appendix A: Payoff Function of the Credit Ratings Game

To fix ideas, We consider two CRAs choosing one of two possible actions $a \in \{0,1\}$ based on expected payoffs, where 0 denotes truthfully reporting the credit risk and 1 represents inflating ratings. The simultaneous game between CRAs yields payoff matrices similar to the strategic entry game framework pioneered by Bresnahan and Reiss (1991). The payoff matrix for Moody's is In the above matrix, π_{00} is the payoff of Moody's if it chooses strict ratings $a = 0$. π_{10} is the

Moody's	S&P $a = 0$	S&P $a = 1$
$a = 0$	π_{00}	π_{00}
$a = 1$	$\pi_{00} + \pi_{10}$	$\pi_{00} + \pi_{10} + \pi_{11}$

extra payoff Moody's gets if it chooses lenient ratings while S&P does not. Hence it should be a function of the characteristic of the CDO. π_{11} is the additional payoff of Moody's if both CRAs choose lenient ratings. Comparing the expected payoffs for $a = 0$ and $a = 1$, we can see the condition in which Moody's will choose $a_i = 1$, inflating ratings is

$$\begin{aligned}
& E(\pi(a_i = 1)) - E(\pi(a_i = 0)) \\
=& [p(a_{-i} = 0)(\pi_{00} + \pi_{11}) + p(a_{-i} = 1)(\pi_{00} + \pi_{10} + \pi_{11})] - \pi_{00} \\
=& \pi_{10} + (p(a_{-i} = 0) + p(a_{-i} = 1))\pi_{11} \\
=& \pi_{10} + E(a_{-i})\pi_{11} \\
\geq& 0
\end{aligned} \tag{12}$$

When Moody's chooses lenient ratings, $a = 1$, its payoff depends not only on the characteristics of the CDO, but also on its belief of its rival's choice, $E(a_{-i})$.

π_{00} is the payoff for $a = 0$ which can be any value since it is the same regardless of the rival's actions. For the payoff π_{01} and π_{11}, we could either derive them from particular assumptions on the economic primitives, or choose an analytically convenient parameterization. Since the estimation using the former approach is typically neither tractable nor flexible enough to accommodate all the patterns in the data, the latter approach has become the standard in the empirical IO literature since Berry (1992). The payoff π_{11} captures the competitive effect that the rival S&P exerts on Moody's, and we use the constant term δ to facilitate the interpretation and measurement of this competitive effect.

To take the strategic game model to data, we choose the payoff of choosing strict ratings $\pi_{00} = 0$ and normalize all other payoffs with regard to π_{00}. We further assume $\pi_{01} = x\beta$ and $\pi_{11} = \delta$, then the payoff function of CRA i can be summarized as

$$\pi_i(x, a_i, a_{-i}; \theta) = \begin{cases} x_i\beta + \delta E(a_j = 1) & if\ a_i = 1 \\ 0 & if\ a_i = 0 \end{cases} \tag{13}$$

Appendix B: Nested Fixed-Point Algorithm

We implement the incomplete information framework using the nested fixed-point approach (Rust (1987, 1994)). We assume error terms ε_is of common unobservables are i.i.d. distributed with distribution function F . In this study, we assume the εs are drawn from the Type I extreme value distribution, which give us an analytical tractable likelihood function, the familiar conditional logit. Let p_i denote the CCP of player i

The NFXP algorithm is generally an maximum likelihood estimation. However, in constructing the log-likelihood function, we need to estimate the CCPs using the the method of fixed-point iteration. So the entire estimation procedure consists of two layers of loops. The outer loop is a MLE procedure, we obtain the parameter estimates Θ by maximizing the pre-specified log-likelihood function against the data.

$$\Theta = \underset{\Theta}{\operatorname{argmax}}\, ln\mathscr{L}$$

Where the log-likelihood function is calculated from the CCPs obtained from the inner loop that solves a fixed-point problem.

Inner loop. The inner loop preforms a fixed-point iteration that solve the Beyesian Nash equilibrium of CCPs,

$$p_i^* = F(x_i\beta_i + \delta_i p_{-i}^*)$$

We use the simple Picard successive approximations to solve the fixed-point problem. For any value of the choice probability p^{k-1} we can always construct a new CCP p^k from the mapping function. If $||p^k - p^{k-1}||$ is smaller than a predetermined value ε, stop and choose p; if the distance $||p^k - p^{k-1}||$ is greater than ε, continue updating p until $||p^k - p^{k-1}|| < \varepsilon$. In our implementation, we choose $\varepsilon = 1E^{-8}$.

Outer loop. After obtaining the CCPs p^* from the fixed-point iteration, feed them into the log-likelihood function in the outer loop,

$$\begin{aligned}\Theta &= \underset{\Theta}{\operatorname{argmax}}\, ln\mathscr{L} \\ &= \underset{\Theta}{\operatorname{argmax}} \sum_{m=1}^{M} \sum_{i\in\{M,S\}} y_{im} ln(p^*_{im}) + (1-y_{im}) ln(1-p^*_{im})\end{aligned}$$

For each attempted solution θ in the MLE procedure, we need to solve the fixed-point problem in the inner loop, and maximize the log-likelihood function to obtain parameter estimates Θ.

Note that for each optimization step, we need to solve the fixed-point problem, which is computationally cumbersome. Another complication is that the underlying game may have multiple equilibria in which the fixed-point problem may admit more than one solution. In this case, the identification condition of the MLE procedure is violated, and the entire NFXP method becomes quite difficult to converge.

Appendix C: Equilibrium Properties of Incomplete Information Discrete Games

A now familiar issue with multi-agent discrete games of incomplete information is that they may have multiple equilibria. Specifically, the underlying latent payoffs could be consistent with more than one equilibrium outcomes of CCPs. The existence of equilibrium is theoretically guaranteed by Brouwer's fixed-point theorem. However, there is no such guarantee for the uniqueness of equilibrium. If there exist multiple equilibria, for a give parameter vector θ, more than one set of CCPs satisfies the system of simultaneous equations 4 that characterizes the Bayesian Nash equilibrium of the game. In this case, we cannot get a well defined likelihood function that is required for the identification of maximum likelihood estimation. The full-solution approach of

NFXP method usually breaks down.

Fortunately, in our setting the CRAs ratings game can be modeled as a two player-two action game, in which we can prove the uniqueness of equilibrium under some situation. The Bayesian Nash equilibrium of a 2×2 game can be solved by finding a pair of probabilities (p_1^*, p_2^*) that satisfy the following set of simultaneous equations 14

$$
\begin{aligned}
p_1 &= \frac{\exp(x_1\beta_1 + \delta_1 p_2)}{1 + \exp(x_1\beta_1 + \delta_1 p_2)} \\
p_2 &= \frac{\exp(x_2\beta_2 + \delta_2 p_1)}{1 + \exp(x_2\beta_2 + \delta_2 p_1)}
\end{aligned}
\tag{14}
$$

Where p_1 is player i's beliefs regarding the CCP of player 2, and we have assumed that stochastic error term ε_i follows type I extreme value distribution

To identify the conditions for the existence and uniqueness of the BNE, define $F = \begin{pmatrix} f_1 \\ f_2 \end{pmatrix}$ where

$$
\begin{aligned}
f_1(p_1, p_2) &= p_1 - \frac{\exp(x_1\beta_1 + \delta_1 p_2)}{1 + \exp(x_1\beta_1 + \delta_1 p_2)} \\
f_2(p_1, p_2) &= p_2 - \frac{\exp(x_2\beta_2 + \delta_2 p_1)}{1 + \exp(x_2\beta_2 + \delta_2 p_1)}
\end{aligned}
\tag{15}
$$

It is obvious that F is a continuous differentiable map from $\{\Omega = p \in R^2, 0 \le p \le 1\}$. Therefore, the existence of equilibrium is theoretically guaranteed by Brouwer's fixed-point theorem, which states that for any continuous function from a convex compact subset mapping into itself there is a fixed point.

To insure the uniqueness of (p_1^*, p_2^*), all we need to show is that F is an one-to-one univalent function on Ω. It is well known that the classical implicit function theorem assures that non-vanishing of the Jacobian alone only implies local univalence, but does not suffice for global univalence in a region. The Gale-Nikaido Theorem (Gale and Nikaido (1965)) generalizes the implicit function theorem and provides sufficient conditions for global univalence: if all the principal minors of the Jacobian matrix of $F : R^n \to R^n$ are positive in any rectangular region, the function is univalent. Therefore, the sufficient condition for the unique solution is that all principal minors of the Jacobian should be positive. Take the partial derivatives with respect to (p_1, p_2) respectively, I get

$$
\begin{aligned}
\frac{\partial f_1(p_1,p_2)}{\partial p_1} &= 1 \\
\frac{\partial f_1(p_1,p_2)}{\partial p_2} &= -\frac{\delta_1 \exp(x_1\beta + \delta_1 p_2)}{(1+\exp(x_1\beta_1 + \delta_1 p_2))^2} \\
\frac{\partial f_2(p_1,p_2)}{\partial p_1} &= 1 \\
\frac{\partial f_1(p_1,p_2)}{\partial p_2} &= -\frac{\delta_2 \exp(x_1\beta + \delta_1 p_2)}{(1+\exp(x_1\beta_1 + \delta_2 p_1))^2}
\end{aligned} \tag{16}
$$

So the Jacobian matrix is

$$
J = \begin{pmatrix} 1 & -\frac{\delta_1 \exp(x_1\beta+\delta_1 p_2)}{(1+\exp(x_1\beta_1+\delta_1 p_2))^2} \\ -\frac{\delta_1 \exp(x_1\beta+\delta_1 p_2)}{(1+\exp(x_1\beta_1+\delta_1 p_2))^2} & 1 \end{pmatrix} \tag{17}
$$

It is obvious that the two first order principal minors of the Jacobian are positive. The sufficient condition for the uniqueness of the Baysesian Nash equilibrium is to require the second-order principal minor $\det(J)$ to be positive

$$
\begin{aligned}
0 &< det(J) \\
&= 1 - \frac{\delta_1 \exp(x_1\beta_1+\delta_1 p_2)}{(1+\exp(x_1\beta_1+\delta_1 p_2))^2}\frac{\delta_2 \exp(x_2\beta_2+\delta_2 p_1)}{(1+\exp(x_2\beta_2+\delta_2 p_1))^2}
\end{aligned} \tag{18}
$$

Let $\begin{cases} \mu_1 &= x_1\beta_1 + \delta_1 p_2 \\ \mu_2 &= x_2\beta_2 + \delta_2 p_1 \end{cases}$ and rearrange terms, the above inequality can be rewritten as

$$
\begin{aligned}
\delta_1\delta_2 &< \frac{(1+e^{\mu_1})^2(1+e^{\mu_2})^2}{e^{\mu_1+\mu_2}} \\
&= \frac{1+2(e^{\mu_1}+e^{\mu_2})+4e^{\mu_1+\mu_2}+2e^{\mu_1+\mu_2}(e^{\mu_1}+e^{\mu_2})+e^{2\mu_1}+e^{2\mu_2}+e^{2(\mu_1+\mu_2)}}{e^{\mu_1+\mu_2}} \\
&= (\frac{1}{e^{\mu_1+\mu_2}} + e^{\mu_1+\mu_2}) + 2(\frac{1}{e^{\mu_1}} + e^{\mu_1}) + 2(\frac{1}{e^{\mu_2}} + e^{\mu_2}) + 4 + (e^{\mu_1-\mu_2} + e^{\mu_2-\mu_1}) \\
&\geq 16
\end{aligned} \tag{19}
$$

Therefore if the product of the two competition coefficients $\delta_1\delta_2$ is not greater than 16, the 2×2 game is guaranteed to have a unique Baysesian Nash equilibrium. If we further assume the two players are symmetric in the competition strength, i.e., $\delta_1 = \delta_2 = \delta$, the condition for the uniqueness of the Bayesian Nash equilibrium boils down to $\delta \leq 4$. This condition provides a useful guideline for the choice of different estimation methods in our application.

Appendix D: Standard Definitions for CDO bonds

In this appendix, we provide a partial list of the standard definitions and acronyms for CDO bonds.

Table 1: Standard Definitions for CDOs.
This table presents a partial list of the acronyms and their standard definitions for CDO bonds that haven been used in this paper.

Acronym	Full Name	Definitions
CDO	Collateralized Debt Obligation	structured products that pools together assets and repackage this asset pool into tranches that can be sold to investors.
CDO^2	CDO Squared	CDOs collateralized by a pool of other CDOs.
MBS	Mortgage backed security	
ABS	Asset backed security	
CLO	Collateralized Loan Obligation	A type of CDO backed by receivables from business loans
FLT	Floater	Coupons adjust periodically based on an index and may have a upper or lower limit.
INV	Inverse floater	Coupons reset periodically based on an index, but vary inversely with changes in the index
FIX	Fixed	Coupons are fixed over the life of the bond
WARF	weighted average rating factor	Value-weighted credit assessment of the underlying collateral

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Table 2: Number of CDOs at each rating grade in our data universe. The Standard & Poor and Fitch 's rating scale is as follows, from excellent to poor: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D. Moody's uses similar rating scale but the naming is slightly different, as shown in parentheses. Ratings below a BBB- rating are considered a speculative or junk bond.

Rating	Number of CDOs		
Panal A: Initial rating	Moody's	S&P	Fitch
AAA (Aaa)	1077	1120	215
AA+(Aa1)	36	18	8
AA (Aa2)	434	470	91
AA- (Aa3)	92	83	23
A+ (A1)	29	21	4
A (A2)	376	403	73
A- (A3)	98	89	18
BBB+ (Baa1)	47	41	7
BBB (Baa2)	421	464	99
BBB- (Ba3)	111	118	23
Speculative grades	175	182	34
Total	2896	3009	595
Panel B: Current ratings	Moody's	S&P	Fitch
AAA (Aaa)	4	2	2
AA+(Aa1)	1	0	0
AA (Aa2)	0	0	0
AA- (Aa3)	0	0	0
A+ (A1)	1	0	0
A (A2)	1	1	0
A- (A3)	2	0	0
BBB+ (Baa1)	0	1	0
BBB (Baa2)	0	3	0
BBB- (Ba3)	4	3	0
Speculative grades	2883	2999	593
Total	2896	3009	595

Table 3: Amount of CDOs at each rating grade in our data universe. The Standard & Poor's rating scale is as follows, from excellent to poor: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D. Moody's uses similar rating scale but the naming is slightly different, as shown in parentheses. Ratings below a BBB- rating are considered a speculative or junk bond.

Rating	Capital ($B)		% Capital	
Panal A: Initial rating	Moody's	S&P	Moody's	S&P
AAA (Aaa)	280.07	283.85	83.83%	83.34%
AA+(Aa1)	1.31	0.78	0.39%	0.23%
AA (Aa2)	23.17	24.15	6.94%	7.09%
AA- (Aa3)	2.25	1.89	0.67%	0.55%
A+ (A1)	0.57	0.48	0.17%	0.14%
A (A2)	10.74	12.25	3.21%	3.60%
A- (A3)	2.24	1.91	0.67%	0.56%
BBB+ (Baa1)	0.81	0.72	0.24%	0.21%
BBB (Baa2)	9.08	10.35	2.72%	3.04%
BBB- (Ba3)	1.75	2.17	0.53%	0.64%
Below investment grades	2.10	2.06	0.63%	0.60%
Total	334.10	340.59	100.00%	100.00%
Panel B: Current ratings	Moody's	S&P	Moody's	S&P
AAA (Aaa)	0.02	0.02	0.01%	0.01%
AA+(Aa1)	0.03	0.00	0.01%	0.00%
AA (Aa2)	0.00	0.00	0.00%	0.00%
AA- (Aa3)	0.00	0.00	0.00%	0.00%
A+ (A1)	0.16	0.00	0.05%	0.00%
A (A2)	0.04	0.01	0.01%	0.00%
A- (A3)	0.34	0.00	0.10%	0.00%
BBB+ (Baa1)	0.00	0.03	0.00%	0.01%
BBB (Baa2)	0.00	0.38	0.00%	0.11%
BBB- (Ba3)	0.32	0.39	0.10%	0.11%
Below investment grades	333.18	339.76	99.73%	99.76%
Total	334.10	340.59	100.00%	100.00%

Table 4: Summary Statistics for Top 20 Underwriters
This table presents summary statistics for the top 20 investment banks in terms of total amounts of CDOs.

Underwriter	Total Amount (Billion $)	Total Tranches	Market Share in Amount	Market Share in CDO number
Merrill Lynch	77.61	604	22.45%	19.66%
UBS	43.05	355	12.46%	11.56%
Citigroup	30.92	284	8.95%	9.24%
Goldman Sachs	27.71	229	8.02%	7.45%
Wachovia Securities	20.46	151	5.92%	4.92%
Deutsche Bank Securities	16.73	204	4.84%	6.64%
Calyon Financial	16.07	109	4.65%	3.55%
RBS Greenwich Capital	13.58	153	3.93%	4.98%
Credit Suisse	11.40	118	3.30%	3.84%
Bank of America	11.37	119	3.29%	3.87%
Lehman Brothers	10.35	89	2.99%	2.90%
ICP Asset Securities	9.97	30	2.88%	0.98%
Bear Stearns	8.47	113	2.45%	3.68%
Fortis Securities LLC	5.31	28	1.54%	0.91%
Morgan Stanley	4.91	86	1.42%	2.80%
Wells Fargo Bank	4.87	23	1.41%	0.75%
Barclays Capital	4.56	82	1.32%	2.67%
Societe Generale	4.49	13	1.30%	0.42%
Dresdner Kleinwort Wasserstein	3.50	15	1.01%	0.49%
Credit Suisse First Boston	3.45	38	1.00%	1.24%

Table 5: Summary Statistics for relation between CRAs and top 20 underwriters
This table presents two measures for the relation between CRAs and underwriters, number of CDOs and amount of CDOs that was arranged by an underwriter was initially rated by CRA *i*.

	Number of CDOs		Amount of CDOs (Billion $)	
Underwriter	Moody's	S&P	Moody's	S&P
Merrill Lynch	597	604	77.39	77.61
UBS	287	355	38.70	43.05
Citigroup	118	119	11.37	11.37
Goldman Sachs	134	153	12.48	13.58
Wachovia Securities	271	284	30.20	30.92
Deutsche Bank Securities	15	23	3.99	4.87
Calyon Financial	221	229	27.47	27.71
RBS Greenwich Capital	118	118	11.40	11.40
Credit Suisse	186	204	14.49	16.73
Bank of America	107	109	15.97	16.07
Lehman Brothers	13	13	4.49	4.49
ICP Asset Securities	113	113	8.47	8.47
Bear Stearns	146	151	20.30	20.46
Fortis Securities LLC	46	54	4.50	5.11
Morgan Stanley	15	15	3.50	3.50
Wells Fargo Bank	87	89	10.28	10.35
Barclays Capital	86	86	4.91	4.91
Societe Generale	26	38	2.69	3.45
Dresdner Kleinwort Wasserstein	82	82	4.56	4.56
Credit Suisse First Boston	35	35	2.21	2.21

Table 6: Summary statistics of CDO and CRA-specific characteristics.
Underwriter relation and issuer relation are quantified using two measures: number of CDOs and amount of CDOs (Billion $) rated by Moody and SP. *Tranche seniority* is a CDO tranche's priority on the collateral and interest payment. Lower value of *Tranche seniority* corresponds to more senior tranche. *Fitch dummy* equals one if the CDO tranche is also rated by Fitch, and zero is the CDO is not rated by Fitch. *Tranche share* represents the tranche's share in amount in the CDO deal. *WARF* < 180 *dummy* equals 1 if the weighted average rating factor of the underlying collateral is higher than 180, and zero if lower than 180. *CDO*^{2} *Dummy* equals 1 if the underlying collateral is also CDO, and zero otherwise. *Hybrid Dummy* equals 1 if the CDO portfolio includes both cash assets and synthetic assets. *Synthetic Dummy* equals 1 if the CDO a synthetic CDO (useing credit default swaps, instead of cash flow assets). *Floating rate Dummy* equals 1 if the coupon adjusts based on an index rather than fixed.

	Observations	Mean	Std. dev.	Median	Min	Max
Moody's-specific characteristics:						
Underwriter relation (number)	3072	252.74	190.36	186	6	597
Issuer relation (number)	3072	18.38	15.05	13	0	63
Underwriter relation (Billion $)	3072	30.29	25.79	20.32	0.14	77.39
Issuer relation (Billion $)	3072	2.27	2.93	1.22	0	14.63
SP-specific characteristics						
Underwriter relation (number)	3072	262.77	192.81	204	0	600
Issuer relation (number)	3072	19.41	15.79	14	0	67
Underwriter relation (Billion $)	3072	31.03	25.9	20.35	0	77.52
Issuer relation (Billion $)	3072	2.36	3.02	1.25	0	14.63
CDO characteristics:						
Tranche seniority	3072	4.3	2.27	4	1	15
Tranche share	3072	0.16	0.21	0.07	0	1
log(tranche size)	3072	17.49	1.39	17.37	0.69	21.6
Fitch rated	3072	0.19	0.4	0	0	1
WARF < 180 dummy	3072	0.38	0.48	0	0	1
CDO^2 Dummy	3072	0.42	0.49	0	0	1
Hybrid Dummy	3072	0.02	0.15	0	0	1
Synthetic Dummy	3072	0.41	0.49	0	0	1
Floating rate Dummy	3072	0.95	0.22	1	0	1

Table 7: the percent of CRAs' ratings actions in different CDO subsamples divided by CDO characteristics. "Fitch rated" represents subsample of CDOs that also have ratings from Fitch. "Synthetic" represents subsample consisting of synthetic CDO. Weighted average rating. "WARF>180" represents subsample of CDOs with weighted average rating factor greater than 180. Tranche seniority represents subsample of CDOs with tranche number 1-10.

Subsample by CDO characteristics	% of lenient ratings		% of strict ratings		Total CDO number
	Moody's	SP	Moody's	SP	
Fitch rated	56%	69%	44%	31%	595
Fitch unrated	72%	72%	28%	28%	2477
Synthetic	65%	66%	35%	34%	1254
non-synthetic	72%	75%	28%	25%	1818
WARF>180	78%	77%	22%	23%	1160
WARF<180	63%	67%	37%	33%	1912
Tranche seniority					
1	93%	97%	7%	3%	324
2	93%	98%	7%	2%	446
3	93%	98%	7%	2%	471
4	90%	92%	10%	8%	479
5	59%	59%	41%	41%	461
6	39%	39%	61%	61%	365
7	27%	26%	73%	74%	251
8	18%	16%	82%	84%	152
9	19%	19%	81%	81%	73
10	16%	16%	84%	84%	25
Full Sample	69%	71%	31%	29%	3072

Table 8: Two-Step Estimates.

This table reports results using the two-step method. I use two measures for underwriter- and issuer-CRA relation: the number of CDOs and the amount of CDOs. The dependent variable is a CRA's rating decision for a CDO tranche; it takes the value of 1 if the CRA has chosen a lenient rating and 0 otherwise. The t-statistics are in parentheses.

Variable	Measure 1: Number of CDOs		Measure 2: Amount of CDOs	
	Model 1	Model 2	Model 1	Model 2
δ	1.54***	1.15**	1.70***	1.27***
	[3.34]	[2.50]	[3.68]	[2.73]
CDO-specific characteristics				
Tranche seniority	-0.54***	-0.61***	-0.52***	-0.59***
	[-8.61]	[-9.84]	[-8.24]	[-9.55]
log(tranche value)	0.47***	0.47***	0.46***	0.46***
	[7.74]	[7.32]	[7.53]	[7.14]
log(deal size)	0.16***	0.28***	0.18***	0.31***
	[2.78]	[4.79]	[2.81]	[5.03]
Fitch rated	-0.58***	-0.61***	-0.55***	-0.59***
	[-5.14]	[-5.51]	[-4.86]	[-5.24]
Weighted Average Rating Factor	0.69***	0.73***	0.64***	0.70***
	[6.03]	[5.74]	[5.66]	[5.55]
Dummy for CDO^2		-0.09		-0.08
		[-0.96]		[-0.88]
Dummy for Hybrid CDO		0.45*		0.55**
		[1.71]		[2.11]
Dummy for Synthetic CDO		0.21**		0.22**
		[2.09]		[2.16]
Dummy for Floating Rate		0.21		0.19
		[1.24]		[1.14]
Moody's-specific characteristics				
Intercept (Moody's)	-9.28***	-11.35***	-9.41***	-11.81***
	[-7.29]	[-9.29]	[-6.96]	[-9.18]
Underwriter relation	0.00***	0.00***	0.01**	0.01**
	[2.72]	[2.73]	[2.39]	[2.44]
Issuer relation	0.01**	0.01*	0	-0.01
	[2.13]	[1.68]	[-0.02]	[-0.50]
S&P-specific characteristics				
Intercept (S&P)	-8.98***	-11.07***	-9.19***	-11.61***
	[-7.02]	[-9.04]	[-6.78]	[-9.01]
Underwriter relation	0.00**	0.00**	0.01**	0.01**
	[2.53]	[2.58]	[2.45]	[2.50]
Issuer relation	0	0	0	-0.01
	[0.86]	[0.58]	[-0.19]	[-0.63]
Log likelihood	-2269.96	-2265.67	-2272.71	-2267.28
Pseudo-R2	0.39	0.40	0.39	0.39
N	3072	3072	3072	3072

* Significant at 10%; ** significant at 5%; *** significant at 1%;.

Table 9: NFXP estimates.

This table reports results using the NFXP method. I use two measures for underwriter- and issuer-CRA relation: the number of CDOs and the amount of CDOs. The dependent variable is a CRA's rating decision for a CDO tranche; it takes the value of 1 if the CRA has chosen a lenient rating and 0 otherwise. The t-statistics are in parentheses.

Variable	Measure 1: Number of CDOs		Measure 2: Amount of CDOs	
	Model 1	Model 2	Model 1	Model 2
δ	2.73***	2.72***	2.65***	2.63***
	[11.86]	[11.50]	[11.74]	[11.33]
CDO-specific characteristics				
Tranche seniority	-0.40***	-0.40***	-0.41***	-0.42***
	[-11.05]	[-10.77]	[-11.59]	[-11.34]
log(tranche value)	0.31***	0.30***	0.33***	0.31***
	[8.65]	[8.44]	[9.18]	[8.76]
log(deal size)	0.12***	0.15***	0.14***	0.17***
	[4.16]	[4.72]	[4.32]	[4.94]
Fitch rated	-0.29***	-0.27***	-0.30***	-0.29***
	[-4.47]	[-4.23]	[-4.70]	[-4.44]
Weighted Average Rating Factor	0.43***	0.43***	0.44***	0.45***
	[7.13]	[6.82]	[7.30]	[7.03]
Dummy for CDO^2		-0.03		-0.04
		[-0.77]		[-0.78]
Dummy for Hybrid CDO		0.30**		0.36**
		[2.13]		[2.53]
Dummy for Synthetic CDO		0.09*		0.10*
		[1.77]		[1.94]
Dummy for Floating Rate		0.12		0.12
		[1.45]		[1.45]
Moody's-specific characteristics				
Intercept	-7.29***	-7.79***	-7.57***	-8.13***
	[-10.85]	[-10.84]	[-10.40]	[-10.33]
Underwriter relation	0.00**	0.00**	0.00**	0.00**
	[2.54]	[2.53]	[2.18]	[2.19]
Issuer relation	0.01***	0.01**	0	0
	[2.65]	[2.33]	[-0.05]	[-0.14]
S&P-specific characteristics				
Intercept	-6.61***	-7.12***	-7.23***	-7.80***
	[-9.40]	[-9.46]	[-9.82]	[-9.78]
Underwriter relation	0	0	0	0.00*
	[0.99]	[0.99]	[1.64]	[1.65]
Underwriter relation	-0.01	-0.01	-0.01	-0.01
	[-1.40]	[-1.54]	[-0.61]	[-0.72]
Log likelihood	-2249.83	-2244.44	-2259.17	-2241.66
Pseudo-R2	0.40	0.40	0.40	0.40
N	3072	3072	3072	3072

* Significant at 10%; ** significant at 5%; *** significant at 1%;.

Table 10: Actual versus Hypothetical odds of CRAs choosing lenient ratings

This table compares the odds of CRAs choosing lenient ratings with the hypothetical counterparts when the strategic interaction between CRAs is shut off. I report results using two measures for underwriter- and issuer-CRA relations: the number and the amount of CDOs. The hypothetical value is calculated by setting $\delta = 0$ in the NFXP estimation. The t-statistics for differences in means are reported.

	Measures for underwriter- and issuer-CRA relations	
% of lenient ratings	Number of CDOs	Amount of CDOs
Moody's:		
Actual	69.08%	69.08%
Hypothetical (δ=0)	37.49%	38.86%
Difference in means	31.59%	30.21%
t-statistics	[33.62]	[31.99]
S&P:		
Actual	71.13%	71.13%
Hypothetical (δ=0)	42.50%	43.88%
Difference in means	28.63%	27.25%
t-statistics	[30.78]	[29.15]

Table 11: Estimates of Competition Strength in Subsamples
This table presents the competition effect in subsamples. Strong underwriters consist of the four biggest underwriters in terms of market share, Merrill Lynch, UBS, Citigroup, and Goldman Sachs. The rest underwriters are classified as weak underwriters. Complex assets include synthetic CDOs, hybrid CDOs, and CDO^2. Less Complex assets include cash CDOs. Panel A reports results using the number of CDOs underwritten as the measure of underwriter- and issuer-CRA relations. Panel B uses the amount of CDOs as the measure for underwriter- and issuer-CRA relations. All the results are obtained using the NFXP method.

Subsample	δ	Std. err	T-stat
Panel A: Number of CDOs			
Strong Underwriter	3.24	0.26	[12.55]
Weak Underwrter	2.42	0.37	[6.45]
Complex Assets	2.79	0.32	[8.59]
Less Complex Assets	1.78	0.61	[2.92]
Panel B: Amount of CDOs			
Strong Underwriter	2.96	0.29	[10.21]
Weak Underwrter	2.44	0.37	[6.64]
Complex Assets	2.62	0.32	[8.22]
Less Complex Assets	1.83	0.59	[3.11]

Table 12: Results in Subsamples with Longer Maturities

The results are calculated based on the full specification using the NFXP method. δ is the competition strength. The hypothetical odds of lenient ratings by CRAs are calculated when the strategic interaction between CRAs is shut off by setting $\delta = 0$. The t-statistics for δ and differences in means are in parentheses.

	Subsamples with Maturities Dates after			
	Year 2030	Year 2035	Year 2040	Year 2045
δ	2.69***	2.69***	2.63***	2.44***
	[11.09]	[11.11]	[10.61]	[7.59]
% of lenient ratings (Moody's):				
Actual	69.09%	69.08%	70.04%	69.27%
Hypothetical	38.34%	39.48%	40.62%	46.99%
Difference in means	30.75%	29.60%	29.42%	22.27%
t-statistics	[32.54]	[31.18]	[29.20]	[18.17]
% of lenient ratings (S&P):				
Actual	71.21%	71.20%	71.26%	70.31%
Hypothetical	43.55%	44.66%	43.83%	49.68%
Difference in means	27.66%	26.54%	27.43%	20.63%
t-statistics	[29.59]	[28.27]	[27.40]	[16.96]
N observations	3067	3066	2717	2001

Table 13: Results with different criteria for classifying lenient ratings

This table reports results from estimating the model with different criteria for classifying lenient ratings. I vary the criterion on the number of downgraded notches from 7 notches to 15 notches. The results are calculated based on the full specification using the NFXP method. δ is the competition strength. The hypothetical odds of lenient ratings by CRAs are calculated when the strategic interaction between CRAs is shut off by setting $\delta = 0$, as shown in Equation 11. The t-statistics for δ and differences in means are in parentheses.

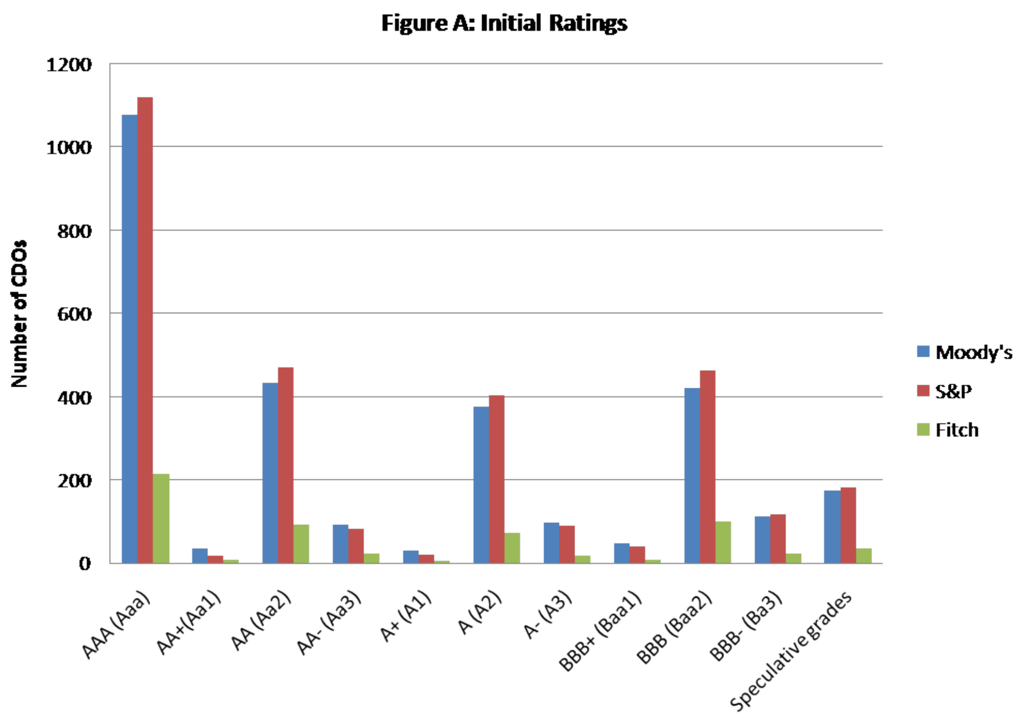
	Number of Notches Downgraded				
	7	9	11	13	15
δ	2.59***	2.57***	2.61***	2.65***	2.80***
	[11.18]	[11.01]	[11.27]	[11.62]	[13.64]
% of lenient ratings (Moody's):					
Actual	69.30%	69.21%	69.04%	68.78%	60.32%
Hypothetical	39.36%	39.51%	38.66%	37.65%	26.16%
Difference in means	29.95%	29.69%	30.38%	31.13%	34.16%
t-statistics	[31.65]	[31.35]	[32.21]	[33.11]	[35.47]
% of lenient ratings (SP):					
Actual	71.42%	71.29%	71.03%	70.87%	70.70%
Hypothetical	44.55%	44.61%	43.53%	42.75%	47.39%
Difference in means	26.87%	26.68%	27.50%	28.12%	23.32%
t-statistics	[28.71]	[28.48]	[29.44]	[30.19]	[24.78]
N observations	3072	3072	3072	3072	3072

Table 14: Results with different classification for lenient ratings

This table reports results when CRAs' rating decisions are classified based on the quality of underlying collaterals. A CRA's initial rating is lenient if the underlying collaterals are below investment grade but the CDO's rating is in the three highest categories. I use two measures for underwriter- and issuer-CRA relation: the number of CDOs and the amount of CDOs. The t-statistics are in parentheses.

Variable	Number of CDOs	Amount of CDOs
δ	2.96***	2.82***
	[12.61]	[8.29]
CDO-specific characteristics		
Tranche seniority	-0.24***	-0.26***
	[-7.64]	[-6.14]
log(face value)	-0.07***	-0.07***
	[-5.31]	[-5.10]
log(deal size)	-0.32***	-0.29***
	[-6.78]	[-5.19]
Fitch rated	0.01	0.03
	[0.24]	[0.93]
Dummy for CDO2	0.18***	0.20***
	[4.48]	[3.94]
Dummy for Hybrid CDO	0.05	0.16*
	[0.45]	[1.69]
Dummy for Synthetic CDO	0.35***	0.40***
	[6.27]	[5.21]
Dummy for Floating Rate	0.27***	0.25***
	[3.74]	[2.94]
Moody's-specific characteristics		
Intercept (Moody's)	6.23***	5.96***
	[5.50]	[4.31]
Underwriter relation	0.00	0.00
	[1.02]	[1.52]
Issuer relation	0.01**	-0.03*
	[2.10]	[-1.72]
S&P-specific characteristics		
Intercept (S&P)	6.36***	6.08***
	[5.46]	[4.35]
Underwriter relation	0.00**	0.00**
	[2.60]	[2.28]
Underwriter relation	0.01*	0.00
	[1.76]	[-0.08]
Log likelihood	-3148.02	-3182.99
Pseudo-R2	0.24	0.24
N	3072	3072

Figure 2: Number of CDOs at each rating grade in our data universe.
The Standard & Poor and Fitch 's rating scale is as follows, from excellent to poor: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D. Moody's uses similar rating scale but the naming is slightly different, as shown in parentheses. Ratings below a BBB- rating are considered a speculative or junk bond.



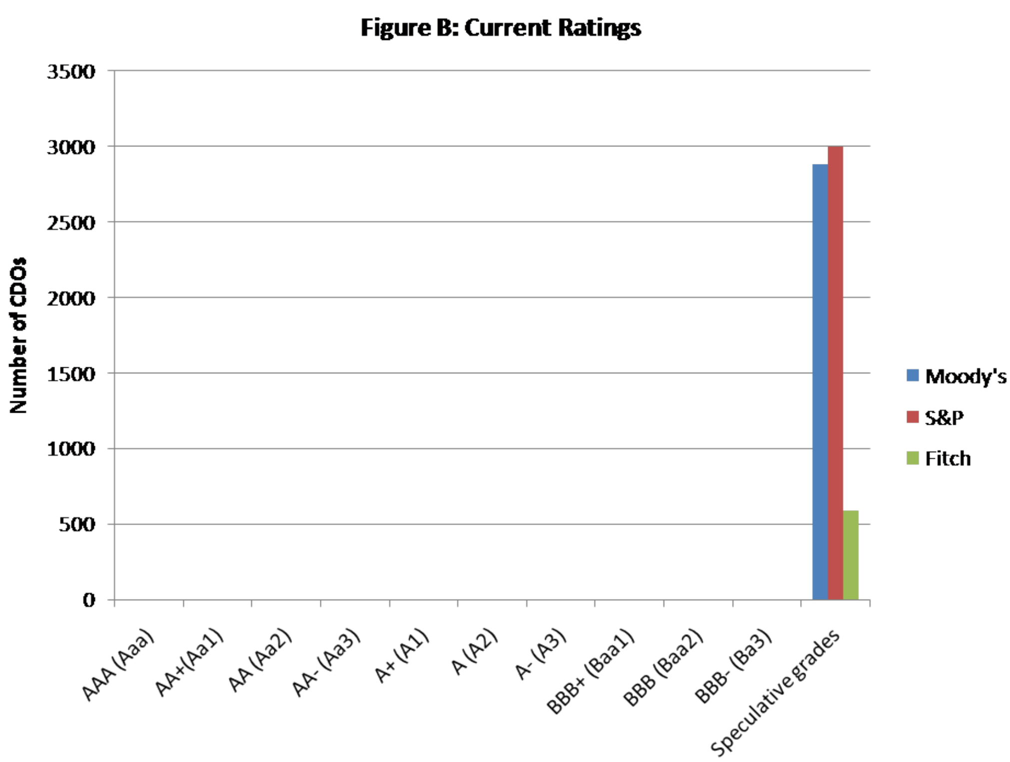
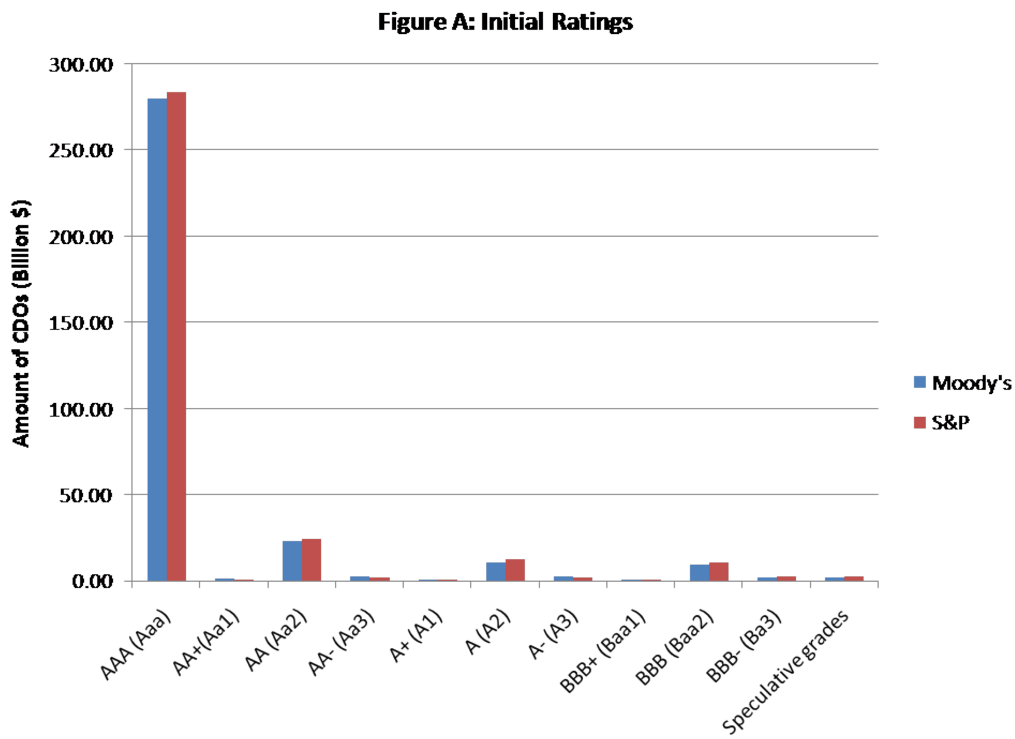


Figure 3: Amount of CDOs at each rating grade in our data universe. The Standard & Poor's rating scale is as follows, from excellent to poor: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D. Moody's uses similar rating scale but the naming is slightly different, as shown in parentheses. Ratings below a BBB- rating are considered a speculative or junk bond.



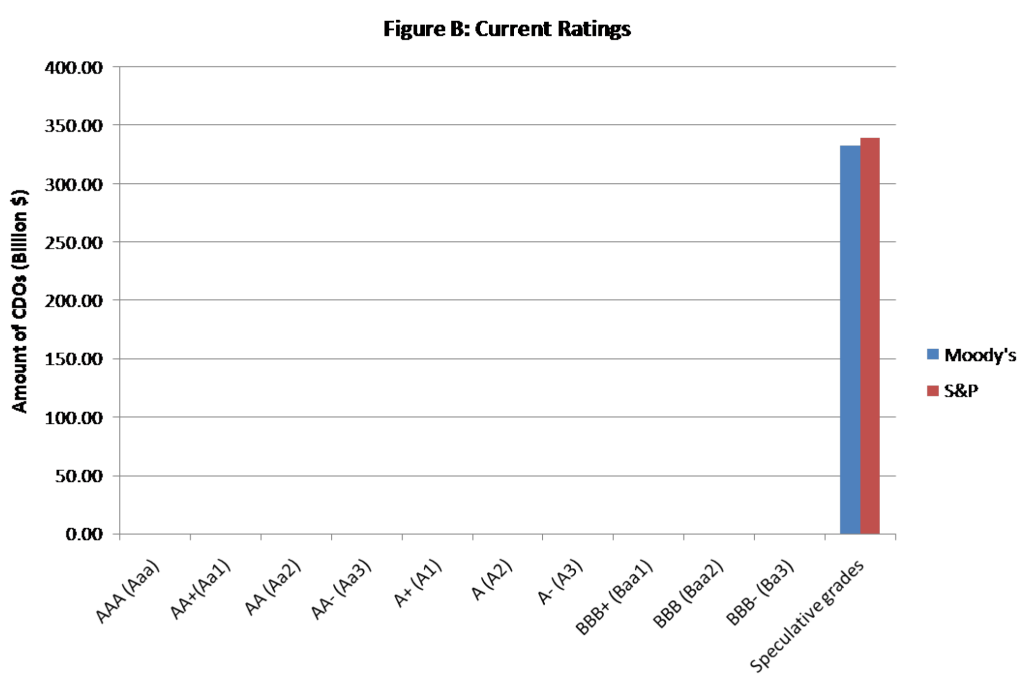


Figure 4: Best response functions and multiple equilibria.
This figure shows CRAs' best response functions for six different cases. $x\beta$ is the deterministic part of the BNE in Equations 4, and δ is the coefficient of the strategic term. Player 1(2)'s best response is on the horizontal (vertical) axis. In plots (a)(b)(c)(e), there is one unique equilibrium, whereas in plots (d)(f) there are three equilibria.

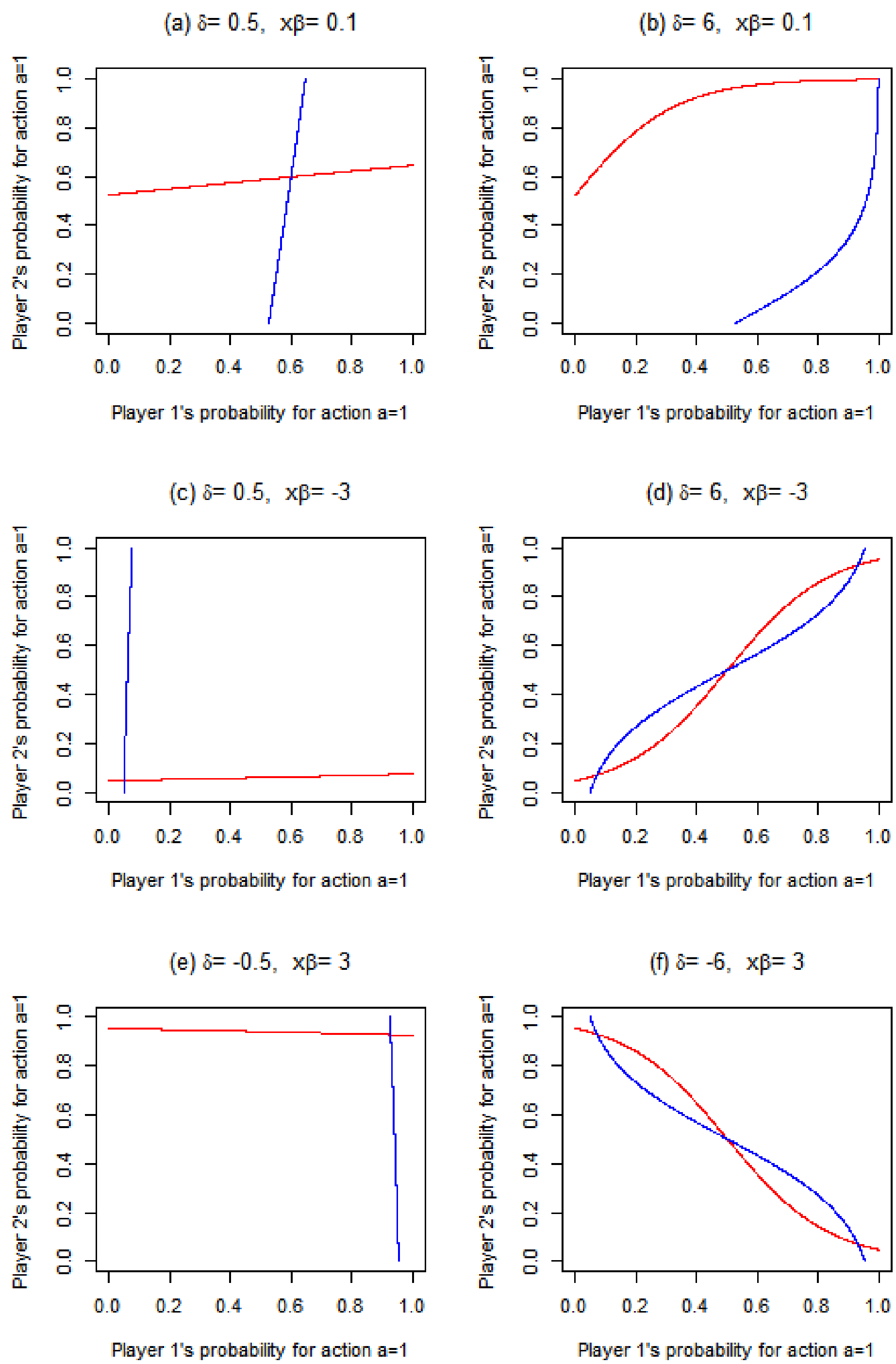


Figure 5: Results with different criteria for classifying lenient ratings
This figure reports results with different criteria for classifying lenient ratings. In the vertical axis of each plot represents the estimated competition strength. The results are obtained using the two-step method. From plot (a)-(f), I require higher initial ratings to be qualified as lenient ratings. In each plot, I plot the estimated competition strength against the change of the number of downgraded notches required to be lenient ratings.