AN EXAMINATION OF THE CREDIT RATING INDUSTRY

by

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ABSTRACT

PATRICK JASON SCHORNO. An examination of the credit rating industry. (Under the direction of DR. W. SCOTT FRAME)

Starting in the early 2000s, after the accounting scandals involving Enron and WorldCom and continuing throughout the subsequent structured finance debacle of 2008, credit rating agencies have been criticized for the inaccuracy of their ratings. A fundamental question that arises from these episodes is: why were the ratings so misrepresentative? With this question in mind, the aim of this dissertation is to study how reputation, competition, and the incentives provided by bond issuers affect credit ratings accuracy.

The first essay presents and solves a reputational maximization problem which simultaneously models both credit rating industry analyst incentives and the degree of competitiveness within the credit rating industry. The results suggest that if credit rating agencies are reputation maximizers, then reputational concerns alone are unlikely to improve ratings accuracy. The second essay aims to decipher the effects of competition on rating agencies by focusing on whether a credit rating agency was the first, second, or third agency to rate a specific bond issue. The empirical results provide evidence that competition leads to less inflated ratings for only the first rating agency that rates a specific bond issue. The third essay examines the link between the level of the rating provided by the third rater and the rater's stream of future ratings coverage following their issuance of that third rating. The results suggest that ratings shopping is prevalent and that the third rater is rewarded with future business for rating above the first two rating agencies on a particular bond issue.

DEDICATION

This dissertation is dedicated to my parents, Edmond and Hollis, who have always provided both support and words of encouragement.

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CHAPTER 1: INTRODUCTION

Starting in the early 2000s, after the accounting scandals involving Enron and WorldCom and continuing throughout the subsequent structured finance debacle of 2008, credit rating agencies have been criticized for the inaccuracy of their ratings. A fundamental question that arises from these episodes is: why were the ratings so misrepresentative? With this question in mind, the aim of this dissertation is to study how reputation, competition, and the incentives provided by bond issuers affect credit ratings accuracy.

The introductory chapter provides a broad overview of the market structure within which credit rating agencies operate along with a discussion of several recent policy innovations by both the U.S. Congress and the U.S. Securities and Exchange Commission. Several competing explanations concerning the inaccuracy of some ratings issued by credit rating agencies will be presented and discussed. In addition, a glimpse into why the public should care about these credit rating inaccuracies and a brief outline of possible solutions will be offered. The final section of the introduction will provide a brief synopsis of the remaining chapters within this dissertation.

1.1 Evolution of the Credit Rating Agency Industry

When John Moody provided the first publicly available bond ratings in 1909 he sparked the creation of an industry designed to foster the availability of information to financial markets. A credit rating is an "opinion" offered by a credit rating agency (CRA) about the relative creditworthiness of a bond issuer, which include corporations, state and local governments, and sovereign governments.[1]

Opp, Opp, and Harris (2013) note that the ratings issued by CRAs serve a dual role in that they both provide information to investors and are also used to regulate many institutional investors. Specifically, a rating defines the minimum quality of the securities that regulated investors can hold within their portfolios and, therefore, the accuracy of such a rating is imperative to ensure that a particular portfolio consists of adequately safe assets. Nonetheless, despite their overwhelming importance to the investment community, CRAs have historically operated in an environment with minimal regulatory interference.

Prior to the creation of the Securities and Exchange Commission (SEC) in 1934, there was no standardization of financial statements and the CRAs were able to earn revenue by selling their assessments of creditworthiness to investors. However, along with the creation of the SEC came the requirement for corporations to issue standardized financial statements. Thus, investors now had the ability to generate their own assessments of creditworthiness, a capability which threatened the business model of the CRAs. In 1936, however, a major change occurred regarding the market environment

[1] In terms of the notion of offering an opinion, Moody's ratings are "opinions of future relative creditworthiness," Fitch's ratings provide "a prospective opinion on the creditworthiness," and Standard & Poor's ratings are "opinions about credit risk."

within which CRAs operated. Specifically, bank regulators prohibited banks from investing in "speculative investment securities," as defined by "recognized rating manuals" (White 2010). More explicitly, banks were now *required* to use ratings issued by one of the published "recognized rating manuals" to determine whether they could invest in a particular security.[2] In the words of White (2010), "Essentially, the creditworthiness judgments of these third-party raters had attained the force of law."

In 1975, the SEC incorporated credit ratings into how broker-dealers went about computing their net capital, a move which reinforced the 1936 innovation and further entrenched the CRAs into financial regulation. The outcome of these modifications was that broker-dealer net capital requirements were to be calculated using ratings from only those agencies designated as Nationally Recognized Statistical Rating Organizations (NRSROs), a designation which the SEC gave to only Fitch, Moody's, and Standard & Poor's.

The NRSRO designation was an attempt to create a more universal definition for the term "recognized rating manual" and to mitigate potential moral hazard problems in rating securities, i.e., that a new CRA might attempt to gain market share by offering higher ratings to firms which were willing to pay for the higher rating. The moral hazard problem is exacerbated by the issuer-pays business model under which the bond issuer (as opposed to the end user) pays for the rating.[3] In an attempt to outline the reasons for the change from the investor-pays model to the issuer-pays model, White (2010) posits the following reasons: (1) it is a consequence of high-speed photocopy machines; (2) it is

[2] The only publishers at this time were Fitch, Moody's, Poor's, and Standard (White 2010).
[3] The issuer-pays business model replaced the investor-pays business model in the early 1970s. See Jiang, Stanford, and Xie (2012) for the exact dates of the change in business model.

a way for an issuer to assure investors that they are low risk and thus willing to pay for a rating; (3) issuers should be willing to pay for multiple “blessings” by the rating agencies in order for their securities to be held by regulated financial institutions; and, (4) it is an attempt to illustrate that the market for ratings is a “two-sided market” and thus issuer and/or investor can pay.

From 1975 until the passage of the Credit Rating Agency Reform Act in 2006 the SEC identified NRSROs through a staff "no-action" letter process, whereby a CRA requested to be recognized by the SEC as an NRSRO. The receipt of a “no-action” letter from the SEC stated that the regulator would not recommend enforcement action if ratings were used by issuers for regulatory compliance purposes. The lack of transparency behind the "no-action" letter review and approval process created a significant barrier to entry for firms attempting to enter the credit rating industry and provided the incumbent CRAs with market power (White 2010).

Pressure began mounting for a stricter regulatory environment for NRSROs after they failed to warn the public about Enron’s financial condition until five days before the firm’s bankruptcy in November 2001.[4,5] Following Enron and other major accounting scandals, the Sarbanes-Oxley Act of 2002 was enacted. One provision of the law required the SEC to prepare a report on the role and function of CRAs to be issued in 2003.[6]

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[4] WorldCom is another example of a highly publicized bankruptcy in which the firm was rated investment grade three months before filing for bankruptcy.

[5] The credit rating agencies argued that they were slow to adjust the ratings because they “rate through the cycle” (as opposed to rating in “real-time”). Moody’s, for example, aims to provide an accurate *relative* ranking of credit risk at each point in time; and, because cardinal accuracy is not the aim, ratings are changed “one-at-a-time” as opposed to changing all ratings in response to business cycle changes (Cantor and Mann 2003).

[6] The *Report on the Role and Function of Credit Rating Agencies in the Operation of the Securities Markets* identified, but did not directly address, numerous issues such as the NRSRO business model (issuer-pays), the NRSRO designation process, and the usage of NRSROs within regulations (White 2010).

In response to the report of the SEC made pursuant to the Sarbanes-Oxley Act of 2002 and in an effort to improve ratings quality and to protect investors by increasing transparency and competition within the credit ratings industry, the Credit Rating Agency Reform Act of 2006 was passed by the U.S. Congress. As part of the new law, the SEC was instructed to cease being a barrier to entry; criteria were specified for NRSRO designation; transparency and due process in SEC decisions were required; and, the SEC was given limited powers to oversee NRSROs (White 2010). Further, NRSROs would now be required to disclose information regarding their ratings methodology, ratings performance, and conflicts of interest.

Around the time of the Credit Rating Agency Reform Act, business was booming for the CRAs within the structured finance market, especially for mortgage-related securities issued and rated in 2005-2007. The CRAs became not only raters, but engineers of the securities themselves. White (2010) states:

> … in calculating appropriate ratings on the tranches of securities backed by subprime mortgages, the credit rating agencies were operating in a situation where they had essentially no prior experience, where they were intimately involved in the design of the securities, and where they were under considerable financial pressure to give the answers that issuers wanted to hear. (p. 221)

Perhaps not surprisingly, the ratings on these securities were highly inflated, to the extent that as of June 30, 2009, 80 percent of collateralized debt obligation tranches issued between 2005 and 2007 which were initially rated AAA were no longer investment grade (White 2010). A potential reason for the overly optimistic ratings, offered by

Mathis, McAndrews, and Rochet (2009), is that the protection of long-run reputation is not as worrisome when operating in a protected oligopoly, especially in an environment with a large percentage of complex securities. In other words, the current market structure is not consistent with ratings accuracy.

Following the widespread problems with mortgage-backed structured finance product ratings, the SEC amended rules governing the conduct of NRSROs. In late 2008, and again in late 2009, the SEC placed restrictions on conflicts of interest arising from the issuer-pays business model (White 2010). Specifically, NRSROs were: (1) to disclose historical ratings actions; (2) not allowed to structure and then rate an issue; and (3) to disclose payment amounts and any potential conflicts of interest.[7] The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 further directed federal agencies to remove any reference to or requirement of reliance on credit ratings.

[7] See *SEC Factsheet: Strengthening the Oversight of Credit Ratings Agencies* www.sec.gov/news/press/2009/2009-200-factsheet.htm.

1.2 Why Were the Ratings So Misrepresentative?

Credit rating agency performance is measured by both ratings accuracy and ratings stability. In terms of ratings accuracy, one can look at the correlation between ratings and subsequent defaults; whereas, in terms of ratings stability, one can look at the frequency and magnitude of ratings changes (Cantor and Mann 2003). Over long horizons, ratings stability may increase the accuracy of ratings, but there may also be a tension between ratings stability and ratings accuracy. This conflict is discussed in Cantor and Mann (2003):

> …a rating agency may be regularly changing ratings and then quickly reversing those actions in response to information that turns out to be wholly unrelated to credit risk. Such rating actions may have very little effect on accuracy but may substantially reduce stability. (p. 2)

Credit ratings for firms such as Enron and WorldCom, as well as for mortgage-related structured finance products, were often wildly optimistic and uninformative. Why? Ruling out bad luck, the first hypothesis may be that the CRAs lacked diligence in their rating actions. In October 2002, the U.S. Senate Committee investigated the monitoring activities of CRAs in the years leading up to the collapse of Enron and concluded that the CRAs displayed a lack of diligence in their coverage and assessment.[8] Partnoy (2006) points to a specific statement made by Senator Joseph Lieberman:

> The credit-rating agencies were dismally lax in their coverage of Enron. They didn't ask probing questions and generally accepted at face value whatever Enron's officials chose to tell them. And while they claim to rely

[8] See *Report of the Staff of the Senate Committee on Governmental Affairs: "Financial Oversight of Enron: The SEC and Private-Sector Watchdogs," Report 107-75* (October 7, 2002).

> primarily on public filings with the SEC, analysts from Standard and Poor's not only did not read Enron's proxy statement, they didn't even know what information it might contain. (p. 68)[9]

In this vein, Frost (2007) summarizes the criticisms made of CRAs as a lack of due diligence and competence leading to an inaccurate assessment of the true condition of Enron. The publicly disclosed information was, in fact, misleading and the CRAs did not probe deeply enough to correctly assess the creditworthiness of Enron, specifically, and many other companies, in general.

The decision to rate ultra-complex deals, such as mortgage-related structured finance products, may have also contributed to ratings inaccuracy. Not only were the CRAs highly involved in the design of the tranches (White 2010), but the tranches turned out to be significantly inflated in terms of the percentage of investment grade securities. Although not an exact comparison, Coval et al. (2009) show that securitization led to a significantly higher percentage of AAA tranches (roughly 60% of all global structured products) when compared to the percentage of AAA rated corporate bonds (less than 1 percent of the corporate issues). The models of Mathis, McAndrews, and Rochet (2009) and Skreta and Veldkamp (2009) show, theoretically, how an increase in the complexity of an asset leads to an increase in the deterioration in the quality of ratings.

Outside of the broader claims that poor diligence and/or asset complexity drove the inaccuracy, the academic literature has focused on several other explanations for the inaccuracy of ratings, including: reputation, competition (including ratings shopping), business cyclicality, and the issuer-pays model.

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[9] *Ibid.*

Starting with reputation, Covitz and Harrison (2003) provide empirical evidence that rating actions are primarily motivated by reputational concern, rather than revenue maximization. The authors illustrate that there are more timely rating actions in cases likely to generate substantial publicity (e.g., fallen angels or large clients).[10] Livingston, Wei, and Zhou (2010) study bond yields and find that when a CRA consistently rates lower than other CRAs, investors put more value on that CRAs' ratings. Han, Pagano, and Shin (2012) investigate the effect of the financial crisis on the reputation of CRAs and their findings suggest that the advantage of obtaining a bond rating from a global rater was fully negated by the financial crisis. Mathis, McAndrews, and Rochet (2009) conclude that reputation only matters when a sufficiently large percentage of CRA income comes from sources other than rating complex products. The authors suggest that this is due to "confidence cycles," wherein an opportunistic CRA (one which inflates ratings after gaining reputation) will be harder to detect when the proportion of unsuccessful projects in the economy becomes large.

The academic literature also focuses on the competitive environment within which CRAs operate. The theoretical literature regarding competition almost unanimously suggests that increased competition leads to a deterioration in ratings quality. Faure-Grimaud et al. (2009) find Bertrand competition between rating intermediaries leads to less information being revealed in equilibrium relative to monopoly.[11] Bolton, Freixas, and Shapiro (2012) compare a ratings industry with a monopoly CRA to one with duopolist CRAs. Their model accounts for the various

[10] A fallen angel is a bond that migrated from investment grade to junk status.

[11] Bertrand duopolists will offer ratings for a fewer set of types, typically of higher quality, since they are unable to engage in cross-subsidization over a firm's types (since Bertrand duopolists must make zero profit on each type they contract with).

particularities of the current ratings industry, including: conflicts of interest, barriers to entry, and opportunities for issuers to shop for the best rating. They find that, in general, a monopoly system is more efficient than a duopoly.[12] Bar-Isaac and Shapiro (2013) also find that when comparing a monopoly CRA to duopolist CRAs, the monopoly CRA is at least as accurate as the duopoly. The outlier in the theoretical literature is Hirth (2012), who finds that, when looking beyond just a duopoly, the impact of a new competitor depends largely on the current number of CRAs. In addition, he finds that a market with only truthful rating agencies can hypothetically be achieved in a perfectly competitive system.

The empirical literature on the role of competition on ratings accuracy is split: some articles find that competition is bad while others find it to be good. Becker and Milbourn (2011) use Fitch's market share as a proxy for the degree of competition and test for an effect on ratings issued by Moody's and Standard & Poor's. They find a significant positive link between Fitch's market share and ratings gravitating toward AAA; as well as evidence of a decline in the ability of ratings to predict default and a lower correlation between a bond's rating and its market-implied yield. Guttler (2011) finds competition hinders ratings quality since all CRAs simply attempt to mimic ratings of other CRAs and, therefore, ratings do not necessarily reflect default risk.

Doherty et al. (2012) find evidence of more informative ratings of insurance companies after the introduction of a new entrant at the end of the 1980s and provide evidence that issuers with similar qualities often receive lower ratings from the new entrant. Xia (2012) examines how ratings from an issuer-paid CRA (Standard & Poor's)

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[12] The authors consider total ex-ante surplus when defining market efficiency. They calculate the surplus of investors, CRAs, and issuers and compare to the first-best and the market solution when there are no CRAs.

responded following the entry of an investor-paid CRA (Egan-Jones Rating Company) in December 1995 and finds that ratings quality improves for Standard & Poor's following initiation of coverage by Egan-Jones.

The topic of ratings shopping, or the ability to choose amongst multiple CRAs, falls under the umbrella of competition and warrants further discussion. The theoretical models in both Bolton et al. (2012) and Bar-Isaac and Shapiro (2013) suggest that the shopping problem is exacerbated by investors willing to buy investments with good ratings regardless of the quality of the ratings. Skreta and Veldkamp (2009) model a system in which issuers can shop and have the right to disclose only the most favorable rating. Their findings suggest that as asset complexity increases, a ratings bias emerges as does the incentive for shopping. Becker and Milbourn (2011) claim that ratings shopping is less of a concern with simple issues like corporate bonds because there is less dispersion amongst ratings.

Given the argument by the CRAs that they are slow to adjust the ratings because they "rate through the cycle," the effects of the business cycle on ratings quality has also been examined within the academic literature. Bolton, Freixas, and Shapiro (2012) and Bar-Isaac and Shapiro (2013) suggest that ratings accuracy is countercyclical (i.e., ratings inflation is more prevalent during economic booms and accuracy is higher during recessions) and that this finding is independent of market structure. He, Qian, and Strahan (2012) present empirical evidence that during boom periods large issuers receive more favorable, or inflated ratings.

Of final interest within the speculated causes for the inaccuracy of ratings is the business model utilized by the CRAs. As discussed above, in the early 1970s the CRA business model switched from investor-pays to issuer-pays. The issuer-pays approach creates a potential conflict of interest, insofar as CRAs might shade ratings higher in order to attract new business. In testing whether Standard & Poor's issues higher ratings relative to Moody's after a switch from investor-pays to issuer-pays in 1974, Jiang, Stanford, and Xie (2012) find that the issuer-pay structure leads to higher ratings. In other words, the conflict of interest seemingly led to ratings inflation.

1.3 Policy Proposals

Whether because of asymmetric information or regulatory requirements, investors rely heavily on the ratings provided by NRSROs to determine the riskiness of a security. When ratings are inaccurate, there may be inefficient investment decisions and the aggregate level of risk in the economy may be higher than would otherwise be the case. Because accurate credit ratings are so important, the next logical question is whether or not regulation is the best way to fix the quality of credit ratings, and if so, then what type of regulation?

A couple of policy proposals to address problems related to ratings accuracy have appeared in the literature on CRAs. Richardson and White (2009) propose that the SEC should house a centralized clearinghouse which operates in the following manner: (1) a company approaches the clearinghouse with debt it would like to be rated; (2) the clearinghouse chooses a rating agency from a sample of approved agencies;[13] and (3) the rating agency would then rate the debt for a fee. This proposed system has a few advantages. First, the issuer still pays, so the business model does not change. Second, the potential moral hazard problem of the issuer-pays system is solved because the clearinghouse selects the appropriate CRA. Third, any problems associated with competition are solved because the clearinghouse bases selection on some performance metric.

Mathis, McAndrews, and Rochet (2009) suggest a similar system, albeit with a couple of minor changes. First, in order to cut any direct links between issuers and CRAs, the authors support a pre-issue fee to the central platform as opposed to a fee directly to

[13] The choice could be either random or based on some historical accuracy metric for the specific type of debt.

the CRA after selection. Second, to avoid competition policy concerns related to collusion amongst CRAs, the authors also propose that the platform (clearinghouse) be self-regulated and not housed within Government.[14]

[14] The owners would be the issuers and the investors, cooperatively, rather than the CRAs or Government.

1.4 Outline of Dissertation Chapters to Follow

The CRA industry exists in order to provide accurate assessments of relative creditworthiness of securities to investors. However, a series of episodes over the past decade in which the ratings were misrepresentative have led the rating agencies to come under scrutiny. This dissertation will touch on several of the outstanding issues believed to affect the accuracy of ratings provided by CRAs, including: the dynamics of reputation, the role of the competitive environment on ratings stability, and the incentives faced by the third rating agency to rate a particular bond issue.

The second chapter analyzes the link between rating agency reputation and ratings accuracy, with special attention paid to the effect of competition on this relationship. Using the argument that CRAs are disciplined by reputational dynamics, a reputation maximization problem which simultaneously models both CRA analyst incentives and the degree of competitiveness within the industry is presented and solved. Economic conditions are captured through default rates, discount rates, average issue quality, and the prevalence and profitability of outside job opportunities for analysts. The results illustrate that if CRAs are reputation maximizers, then reputational concerns alone are unlikely to improve ratings accuracy. Moreover, contrary to the current literature, when compared to a monopolistic environment, there are conditions under which ratings accuracy is at least as high in a competitive environment. Finally, in line with the current literature, ratings accuracy is found to be countercyclical.

The third chapter looks to decipher whether increased competition positively or negatively affects ratings stability. This chapter isolates the effects of competition on rating agencies with a focus on whether a CRA was the first, second, or third agency to rate a specific bond issue. The empirical results show that competition leads to less inflated ratings for only the first rating agency to rate a specific bond issue. Also, competition is especially counterproductive when a CRA has the ability, as the second or third rater, to determine the rating used for regulatory purposes for a specific issue. Finally, increased competition at the time of the initial rating leads to larger initial revisions, a result suggesting that initial ratings were more inaccurate with more competition.

The fourth chapter examines the underlying incentives faced by a third CRA to rate a particular bond issue. Specifically, it examines the link between the relative level of the rating provided by the third rater and that rater's stream of future ratings coverage following their issuance of the third rating. The results suggest that ratings shopping is prevalent; the third rater is rewarded with future business for rating above the first two rating agencies to rate a particular bond issue. Also, in non-financial industries, the third rater appears to be utilized only when certification at the investment grade line is necessary and, after certifying an issue, the third rater is less likely to rate the subsequent bond issue by that same issuer.

The final chapter of this dissertation will summarize and offer conclusions.

CHAPTER 2: REPUTATION AND CREDIT RATINGS

When the incidence of bond defaults and rating revisions are low, few question the accuracy of credit rating agencies (CRAs). However, in times of distress, when highly rated bond issues are migrating to junk status, investors often accuse CRAs of providing false or misleading information. With their inherent conflicts of interest, a CRA's ability to remain both unbiased and accurate in a market of minimal regulation and few competitors will be questioned. Yet, CRAs are adamant that their behavior is disciplined by reputational factors. In fact, rating agencies are not alone in this belief. In a statement of response to the SEC's Hearing on Credit Rating Agencies in November 2002, Steven L. Schwarcz, Professor of Law at Duke University, provided the following outlook:

> …the negative reputational consequences of providing a rating that, in retrospect, turns out to be incorrect far outweigh the fee a rating agency can charge for providing that rating.[15]

Using the argument that reputational concerns alone are sufficient to regulate the entire industry, we construct a theoretical model in which the objective function is to maximize CRA reputation.[16] An advantage to maximizing reputation, as opposed to maximizing profit, is the ability to model rewards and punishments associated with securities that a CRA both does and does *not* rate. As CRAs are only as good as the

[15] See Schwarcz (2002) for more detail.

[16] Empirical work by Covitz and Harrison (2003), Livingston, Wei, and Zhou (2010), and Han, Pagano, and Shin (2012) provide empirical support for the decision to maximize reputation when modeling a CRAs' decision making process. See Section 2.1 for more detail.

analysts in their employ, this paper follows Bar-Isaac and Shapiro (2011) in modeling analyst incentives by looking at both wage contracts and outside employment opportunities. In the model, changes in economic conditions are modeled through the default rate, the discount rate, bond issue quality, and the probability and profitability of an analyst moving on to an investment banking position. Finally, the model adds to Bar-Isaac and Shapiro (2011) a variable which represents the level of market concentration within the CRA industry in order to illustrate the effect of competition on ratings accuracy.

Several conclusions from this paper add to the growing theoretical literature concerning CRA ratings accuracy. First, if CRAs are reputation maximizers, we find that reputational incentives alone are unlikely to improve ratings accuracy and reputational punishments alone will only improve ratings accuracy in a highly concentrated CRA industry. Second, if reputational incentives are relatively large compared to reputational punishments, a more competitive environment leads to more accurate ratings. Third, in order for an increase in the probability of an analyst landing an outside job opportunity to improve rating accuracy, the returns from getting that job must be above a threshold. This result is contrary to that in the model of Bar-Isaac and Shapiro (2011). Fourth, consistent with the current literature, we find ratings accuracy to be countercyclical (Bar-Isaac and Shapiro 2013; Bolton, Freixas, and Shapiro 2012; He, Qian, and Strahan 2012). Several other minor model implications are discussed within the analysis section.

2.1 Literature Review

In order to use a reputational model, it is first necessary to show that reputation matters to the CRAs. In looking at events associated with negative publicity, Covitz and Harrison (2003) find that CRAs are primarily motivated by reputational concerns. The authors show that CRAs take action quicker in downgrading either fallen angels or large clients, a finding which provides support for CRAs acting to protect their reputations. Livingston, Wei, and Zhou (2010) provide empirical evidence that reputation matters by showing that when a rating agency consistently rates lower than other agencies, investors put more value on the more conservative CRA's ratings. Han, Pagano, and Shin (2012) discuss how the financial crisis tarnished the reputation of CRAs and show that the benefits from obtaining a rating from a global rater diminished.[17] The empirical evidence within the literature suggests that both CRAs and investors value CRA reputation.

A few theoretical models discuss the consequences of reputation building. Mathis, McAndrews, and Rochet (2009) find that when complex products are a major source of income for a CRA, and their reputation is good enough, the CRA inflates ratings with probability one.[18] Mariano (2012) finds that in an attempt to increase reputation, an incumbent CRA may take excessive risks in rating in order to protect market power. Bouvard and Levy (2012) find that when a rating agency has a good reputation, it tends to be more lenient in order to attract future business since its payoff is non-monotone in reputation.

[17] In their case, Standard & Poor's and Moody's were the global raters which were studied.
[18] The authors suggest that this is due to "confidence cycles," wherein an opportunistic CRA (one which inflates ratings after gaining reputation) will be harder to detect when the proportion of unsuccessful projects in the economy becomes large.

In terms of modeling analyst incentives, this paper follows Bar-Isaac and Shapiro (2011), in which the authors examine a CRA that looks to structure analyst wages and bonuses in order to maximize the sum of its discounted profits. They find that the accuracy of a CRA's ratings increases with the CRA's ability to monitor their analysts and the returns for an analyst from taking an outside job opportunity, and is non-monotonic in the probability that an analyst leaves for an outside opportunity. By solving a reputation maximization problem, as opposed to a profit maximization problem, the results in this paper lead to findings that are contrary to those of Bar-Isaac and Shapiro (2011) with respect to the relationship between the probability of an analyst leaving and the accuracy of the CRA.

The accuracy of ratings over the business cycle has also been a focus of the academic literature. In analyzing a dynamic model of ratings with varying economic conditions and endogenously determined reputation, Bar-Isaac and Shapiro (2013) conclude that ratings accuracy is countercyclical. He, Qian, and Strahan (2012) present empirical evidence that during boom periods, large issuers receive more favorable, or inflated, ratings.

There are divergent results found in the literature on the effect of competition. The theoretical literature tends to be decisive in the view that competition negatively affects ratings quality (Faure-Grimaud et al. 2009; Bolton, Freixas, and Shapiro 2012; Camanho, Deb, and Liu 2012; Bar-Isaac and Shapiro 2013). However, the empirical evidence is split. Some empirical studies find competition to hinder ratings quality (Becker and Milbourn 2011; Guttler 2011) and others find competition to improve ratings quality (Doherty et al. 2012; Xia 2012; Hirth 2012). Our model suggests that there is an optimal level of competition (between the extremes) where ratings accuracy is maximized, and this level is dependent upon the ratio of reputational incentives to reputational punishments.

2.2 Model

The model is a two-period overlapping generations model in which a CRA employs both novice and seasoned analysts. The average ability of all the analysts working at the CRA is denoted by z and it affects the ratings accuracy of the CRA. Therefore, the CRA will write contracts to attract the best analysts in order to improve its reputation by rating more accurately. Now, consider a single CRA that rates investments that are "good" with probability λ and "bad" with probability $(1-\lambda)$.[19] Good investments never default and bad investments default with probability ρ. Furthermore, good investments are perfectly identified by the CRA as such, whereas bad investments are identified with probability $z \in (0, 1)$.[20]

The reputation of the CRA is modeled using both reputational incentives (R_I) and reputational punishments (R_p).[21] Whenever a CRA rates a good investment, the firm automatically gains R_I. When an investment is rated as bad, the CRA attains R_I or R_p depending on how the CRA rated the investment and whether or not the investment defaults in the subsequent period. In other words, absolute truthfulness is not always associated with reputational incentives. Instead, there are conditions under which the CRA might be motivated to misrepresent the true nature of the bond.

The CRA can also face a varying degree of competitiveness within the CRA industry. The level of competition within the industry (c) can lie anywhere in the set [0, 1], for which a value of 0 represents a monopoly and 1 represents a perfectly competitive environment. Decision making by CRAs in this model is purely motivated by reputation

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[19] The value of λ is determined exogenously of the CRAs maximization problem.

[20] The average ability of all the analysts, z, is the sole determinant in the probability that the CRA correctly identifies bad investments.

[21] Both incentives and punishments are positive valued.

and thus the level of competition does not impact rating decisions. Rather, competition is solely a way to reveal the accuracy of ratings on issues which may not have taken place in a less competitive environment. For instance, in a monopoly, no reputational incentives or punishments will be received if a CRA rates a bad product properly because that product will never be rated by another CRA.[22] However, as competition increases, so too does the probability that the bad product is rated inaccurately by another CRA. In instances where the bad product receives a good rating, all CRAs which rated the bad product appropriately will receive reputational incentives.

Analyst incentives are modeled as in Bar-Isaac and Shapiro (2011), where analysts are either novice (n) or seasoned (s).[23] A novice analyst works at a CRA, whereas seasoned analysts have the ability to work at either the CRA or at an investment bank. The ability of an analyst depends on his/her effort level, where the effort level of a seasoned analyst is additive over time periods. At career level i within the life of an analyst, where $i = (n, s)$, and at date t, an analyst can exert effort $e_{i,t}$ to improve his/her ability. At date t, a seasoned analyst has additive efforts from his/her career: $e_{n,t-1} + e_{s,t}$. As in Bar-Isaac and Shapiro (2011), the effort of an analyst is unobservable and costly to the analyst, taking on a quadratic cost function: $\frac{e_i^2}{2}$.

By exerting effort, analysts improve their ability to land a more lucrative job. The probability of getting an investment banking job is γ and the profitability from such a job is b. The parameters γ and b can be used to describe changing economic conditions. There is also a parameter for luck, $L \in (0, 1]$, which captures the ability of the CRA to

[22] As in Mathis, McAndrews, and Rochet (2009), the assumption is that no issue takes place if the rating is bad.
[23] See Bar-Isaac and Shapiro (2011) for more detail behind the modeling of analyst incentives.

monitor analyst effort; a value of L=0 would represent perfect monitoring and a value of L=1 would represent the complete inability to monitor effort. Finally, both the CRA and the analysts are risk-neutral with discount factor δ.

2.3 Analysis

In order to determine the level of ratings accuracy, the first parameter to be modeled is the average ability of the analysts employed by a given CRA. To do so, we follow Bar-Isaac and Shapiro (2011) and utilize their effort choices for the novice and seasoned analysts at time *t*:

$$e_{n,t} = w_{n,t}(1-L) + \delta\gamma \mathrm{b} \tag{1}$$

$$e_{s,t} = w_{s,t}(1-L). \tag{2}$$

Normalizing the number of novice analysts to 1 implies that the credit rating agency employs (1 - γ) seasoned analysts for each novice analyst. Because ability is dependent upon cumulative effort level, seasoned analysts have ability $e_{n,t-1} + e_{s,t}$ and novice analysts have ability $e_{n,t}$. Given this and the effort choices in equations (1) and (2), the average ability of the CRA is:

$$z_t = \frac{e_{n,t}}{2-\gamma} + \frac{1-\gamma}{2-\gamma}\left(e_{n,t-1} + e_{s,t}\right). \tag{3}$$

The CRA looks to maximize its overall reputation by choosing its analysts' wages, $w_{n,t}$ and $w_{s,t}$, in each period:

$$\begin{aligned} \max_{w_{n,t},w_{s,t}} \mathrm{R_I}\Big(\big(\delta(\lambda + (1-\lambda)(1-z)(1-\rho) + c(1-\lambda)z\rho)\big) + \delta^2\big(c(1-\lambda)z\rho\big)\Big) \\ -\mathrm{R_p}\Big(\delta\big((1-\lambda)(1-z)\rho + c(1-\lambda)z(1-\rho)\big) + \delta^2\big((1-\lambda)(1-z)\rho\big)\Big) \qquad (4) \\ -w_{n,t}\Big(L + (1-L)\big(w_{n,t}(1-L) + \delta\gamma\mathrm{b}\big)\Big) - (1-\gamma)w_{s,t}\Big(L + (1-L)\Big(w_{s,t}(1-L)\Big)\Big). \end{aligned}$$

The first line represents the reputational incentives that a CRA can earn for actual or perceived accuracy. A CRA can experience a gain in reputation in the following ways: the CRA rates a good project as good (λ); the CRA rates a bad project as good and it does not default ((1–λ)(1–z)(1–ρ)); the CRA rates a bad project as bad and it defaults in either the first or second period (c(1–λ)zρ).

The second line represents the reputational punishments a CRA receives for actual or perceived inaccuracy. A CRA has the potential to realize such a penalty in the following ways: the CRA rates a bad project as good and it defaults in either the first or second period ((1–λ)(1–z)ρ); the CRA rates a bad project as bad and it does not default (c(1–λ)z(1–ρ)).

As in Bar-Isaac and Shapiro (2011), the third line in our maximization problem represents the cost of wages in period t for employing a mix of novice and seasoned analysts.

Following Bar-Isaac and Shapiro (2011), substitutions are made for the analysts' efforts, $e_{n,t}$ and $e_{s,t}$, and the average analysts ability, z_t. Then, the optimization problem is solved for the CRAs optimal choice of wages, $w_{n,t}$ and $w_{s,t}$, by finding the first-order conditions with respect to these wages. Within the first-order conditions, the stationarity of the problem is imposed, wherein $w_{i,t} = w_i$, $e_{i,t} = e_i$, and $z_t = z$. Finally, optimal wages are substituted into equations (1) and (2) and then effort levels into equation (3) to obtain an expression for the level of accuracy:

$$z^* = \frac{1}{2(\gamma-2)^2(L-1)}\left[\begin{array}{c}(\gamma-2)(\mathrm{b}(\gamma-2)\gamma\delta(L-1)+(2\gamma-3)\mathrm{L}) \\ +(2\gamma-3)\delta(L-1)(\lambda-1)\begin{pmatrix}\mathrm{R_I}\rho\left(1+c+\delta-\frac{c}{\rho}\right) \\ +\mathrm{R_p}\rho\left(1+c+c\delta-\frac{1}{\rho}\right)\end{pmatrix}\end{array}\right]. \tag{5}$$

With this expression, comparative statics of ratings accuracy (z*) can be derived with respect to the exogenous parameters that affect the analysts' incentives when the CRAs optimization problem involves maximizing reputation. Taking the derivative of equation (5) with respect to competition (*c*) gives the following proposition:

Proposition 1: In equilibrium, the accuracy level of the CRA (i) increases with the level of reputational incentives R_I when $c > (1-\rho)/((1+\delta)\rho)$; (ii) increases with the level of reputational punishments R_p when $c < ((1+\delta)\rho)/(1-\rho)$; (iii) increases with the level of competition *c* when $\rho > R_p/(R_p + R_I(1+\delta))$; and (iv) increases with the probability of an analyst getting an investment bank job γ when the return on such an opportunity is sufficiently high.

Proof: Claim (i) follows from taking the derivative of z^* with respect to reputational incentives R_I where:

$$\frac{\partial z^*}{\partial R_I} = \frac{(2\gamma-3)\delta(\lambda-1)(\rho(1+c+c\delta)-1)}{2(\gamma-2)^2},$$

which is positive when $\rho(1+c+c\delta)-1>0$. Rearranging in terms of the level of competition, the condition becomes that when $c > (1-\rho)/((1+\delta)\rho)$ the level of accuracy is increasing in the level of reputational incentives.

Claim (ii) follows in the same manner as Claim (i) where:

$$\frac{\partial z^*}{\partial R_p} = \frac{(2\gamma-3)\delta(\lambda-1)(c(\rho-1)+(1+\delta)\rho)}{2(\gamma-2)^2},$$

which is positive when $c(\rho-1)+(1+\delta)\rho>0$. Rearranging in terms of the level of competition, the condition becomes that when $c < ((1+\delta)\rho)/(1-\rho)$ the level of accuracy is increasing in the level of reputational incentives.

Claim (iii) follows from taking the derivative of z^* with respect to the level of competition *c*, yielding:

$$\frac{\partial z^*}{\partial c} = \frac{(2\gamma - 3)\delta(\lambda - 1)\big(\mathrm{R_p}(\rho - 1) + \mathrm{R_I}(1 + \delta)\rho\big)}{2(\gamma - 2)^2}.$$

Analyzing term by term, this is positive when $\mathrm{R_p}(\rho - 1) + \mathrm{R_I}(1 + \delta)\rho > 0$. After rearranging, it can be seen that the level of accuracy is increasing in the level of competition when $\rho > \mathrm{R_p}/(\mathrm{R_p} + \mathrm{R_I}(1 + \delta))$.

For Claim (iv), comparative statics are used in order to evaluate the derivative of z^* with respect to γ. Accuracy is increasing in γ when the following expression is negative

$$\frac{\partial z^*}{\partial \gamma} = 2\delta(1 - \gamma)(1 - L)(1 - \lambda)\begin{bmatrix} \mathrm{R_p}\rho\left(1 + c + \delta - \frac{c}{\rho}\right) \\ +\mathrm{R_I}\rho\left(1 + c + c\delta - \frac{1}{\rho}\right)\end{bmatrix} + \mathrm{b}\delta(\gamma - 2)^3(L - 1) + L(2 - \gamma). \tag{6}$$

When $\gamma = 0$, equation (6) is equivalent to the following:

$$b > \frac{\delta(1 - L)(1 - \lambda)\left[\mathrm{R_p}\rho\left(1 + c + \delta - \frac{\mathrm{c}}{\rho}\right) + \mathrm{R_I}\rho\left(1 + c + c\delta - \frac{1}{\rho}\right)\right] + L}{4\delta(L - 1)}.$$

When b meets this condition, accuracy is increasing in γ. The derivative of equation (6) with respect to γ is equivalent to the following:

$$\frac{\partial z^*}{\partial \gamma^2} = -2\delta(1 - L)(1 - \lambda)\left[\mathrm{R_p}\rho\left(1 + c + \delta - \frac{c}{\rho}\right) + \mathrm{R_I}\rho\left(1 + c + c\delta - \frac{1}{\rho}\right)\right] + 3b\delta(\gamma - 2)^2(L - 1) - L,$$

which is negative and monotonically decreasing in γ when $\rho > \frac{\mathrm{R_p}c + \mathrm{R_I}}{\mathrm{R_p}(1 + c + \delta) + \mathrm{R_I}(1 + c + c\delta)}$. When $\gamma = 1$, equation (6) reduces to $-b\delta(L - 1) + L$, which is positive. Therefore, as long as the profitability from attaining an investment banking job is sufficiently high, the level of accuracy increases with the probability of getting an investment bank job. ■

The initial focus of Proposition 1 is the effect which reputational concerns of CRAs have on their accuracy. For reputational incentives to have a positive effect on accuracy there must be both a sufficiently high default rate and level of competition

(Claim (i)). Figure 2.1 illustrates that the necessary condition is unlikely to be met. For instance, within a perfectly competitive environment, there would need to be a default rate of over 30% for reputational incentives to improve ratings accuracy in this model. Further, the default rate would need to be even larger for any lower level of competition to lead to reputational incentives improving ratings accuracy.

In terms of reputational punishments, these are most effective in increasing accuracy when there are low levels of competition (Claim (ii)). Figure 2.2 displays the necessary conditions, where any area under the contour lines represents areas in which reputational punishments improve ratings accuracy. In a very highly concentrated CRA industry, it is possible for the necessary condition to be met in terms of the default rate. Along with illustrating the asymmetry of reputation, this finding also shows that, when CRAs operate in a very highly concentrated industry, reputational punishments may assist in improving ratings accuracy.

Contrary to Bar-Isaac and Shapiro (2013), Claim (iii) of Proposition 1 suggests that the level of accuracy increases with the level of competition. The necessary condition for this claim is illustrated in Figure 2.3. If the asymmetry in reputation is such that reputational incentives are relatively large compared to reputational punishments, this condition is satisfied.

The first three claims of Proposition 1 suggest that ratings accuracy can be improved with reputational punishments or competition. However, the necessary conditions for reputational punishments to improve ratings accuracy are unlikely to occur in realistic economic settings. Therefore, just as with reputational incentives, reputational punishments are unlikely to improve ratings accuracy on a stand-alone basis. However, with a large enough ratio of incentives to punishments, ratings accuracy can be improved with industry competition.

As in Bar-Isaac and Shapiro (2011), the model here also finds that accuracy increases as the probability of landing an investment banking position increases. However, contrary to Bar-Isaac and Shapiro (2011), the model suggests that given a sufficiently high profitability of such an employment opportunity, rating agency accuracy is monotonic in the probability of an analyst leaving (Claim (iv)). Intuitively, if the returns from taking an investment banking position are not above some threshold, an analyst has little incentive to expend more effort to increase accuracy, even if the likelihood of getting a position at an investment bank is high.

A couple of other interesting results fall out of Proposition 1. First, accuracy is increasing in the probability of default. When more bonds default, CRAs have less room for error. However, during periods of economic growth, when the default rate is lower, ratings inflation tends to occur as the number of bad projects which do not initially default increase. This result matches the previous literature in that ratings accuracy is counter-cyclical (Bar-Isaac and Shapiro 2013; Bolton, Freixas, and Shapiro 2012; He, Qian, and Strahan 2011). Second, the accuracy level of the CRA decreases in the level of effort-monitoring noise and increases with the benefits from investment bank jobs. These results match identically with the results of Bar-Isaac and Shapiro's (2011) model. The parameter L also measures the level of "luck," rather than effort or ability of an analyst. Hence, the overall accuracy of ratings decreases as the amount of luck increases compared to the skill and ability of an analyst. Additionally, when investment banks are profitable, the employment offers for seasoned analysts tend to be more lucrative, which in turn causes a boost in the effort of the analysts in order to be in a better position to attain such a job.

The following proposition looks to detail the marginal effect of competition on the exogenous variables in the model to determine what effect, if any, the level of competition has on the rate of change in the level of ratings accuracy.

Proposition 2: As the level of industry competition increases, the accuracy level of the CRA (i) increases at an accelerated rate with the level of reputational incentives R_I; and (ii) increases at a decelerated rate with the level of reputational punishments R_p.

Proof: Claim (i) follows directly from taking the second derivative of z^*, first with respect to reputational punishments R_I, and then to the level of competition c:

$$\frac{\partial z^*}{\partial R_I \partial c} = \frac{(2\gamma - 3)\delta(\lambda - 1)(1 + \delta)\rho}{2(\gamma - 2)^2},$$

which is positive.

Claim (ii) follows directly from taking the second derivative of z^*, first with respect to reputational punishments R_p, and then to the level of competition c:

$$\frac{\partial z^*}{\partial R_p \partial c} = \frac{(2\gamma - 3)\delta(\lambda - 1)(\rho - 1)}{2(\gamma - 2)^2},$$

which is negative. ■

As competition increases, accuracy increases faster with the level of reputational incentives; however, accuracy increases slower with the level of reputational punishment. As the level of competition within the industry increases, CRAs care more about the reputational incentives they receive for being accurate than they do about the reputational punishments that they incur for being inaccurate. However, in an environment with a low level of competition, such as the monopoly case that is often modeled in the literature, the CRAs seem to be more concerned with the negative impact of being inaccurate. The above suggests that both the manner and the amount that CRAs are rewarded for being accurate and punished for being inaccurate should be reflective of the level of competition within the industry.

A couple of other interesting results come from Proposition 2. First, as the level of competition increases, the level of accuracy will increase at an accelerated rate with increases in the probability of default. The model shows that when a CRA acts as a reputation maximizer, a competitive environment reflects an accuracy level that is at least as high as that of a monopoly. Second, as the level of competition increases the level of accuracy increases at an accelerated rate with increases in the probability of getting an investment bank job. With the prevalence of investment bank positions, seasoned analysts are assumed to increase effort in order to increase the probability of acquiring such a position; this in turn increases the level of accuracy of the CRA, as the overall analyst ability rises with effort. With a more competitive environment in the industry, the number of qualified analysts is higher; yet, the number of outside opportunities remains fixed. Thus, more competition in the industry creates more competition amongst the seasoned analysts for the investment bank positions, leading to an elevated level of accuracy.

2.4 Conclusions

In the model presented in this chapter, CRAs attempt to maximize their reputation by accurately rating bonds. The CRAs employ analysts of differing levels of ability and their collective ability level determines the accuracy of the ratings which they issue. Economic conditions are modeled through the prevailing default rate, the discount rate, the product quality of issues, and the probability and profitability of outside job opportunities. For a pure reputation maximizer, competition will not impact rating decisions. Rather, competition only reveals the accuracy of ratings on issues which may not have taken place in less competitive environments.

This paper makes contributions to the literature regarding credit rating agencies. Adding to the current literature, the results from the model within this paper show that, stand-alone, reputational incentives and reputational punishments are unlikely to increase ratings accuracy under normal economic conditions. Also, contrary to Bar-Isaac and Shapiro (2013), a competitive industry of reputation maximizing CRAs will lead to a level of ratings accuracy that is at least as high as that found within a monopolistic industry. Finally, given sufficiently profitable outside employment opportunities for an analyst, the level of ratings accuracy increases with the probability of attaining such employment, a finding differing from that of Bar-Isaac and Shapiro (2011).

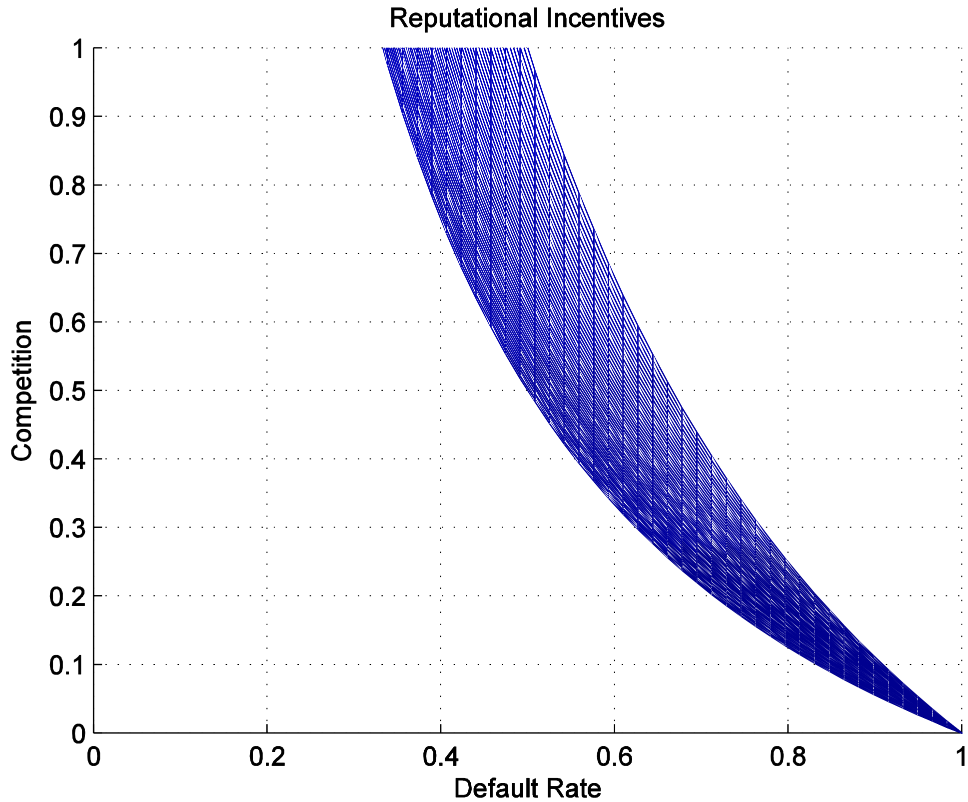

Figure 2.1 illustrates the necessary condition for reputational incentives to improve ratings accuracy in an industry of reputational maximizers. The condition is met for any area located above the contour lines. Default rate represents the prevailing default rate in the economy, where 1 represents 100% default. Competition represents the degree of concentration within the CRA industry, where 1 represents a perfectly competitive environment and 0 a monopoly. The third dimension represents the discount rate, where 1 represents unity across time.

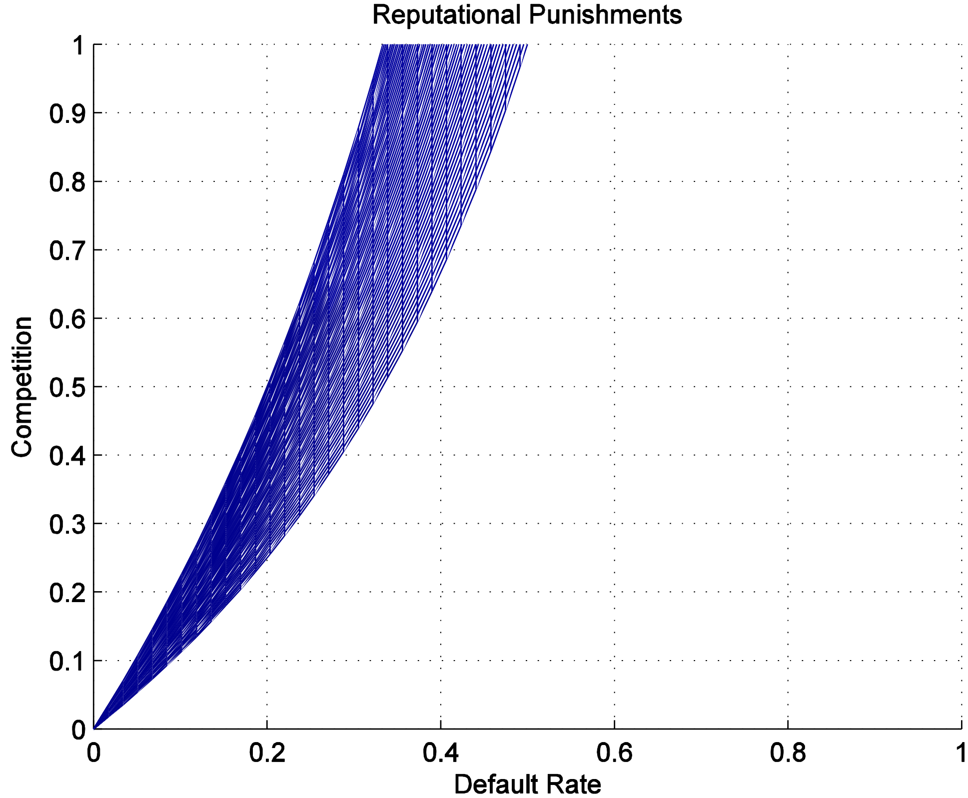

Figure 2.2 illustrates the necessary condition for reputational punishments to improve ratings accuracy in an industry of reputational maximizers. The condition is met for any area located below the contour lines. Default rate represents the prevailing default rate in the economy, where 1 represents 100% default. Competition represents the degree of concentration within the CRA industry, where 1 represents a perfectly competitive environment and 0 a monopoly. The third dimension represents the discount rate, where 1 represents unity across time.

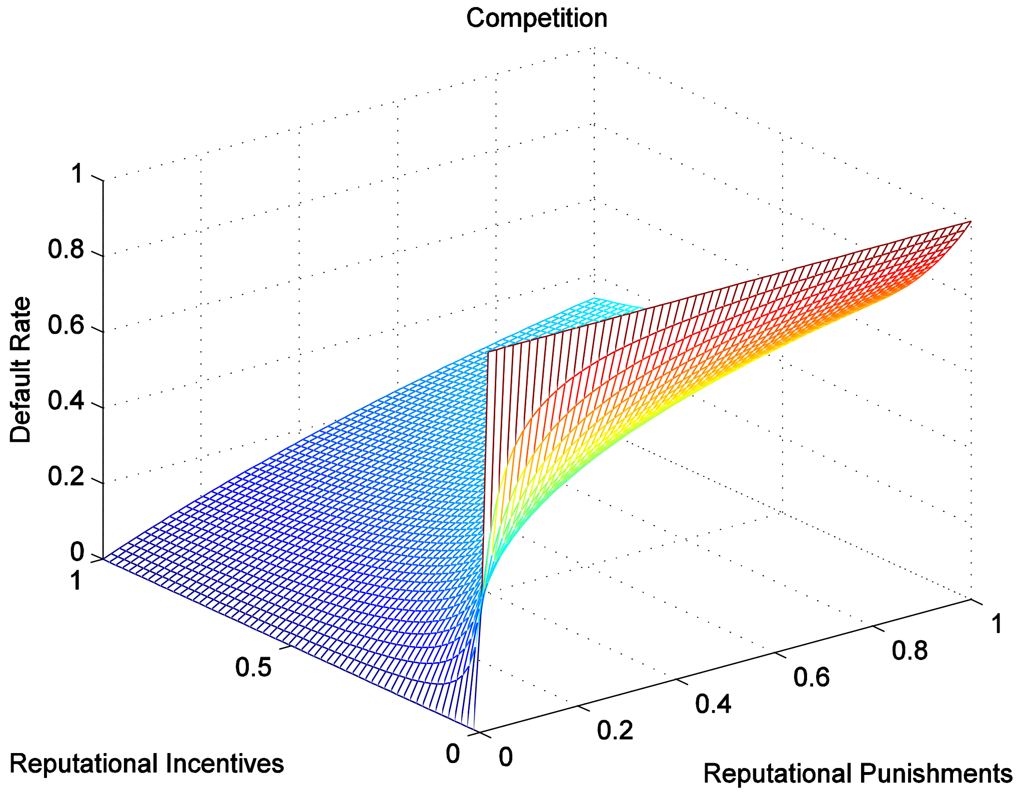

Figure 2.3 illustrates the necessary condition for competition to improve ratings accuracy in an industry of reputational maximizers. The condition is met for any area located above the contour lines. Default rate represents the prevailing default rate in the economy, where 1 represents 100% default. Reputational punishments and reputational incentives are scaled to fit. The discount rate is set to 0.95 for the purposes of illustration. However, the figure is robust to changes in the discount rate, especially for low levels of the default rate.

CHAPTER 3: COMPETITION AND CREDIT RATINGS

Credit rating agencies (CRAs) have been a seemingly daily fixture in the news since the financial crisis. The ratings issued by CRAs are extremely important to the proper functioning of capital markets because they serve a dual role of providing information to investors and regulating institutional investors (Opp, Opp, and Harris 2013). Academics and regulators alike have attempted to decipher just what went wrong within the CRA industry in both this most recent crisis and in the accounting scandals such as Enron and WorldCom in the early 2000s. The purpose of this paper is to empirically isolate the effects of competition on CRAs' accuracy with a focus on whether a CRA was the first, second, or third to rate a specific bond issue.

The findings in this paper represent several major contributions to the literature on credit rating agencies. First, competition appears to discipline only the first rating agency to rate a specific bond issue. The second and third agencies to provide a rating on a particular bond issue tend to inflate ratings within a more competitive environment. Second, competition appears to be especially counterproductive when a rating agency has the ability (as the second or third rater) to change the rating utilized for regulatory purposes. In other words, competition is associated with ratings instability for the second rater, and then, conditional on the first two ratings being different, for the third rater. Further, ratings split at the investment grade line tend to be associated with the third rater rating above the lower of the split ratings, i.e., the third rater is a regulatory certifier insofar as their rating can determine investment grade status. Finally, increased competition at the time of the initial rating leads to larger revisions, a result suggesting that initial ratings were more inaccurate with more competition.

3.1 Literature Review

The theoretical literature almost unanimously finds that competition leads to a deterioration in ratings quality. Faure-Grimaud et al. (2009) find that competition between CRAs leads to less information being revealed because, in equilibrium, Bertrand duopolists offer ratings for a fewer (and better) set of types than a monopolist. Therefore, if the value of the information for lower quality firms is high, competition might be discouraged for CRAs. Bolton, Freixas, and Shapiro (2012) and Bar-Isaac and Shapiro (2013) show that, in general, a monopoly system is more efficient and provides higher quality ratings than a duopoly.[24] The outlier in the theoretical literature is Hirth (2012), who finds that a market with only truthful CRAs can potentially be achieved in a perfectly competitive industry.

The empirical literature is split with regards to whether or not ratings quality declines or improves in the presence of competition. Guttler (2011) finds competition negatively affects ratings quality, which is measured by how well the ratings reflect default risk. He presents empirical evidence that rating migration rates are higher given a rating change by another CRA and that there is a tendency for the revised rating to converge towards the other CRA's rating. Becker and Milbourn (2011) use Fitch's market share as a proxy for competition within industry-year clusters in order to test the effect of competition on ratings issued by Moody's and Standard & Poor's. They find a significant positive link between Fitch's market share and rating inflation (i.e., an increase in ratings levels). Becker and Milbourn also find evidence of a decline in the

[24] Bolton, Freixas, and Shapiro (2012) define efficiency through the level of total ex-ante surplus. Surplus of investors, CRAs, and issuers is compared to the first-best and the market solution when there are no CRAs. Bar-Isaac and Shapiro (2013) define efficiency as increased ratings accuracy.

ability of ratings to predict default and a lower correlation between a bond's rating and its market-implied yield within more competitive industry-year groups.

Other papers find that competition improves ratings quality. Xia (2012) examines how ratings from an issuer-paid CRA respond following the entry of an investor-paid CRA in December 1995 and provides empirical evidence that ratings quality improves for Standard & Poor’s (issuer-paid) following initiation of coverage by Egan-Jones (investor-paid). Doherty et al. (2012) study the entrance of Standard & Poor's into the previously monopolistic insurance rating industry at the end of the 1980s. They find that this increased competition was associated with more informative ratings. Specifically, for a firm to achieve a similar rating, the entrant (Standard & Poor’s) applied higher standards than the incumbent (A.M. Best).

The evidence of this chapter suggests that competition among CRAs is good in some instances and bad in others. Specifically, the first rater provides inflated ratings in a less competitive environment, whereas the second and third raters provide inflated ratings in a more competitive environment.

Recent research has asked whether or not ratings accuracy is countercyclical. Bolton, Freixas, and Shapiro (2012) find that ratings inflation is more apt to happen in economic booms, when the risk of potential damage to a CRA's reputation is lower. Bar-Isaac and Shapiro (2013) show that a CRA, whether a monopoly or a duopolist, is more likely to provide more accurate ratings during recessions in order to build up reputation for a future boom. He, Qian, and Strahan (2012) provide evidence of counter cyclicality in ratings accuracy through the examination of large issuers of mortgage-backed securities.

The idea of ratings shopping, or the ability to choose amongst multiple CRAs, is important in the debate about competition within the ratings industry. Skreta and Veldkamp (2009) show that as asset complexity increases and ratings heterogeneity increases, so too does the incentive for ratings shopping; and that, increased competition aggravates the problem of such shopping.[25] Theoretical research by Bolton, Freixas, and Shapiro (2012) and Bar-Isaac and Shapiro (2013) find that ratings shopping is exacerbated by investors willing to buy investments with good ratings regardless of the quality of the ratings. Becker and Milbourn (2011) point out that ratings shopping is less of a concern among corporate bonds than structured products since bonds are less complex and therefore have less heterogeneity between ratings. Becker and Milbourn (2011) and Bongaerts et al. (2012) provide empirical evidence of shopping at the investment grade line.

The motives of CRAs have long been questioned. Researchers and regulators alike have tried to answer whether their actions are driven by profit or reputation maximization. In Covitz and Harrison (2003), the authors illustrate that rating actions are motivated primarily by reputational concerns. On the other hand, Mathis, McAndrews, and Rochet (2009) find that reputation only matters when a sufficiently large percentage of the income for the CRA comes from sources other than the rating of complex products.[26] Mariano (2012) models rating agencies seeking to maximize their reputation and protect their market power and finds that an incumbent CRA is more willing to

[25] An increase in asset complexity refers to an increase in the prevalence of mortgage-backed securities and collateralized debt obligations. For more on structured finance and manufacturing of securities see Acharya et al. (2009) and Coval, Jurek, and Stafford (2009).
[26] The authors also find that when most of the income is from rating complex products, ratings quality is adversely affected.

gamble on being correct in order to increase reputation.[27] Livingston, Wei, and Zhou (2010) provide evidence that reputation is important by showing that when a CRA consistently rates lower than other CRAs, investors put more value on that CRA's ratings.

Also related to the analysis and conclusions within this paper is the stream of literature related to the current regulatory environment within which the CRAs operate. Stolper (2009) presents a model which finds that CRAs may collude to assign inflated ratings while operating within their current market structure since a regulator would not be able to determine whether high default rates are due to a common shock or collusion. White (2010) cites regulatory arbitrage, or financial institutions seeking the weakest regulator, as a major reason for ratings inflation. Cornaggia and Cornaggia (2011) argue that both issuers and regulated investors would prefer inflated ratings due to regulatory arbitrage. Further, Bongaerts et al. (2012) discuss the prevalent institutional rules in terms of classifying ratings and find that Fitch is essentially a regulatory certification tiebreaker when Moody’s and Standard & Poor’s are split at the investment grade line. Finally, the empirical work of Jiang, Stanford, and Xie (2012) suggests that the issuer-pay structure leads to higher ratings.

[27] See Horner (2002) for an analysis of how competition generates reputation-building behavior.

3.2 Data

Bond issue data from the Mergent Fixed Income Securities Database (FISD) is used for the main analysis of this paper. The data set includes bond characteristics (callable, putable, maturity, etc.) and issue credit ratings from Fitch, Moody's, Standard & Poor's, and Duff & Phelps. The data also includes industry codes (NAICS).[28]

Firm level ratings are not used in the analysis for a few important reasons. First, the Mergent FISD includes bonds rated by Fitch, Moody's, Standard & Poor's, and Duff & Phelps, whereas the firm level ratings available are only issued by Standard & Poor's. Second, individual bond ratings vary more than firm ratings. Therefore, bond ratings provide a more comprehensive and informative sample from which to draw inferences.

The sample period begins January 1st, 2001 because changes in the data collection procedures of Mergent led to incomplete ratings prior to that time period (Bongaerts et al. 2012). Further, FISD still has Duff & Phelps rating bond issues until the end of June 2000 even though Fitch acquired Duff & Phelps in March 2000. Therefore, starting the sample in 2001 eliminates ratings made by Duff & Phelps and also accounts for the organic growth of Fitch due to acquisitions of not only Duff & Phelps, but also Thomson BankWatch in October 2000. Ending the sample at the end of the second quarter of 2007 is a way to avoid potential reputational spillovers from the widespread downgrades of privately issued mortgage-backed securities.

[28] Following Becker and Milbourn (2011), industries are classified based on 2-digit North American Industry Classification System (NAICS) sector code.

Several steps are taken to clean the data. First, only bonds classified under some category of U.S. Corporate are included.[29] Second, all issues with ratings of "NR" are dropped along with those issues with ratings which are suspended, expired, or defaulted. It is important to note that this eliminates almost half of the bond issues in the Mergent FISD.[30] Third, we eliminate any bonds with any of the following characteristics: asset backed, callable, convertible, enhancement, exchangeable, foreign currency, fungible, junior, pay-in-kind, perpetual, preferred security, putable, secured, subordinated, variable coupon, yankee, and zero coupon. Elimination of bonds with any of these characteristics leaves a trimmed down set of "plain vanilla" bonds.

We convert letter ratings into the following numeric scale for Fitch and S&P ratings (Moody's), 21 for AAA (Aaa), 20 for AA+ (Aa1), 19 for AA (Aa2), 18 for AA− (Aa3), 17 for A+ (A1), 16 for A (A2), 15 for A− (A3), 14 for BBB+ (Baa1), 13 for BBB (Baa2), 12 for BBB− (Baa3), 11 for BB+ (Ba1), 10 for BB (Ba2), 9 for BB− (Ba3), 8 for B+ (B1), 7 for B (B2), 6 for B− (B3), 5 for CCC+ (Caa1), 4 for CCC (Caa2), 3 for CCC- (Caa3), 2 for CC (Ca), and 1 for C (C).[31]

With these numerical classifications, we calculate the differences in ratings between first, second, and third raters on specific bond issues (Rating Difference). Next, a binary variable is generated to indicate the first time that a specific rating agency rated a specific bond issue. Additionally, variables for the time until the first revision (Time to Revision) and the size of the first revision (Revision Size) are created. Assuming a bond

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[29] Other types of debt securities included in the Mergent FISD are: U.S. Agency, Canadian Treasuries, Brady Bonds, Foreign Governments, etc.

[30] There is a large portion of bond issues by Freddie Mac, Fannie Mae, and the Federal Home Loan Banks within the Mergent FISD database.

[31] These numerical ratings are similar to those used by Cantor and Packer (1997), Depken and LaFountain (2006), and Bongaerts et al. (2012).

issue is initially rated by a specific CRA, we track both the time, in months, until a rating change took place and the rating change. The size of the rating revision is measured as the difference between the newly revised rating and the initial rating by that same CRA on that same bond issue. Finally, a variable which tracks the order in which the CRAs rated a specific bond issue is created (Rating Order). For instance, if both S&P and Moody's rated a bond issue for the first time on the same day, both would be considered the first rater; however, if S&P rated a bond issue for the first time prior to Moody's rating that same issue for the first time, S&P would be the first rater and Moody's the second rater. Table 3.1 presents how often each rating agency is the first, second, or third rater within the sample. After these variables are created, the sample is cut down to our defined sample period of January 1st, 2001 through June 30th, 2007. This leaves a final data set of 8,299 bond issue credit ratings.

Two measures of market structure are used: the two-firm Concentration Ratio (CR) and the Herfindahl-Hirschman Index (HHI).[32] The CR index is the sum of the market shares of the two firms with the highest market shares. The HHI is the sum of the squares of the market shares of all firms within the industry.[33] In computing these indices, we use the market share of initial ratings on bond issues within a given industry in a given year. Irrespective of whether a CRA is the first, second, or third to rate a specific issue, it still counts towards their market share in the industry and year which the rating

[32] The U.S. Securities and Exchange Commission uses the HHI in its annual report on Nationally Recognized Statistical Rating Organizations, see U.S. Securities and Exchange Commission (2012) for the latest report. Additionally, the HHI is commonly used by the Federal Reserve and the Department of Justice in antitrust oversight of bank mergers. See Berger et al. (1999) for an overview of bank mergers and antitrust policy. HHI is also used by both Cetorelli and Strahan (2006), who analyze how competition in the banking industry affects market structure in nonfinancial industries, and Degryse and Ongena (2005), who test the effect of banking concentration on loan conditions.

[33] An HHI of one would represent a monopoly, while lower values represent a more equal distribution of market shares amongst market participants.

takes place. The necessary condition for a bond rating to be counted towards the market share of a CRA is that it is the first rating the agency has provided for a unique bond issue.[34]

Reported in Table 3.2 are summary statistics for some of the variables of interest. The CR ratio reflects that, on average, the top two raters in each industry-year cluster control 72 percent of all initial ratings. The median industry-year clustered HHI level of 0.34 is very representative of the standard reported market shares of Fitch, Standard & Poor's, and Moody's of approximately 20%, 40%, and 40%, respectively.[35] Time to Revision represents the time, in months, until the first revision is made by a CRA on their initial rating. For computational ease, the number of months is capped at 120 in order to get rid of some extreme values. The average revision takes place approximately 18 months after the initial rating is released. The absolute size of this revision, labeled as Revision Size, is 1.46. This means that the average revised rating is more than one category away from the initial rating. The Direction of Revision variable illustrates that 33.2% of the revisions are higher ratings than the initial rating. The predominance of downward rating revisions suggests overly optimistic initial ratings. The average initial rating in our sample of 16.7 is between an A (A2) and an A+ (A1) for Fitch and Standard & Poor's (Moody's).

Of final interest, we track the difference between the first and second rating by differing CRAs, as well as the difference between the third CRA's rating and the lower of the first and second ratings by differing CRAs. We find that the second rating is, on

[34] We elect not to use revised ratings in determining market share because Fitch accounts for almost 90% of the revisions within the sample.

[35] See 2012 Summary Report of Commission Staff's Examinations of Each Nationally Recognized Statistical Rating Organization, SEC Report (Nov. 2012) (as required by Section 15E(p)(3)(C) of the Securities Exchange Act of 1934).

average, higher than the first rating; and, that the third rating is, on average, lower than either of the first two ratings. However, this is potentially due to a skewed distribution; when looking at the median, we see no difference between the first and second rating or the third rating and the lower of the first two ratings.

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3.3 Methodology and Results

We aim to decipher the effects of competition on CRAs in a novel way by examining whether a CRA is the first, second, or third agency to rate a particular bond issue and testing whether competition has a consistent effect across the ordering.

We specify the following regression to test whether competition has an effect on ratings stability:

(1) Ratings Level = *f* (Competition, Rating Agency, Maturity, Industry, Year)

where Ratings Level is the numerical classification of the bond rating; Competition represents either the CR or HHI concentration index within the given industry-year cluster; Rating Agency controls for potential differences in rating methodologies across rating agencies; Maturity accounts for differing risk exposures across bond issues; and, Industry and Year account for unobserved heterogeneity across time and industry. Given that the probability of moving from one category to another likely varies across levels of the ratings scale, we use an ordered probit model to account for potential differences in the effect of competition at different levels of the ratings scale.

All regressions are first estimated including bond issues for all industries then on a sample that excludes the finance industry (NAICS 52) since financial firms issue a large share of the corporate bonds and these may be fundamentally different from non-financial firms' bonds. Results for specification (1) on the full sample of initial ratings (first, second, and third rating) are shown in Table 3.3. We find a positive and significant relationship between both the CR and HHI indices and the ratings level. Because an increasing ratio represents a less competitive environment, these results point to competition disciplining the rating agencies, i.e., less competition associated with ratings inflation. Further, S&P and Moody's are shown to rate higher than Fitch with their initial rating. After removing finance bond issues (NAICS 52), the significance of the results all but disappears. In other words, competition seems to have no overriding influence on initial ratings outside of the finance industry, and Fitch no longer rates below the other rating agencies.

Tables 3.4, 3.5, and 3.6 also follow specification (1), however they are estimated on samples dependent upon whether the rating issued was the first, second, or third rating on a particular bond issue, respectively.

The results in Table 3.4 provide evidence that, with lower levels of competition, the first rater typically inflates their initial rating on a bond issue. This result is consistent with the results from the full sample. However, the level of rating is not statistically significant across rating agencies. Additionally, the results are robust to the removal of finance industry bond issues.

The competitive environment in which CRAs operate appears to have no impact on the level of ratings issued by the second rater (Table 3.5). Also, there is no significant variation across the CRAs. The results that competition has no impact on the rating level of the second rater and that there is no agency variation are robust to the removal of the finance industry bond issues.

For the third rater, the coefficients on the competition indices are statistically significant and negative (Table 3.6). A negative coefficient suggests that more competition is associated with inflated ratings from the third rating agency to rate a bond issue, a result that is consistent with Bongaerts et al. (2012). After removing finance industry bonds, we find that the coefficient estimates actually increase.

To summarize, we find that competition (i) disciplines the first rater (Table 3.4), (ii) has no effect on the second rater (Table 3.5), and (iii) adversely affects the third rater (Table 3.6).

The first part of the empirical analysis studies the effect of competition on the overall level of ratings. The next part looks at the ratings of the second rater relative to ratings issued prior to their coverage. The dependent variable for this regression, Rating Difference, is the difference in rating level between the second rater's rating and the first rater's rating, where a positive value represents a higher second rating. The dependent variable is categorized into three buckets: a lower second rating, the same second rating, and a higher second rating. The base case is set to be that the second rater issues a lower second rating. Because of the discrete and bounded nature of the dependent variable and the goal of comparing the relative rating, we utilize a multinomial logit specification. We start with the relative rating of the second rater to rate an issue, for which we employ the following specification:

(2) Rating Difference = *f* (Competition, Rating Agency, Rating Level, Maturity, Industry, Year)

where the independent variables for this regression are the same as in specification (1) with the addition of Rating Level, which represents a control for the numerical rating. By controlling for the rating level, we control for the potential asymmetry in the Rating Difference variable across rating levels.

In Table 3.7, the first column represents the relative risk of the second rater providing the same rating as the first rater versus the second rater providing a rating below the first rater, holding all other variables in the model constant. The second column represents the relative risk of the second rater providing a rating above the first rating versus the second rater providing a rating below the first rater, holding all other variables constant.

Table 3.7 shows that as the level of competition increases, so too does the relative risk that the second rater provides a rating that is either the same or above the first rating (versus the second rater providing a lower rating than the first rater). In other words, more competition increases the probability that the second rater either matches the first rater's rating or provides a higher rating than the first rater. From a regulatory standpoint, this is very important. The Basel Committee on Banking Supervision and the National Association of Insurance Commissioners specify that if a security is rated by two Nationally Recognized Statistical Rating Organizations (NRSROs), the lowest rating is used; and, if rated by three or more NRSROs, the second lowest is selected.[36] In this analysis, the second rater is less likely to lower the rating used for regulatory purposes when operating in a more competitive environment than when operating in a less competitive environment. This result is robust to the removal of the finance industry bonds as well.

Another interesting result in Table 3.7 illustrates the benefits of looking at relative ratings as opposed to the overall ratings level. Both S&P and Moody's as second raters are more likely to rate below the first rating. So, although our ratings level regressions

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[36] See Basel Committee on Banking Supervision (2000), and NAIC (www.naics.org).

would point to Fitch inflating ratings the least, that finding may be a result specific to the bonds which they are rating (and not rating). After removing the finance industry, the only remaining significant result in terms of the rating agencies themselves is that Moody's is less likely to rate above than rate below the first rating when compared to Fitch.

Next, we turn our attention to the third rating agency to rate a particular bond issue. Once again, a multinomial logit specification is utilized for the following regressions:

(3) Rating Difference Low = *f* (Competition, Rating Agency, Split at Investment Grade Dummy, Same Rating Dummy, Rating Level, Maturity, Industry, Year),

(4) Rating Difference Low = *f* (Competition, Rating Agency, Split at Investment Grade Dummy, Rating Level, Maturity, Industry, Year),

(5) Rating Difference Low = *f* (Competition, Rating Agency, Rating Level, Maturity, Industry, Year)

where Split at Investment Grade Dummy is an indicator variable taking the value 1 if the first two raters have provided ratings on opposite sides of the investment grade line, and 0 otherwise; Same Rating Dummy is an indicator variable taking the value 1 if the first two raters have provided the same rating, and 0 otherwise; and, the other controls are the same as in the previous regression specification.

The dependent variable, Rating Difference Low, is the difference in rating level between the rating provided by the third rater and the lowest of the first two ratings, where a positive value represents a higher third rating, and vice versa. If the first two ratings are equivalent, they are both considered the lowest rating. We elect to look at the difference between the third rating and the lowest, as opposed to the highest, since the middle rating is used for regulatory purposes when there are three ratings. Just as with the second rater, we once again group the dependent variable into three classifications: a lower third rating, the same third rating, and a higher third rating.

Using specification (3), the results in Table 3.8 suggest that competition has no influence on the difference in ratings between the third rater and the lower of the first two ratings when looking at the full sample. However, a couple of interesting results invite further analysis. First, we find that when the two ratings are split at the investment grade line, there is a higher relative risk of rating at or above the lowest rating than rating below the lowest rating. This finding illustrates that the third rater, regardless of which CRA is rating third, acts as a regulatory certifier at the investment grade line, a finding in line with Bongaerts et al. (2012). Second, the coefficient on Same Rating is negative and significant indicating the third rater rating below the other two raters. This is in line with the reputational hypotheses within the literature: CRAs aim to not inflate ratings in order to protect their reputation.

Given the two findings in Table 3.8, we re-estimate the multinomial logit regressions on two subsamples. First, we use specification (4) when the first two rating agencies are split (Table 3.9); and, second, we use specification (5) when the first two rating agencies have provided the same rating (Table 3.10). Dissimilar results across these two samples would allude to the fact that the distribution of prior ratings plays a role in the decision making process of the third rater.

Table 3.9 presents results suggesting that competition once again matters when the first two ratings are not the same. With more competition, the third rater is more likely to match the lowest rating than to rate below it. Also, S&P and Moody's are both more likely than Fitch to rate at or above the lowest rating of the first two. Finally, when the ratings are split at investment grade, the same finding of inflation of the third rating is present. This finding confirms the results found in Table 3.8 that the third rater acts as a regulatory certifier at the investment grade line. Although competition is no longer significant after removing bonds issued by firms in the finance industry, the result that the third rater acts as a regulatory certifier is strengthened.

Table 3.10 presents results suggesting that competition is not significant when the first two ratings are equivalent. The results, however, provide evidence that S&P and Moody's are both less likely than Fitch to rate at or above the first two ratings, a finding consistent with S&P and Moody's aiming to protect their reputation when the rating they are providing has no regulatory influence. Perhaps interesting, after removing bonds issued by firms within the finance industry, the direction of the coefficient on the dummy variable representing Moody's flips from negative to positive, i.e., Moody's is more likely than Fitch to rate at or above the lowest of the first two ratings.

The final part of the empirical analysis within this chapter looks at the size of the revisions made by CRAs on their initial ratings. For ratings revisions, there are essentially two aspects to consider: either the market has received new information that it perceives as a change in the issuer's ability to repay the debt, or the initial rating did not accurately classify the risk inherent in the bond, or elements of each. If the flow of information is properly accounted for within the specification then the magnitude of the revision speaks mainly to the CRA's accuracy on its original attempt at the bond rating. We use the following regression for this analysis:

(6) Absolute Revision Size = *f* (Competition, Rating Agency, Rating Order Dummies, Direction of Revision, Time to Revision, Rating Level, Maturity, Industry, Year)

where Absolute Revision Size is the absolute value of the first revised rating less the initial rating made on a bond issue by the same CRA; Rating Order Dummies control for whether the CRA was the first, second, or third to rate a particular bond issue; Direction of Revision is an indicator variable taking the value 1 for upgrades and 0 for downgrades (controls for the potential asymmetry in the magnitude of upgrades and downgrades); Time to Revision is the time, in months, until the revision takes place; and the remaining controls are those utilized in prior specifications. A Tobit specification is used in order to account for the bounded and non-continuous nature of the dependent variable. The dependent variable ranges from 1 to 12.

The results in Table 3.11 again show that competition may not improve ratings accuracy. As competition decreases, we see smaller revisions made by rating agencies. Also, S&P and Moody’s systematically make smaller revisions than Fitch. Removing the finance industry bond issues, the results illustrate that the second and third raters to rate a bond make smaller revisions than the first rater. These results are in line with the other results of our paper: the first rater is consistently less accurate than the second and third raters.

3.4 Conclusions

In an almost unanimous fashion, the theoretical literature has concluded that competition is bad for CRAs. The empirical literature is split regarding this conclusion: some papers find competition improves ratings quality and others find competition to be detrimental to ratings quality. Both theory and empirics have failed to isolate the effects of competition on CRAs dependent upon whether a CRA was the first, second, or third to rate a specific bond issue.

This chapter represents the first analysis of the effect of competition on the CRAs based on the order in which they rated a particular bond issue. In doing so, we find that competition only disciplines the first CRA to rate a new bond issue. Not only does the first rater inflate ratings within a less competitive industry-year grouping, but the rating revisions made later are larger than those revisions made by the second and third rater. In other words, our results suggest that the inaccuracy of CRAs may stem from the first rating on a bond issue and that the accuracy of the first rating can potentially be improved through increased competition.

In looking at the ratings of the second and third rater relative to the first rater and the lower of the first two raters, respectively, we find that higher levels of competition lead to an increased probability of providing a higher rating. Also, when the first two ratings are equivalent, the third rater tends to protect its reputation by rating below that rating; a result that is strengthened when the third rater is S&P or Moody's. This result is consistent with the notion that reputation building is part of the decision making process for a CRA. However, these incentives appear to only exist when the CRA has no ability to effect the regulatory classification of the issue, i.e., they only exist when the first and second ratings are the same.

Table 3.1: Rating order by rating agency

Table 3.1 shows the frequency with which each rater was the first, second, or third rating agency to rate a particular bond issue. If both S&P and Moody's rated a bond issue for the first time on the same day, both are considered the first rater; however, if S&P rated a bond issue for the first time prior to Moody's rating that same issue for the first time, S&P is the first rater and Moody's the second rater.

	First	Second	Third	Total
Fitch	1,411	190	1,297	2,971
S&P	2,186	271	221	2,683
Moody's	2,164	325	151	2,645
Total	5,761	786	1,669	8,299

Table 3.2: Summary statistics

Table 3.2 shows summary statistics for variables of interest. HHI is the Herfindahl-Hirschman Index calculated within year industry clusters. CR is the two-firm concentration ratio calculated within year industry clusters. Time to Revision represents the time, in months, until the first revision was made by an agency on their initial rating (capped at 120 months). Revision size is the absolute value of the size of the revision (using the numeric scale). Direction of Revision is 1 when a bond is revised upwards by the same agency which initially rated it for the first time, 0 otherwise. Rating Level is the numeric equivalent of the alphabetic ratings scale. Diff in Second Rating is the rating given by the second rating agency to rate a bond less the rating given by the first agency to rate that bond. Diff in Third Rating is the rating given by the third agency to rate a bond less the lowest rating given by the first two rating agencies on that same bond issue.

	HHI	CR	Time to Revision	Revision Size	Direction of Revision	Rating Level	Diff in Second Rating	Diff in Third Rating
Mean	0.341	0.721	17.630	1.464	0.332	16.70	0.034	-0.159
Median	0.337	0.706	10	1	0	17	0	0
Min	0.333	0.666	1	1	0	1	-4	-11
Max	0.508	1	104	12	1	21	4	6
Std Dev	0.014	0.042	20.058	1.274	0.471	3.411	0.962	2.142
Obs	8299	8299	722	722	722	8299	786	1669

Table 3.3: The effect of competition on the initial rating of a bond issue

Table 3.3 represents the slope coefficients from ordered probit regressions. The sample period is from 2001 through Q2 2007. The dependent variable ranges from 21 (AAA) to 1 (C). CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the omitted variable. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds	All Bonds	Exclude NAICS 52	Exclude NAICS 52
CR	1.365**		0.616	
	(0.619)		(0.660)	
HHI		5.041***		3.324*
		(1.856)		(1.828)
S&P	0.125***	0.126***	-0.027	-0.03
	(0.028)	(0.028)	(0.052)	(0.051)
Moody's	0.178***	0.178***	-0.041	-0.042
	(0.027)	(0.027)	(0.048)	(0.048)
Year	X	X	X	X
Industry	X	X	X	X
Maturity	X	X	X	X
Pseudo R^2	0.108	0.109	0.061	0.061
Observations	8299	8299	2660	2660

Table 3.4: The effect of competition on the first raters initial rating of a bond issue

Table 3.4 presents the slope coefficients from ordered probit regressions. The sample period is from 2001 through Q2 2007. The dependent variable ranges from 21 (AAA) to 1 (C). CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the omitted variable. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds	All Bonds	Exclude NAICS 52	Exclude NAICS 52
CR	4.296***		3.626***	
	(0.868)		(0.860)	
HHI		14.477***		11.937***
		(2.686)		(2.500)
S&P	-0.016	-0.017	-0.08	-0.086
	(0. 034)	(0.034)	(0.070)	(0.070)
Moody's	0.042	0.041	-0.105	-0.115
	(0.034)	(0.034)	(0.071)	(0.071)
Year	X	X	X	X
Industry	X	X	X	X
Maturity	X	X	X	X
Pseudo R^2	0.118	0.119	0.084	0.085
Observations	5761	5761	1463	1463

Table 3.5: The effect of competition on the second raters initial rating of a bond issue

Table 3.5 presents the slope coefficients from ordered probit regressions. The sample period is from 2001 through Q2 2007. The dependent variable ranges from 21 (AAA) to 1 (C). CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the omitted variable. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds	All Bonds	Exclude NAICS 52	Exclude NAICS 52
CR	1.236		1.552	
	(2.204)		(2.412)	
HHI		-0.901		2.287
		(5.728)		(6.287)
S&P	-0.132	-0.13	-0.22	-0.223
	(0.101)	(0.101)	(0.182)	(0.182)
Moody's	0.075	0.076	-0.133	-0.135
	(0.095)	(0.095)	(0.166)	(0.166)
Year	X	X	X	X
Industry	X	X	X	X
Maturity	X	X	X	X
Pseudo R^2	0.139	0.138	0.098	0.098
Observations	786	786	337	337

Table 3.6: The effect of competition on the third raters initial rating of a bond issue

Table 3.6 presents the slope coefficients from ordered probit regressions. The sample period is from 2001 through Q2 2007. The dependent variable ranges from 21 (AAA) to 1 (C). CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the omitted variable. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds	All Bonds	Exclude NAICS 52	Exclude NAICS 52
CR	-8.668***		-10.931***	
	(1.420)		(1.732)	
HHI		-29.252***		-34.215***
		(3.769)		(4.162)
S&P	0.647***	0.647***	0.676***	0.670***
	(0.080)	(0.081)	(0.176)	(0.185)
Moody's	0.348***	0.334***	0.238	0.195
	(0.089)	(0.091)	(0.165)	(0.170)
Year	X	X	X	X
Industry	X	X	X	X
Maturity	X	X	X	X
Pseudo R^2	0.116	0.119	0.101	0.107
Observations	1669	1669	810	810

Table 3.7: The effect of competition on the relative level of the second raters initial rating of a bond issue

Table 3.7 presents the slope coefficients from multinomial logit regressions. The sample period is from 2001 through Q2 2007. The dependent variable is the difference in rating level between the second rater's rating and the first rater's rating, where a positive value represents a higher second rating and vice versa. CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the base. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds		All Bonds		Exclude NAICS 52		Exclude NAICS 52	
	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating
CR	-11.320*	-13.881**			-7.77	-13.233*		
	(6.634)	(6.988)			(7.154)	(8.033)		
HHI			-15.685	-46.868**			-11.24	-40.243*
			(18.575)	(20.886)			(19.570)	(23.378)
S&P	-0.660**	-1.480***	-0.652*	-1.453***	0.293	-0.702	0.305	-0.655
	(0.336)	(0.369)	(0.336)	(0.369)	(0.622)	(0.640)	(0.622)	(0.641)
Moody's	-0.811**	-1.930***	-0.803**	-1.901***	-0.214	-2.552***	-0.216	-2.522***
	(0.328)	(0.370)	(0.328)	(0.371)	(0.572)	(0.647)	(0.573)	(0.647)
Year	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Maturity	X	X	X	X	X	X	X	X
Pseudo R^2	0.166		0.167		0.323		0.324	
Observations	786		786		337		337	

Table 3.8: The effect of competition on the relative level of the third raters initial rating of a bond issue

Table 3.8 presents the slope coefficients from multinomial logit regressions. The sample period is from 2001 through Q2 2007. The dependent variable is the difference in rating level between the third rater's rating and the lowest of the first two ratings, where a positive value represents a higher third rating and vice versa. CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the base. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds		All Bonds		Exclude NAICS 52		Exclude NAICS 52	
	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating
CR	-4.105	-3.528			-0.017	2.113		
	(3.531)	(3.809)			(4.727)	(4.795)		
HHI			-15.836	-6.298			0.017	12.252
			(9.811)	(11.410)			(11.865)	(13.306)
S&P	-0.181	-2.308***	-0.178	-2.315***	0.959	0.634	0.952	0.59
	(0.244)	(0.303)	(0.244)	(0.303)	(0.700)	(0.682)	(0.692)	(0.676)
Moody's	0.17	-0.086	0.158	-0.1	2.641***	1.177	2.639***	1.178
	(0.319)	(0.323)	(0.318)	(0.323)	(0.709)	(0.780)	(0.710)	(0.782)
Split at IG	1.702*	1.926**	1.676*	1.910**	3.327**	4.000***	3.316**	4.033***
	(0.929)	(0.855)	(0.927)	(0.854)	(1.552)	(1.366)	(1.564)	(1.377)
Same Rating	-0.21	-1.436***	-0.227	-1.454***	0.825***	-0.879***	0.821***	-0.878***
	(0.171)	(0.181)	(0.170)	(0.180)	(0.263)	(0.277)	(0.258)	(0.273)
Year	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Maturity	X	X	X	X	X	X	X	X
Pseudo R^2	0.309		0.309		0.398		0.399	
Observations	1669		1669		810		810	

Table 3.9: The effect of competition on the relative level of the third raters initial rating of a bond issue when the first two ratings are split

Table 3.9 presents the slope coefficients from multinomial logit regressions. The sample period is from 2001 through Q2 2007. The dependent variable is the difference in rating level between the third rater's rating and the lowest of the first two ratings, where a positive value represents a higher third rating and vice versa. CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the base. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds		All Bonds		Exclude NAICS 52		Exclude NAICS 52	
	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating
CR	-20.704***	-8.751			-6.04	1.728		
	(6.926)	(6.416)			(9.441)	(8.026)		
HHI			-54.094**	-21.69			-2.444	1.103
			(21.330)	(20.945)			(27.192)	(24.254)
S&P	2.219***	0.266	2.221***	0.262	2.330*	2.410**	2.191*	2.416**
	(0.552)	(0.570)	(0.552)	(0.570)	(1.305)	(1.183)	(1.318)	(1.197)
Moody's	2.811***	2.196***	2.736***	2.123***	4.035***	2.050*	3.978***	2.112**
	(0.772)	(0.759)	(0.753)	(0.742)	(1.033)	(1.058)	(1.031)	(1.058)
Split at IG	1.289	2.154**	1.272	2.116**	2.612	4.637**	2.706	4.764**
	(1.015)	(1.029)	(1.008)	(1.022)	(2.356)	(2.194)	(2.310)	(2.174)
Year	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Maturity	X	X	X	X	X	X	X	X
Pseudo R^2	0.318		0.317		0.440		0.439	
Observations	844		844		378		378	

Table 3.10: The effect of competition on the relative level of the third raters initial rating of a bond issue when the first two ratings are equivalent

Table 3.10 presents the slope coefficients from multinomial logit regressions. The sample period is from 2001 through Q2 2007. The dependent variable is the difference in rating level between the third rater's rating and the lowest of the first two ratings, where a positive value represents a higher third rating and vice versa. CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the base. Year represents yearly fixed effects, industry represents controls for NAICS, and Maturity represents the time, in months, until the bond matures. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds		All Bonds		Exclude NAICS 52		Exclude NAICS 52	
	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating	Same Rating	Above Rating
CR	-1.852	-10.191*			-4.527	-2.027		
	(5.117)	(5.508)			(6.770)	(7.733)		
HHI			4.648	-19.5			9.589	18.729
			(13.527)	(15.648)			(16.287)	(19.208)
S&P	-1.612***	-4.355***	-1.612***	-4.361***	-0.862	-1.317	-0.786	-1.246
	(0.365)	(0.620)	(0.364)	(0.619)	(0.911)	(1.171)	(0.888)	(1.159)
Moody's	-1.079**	-1.213***	-1.070**	-1.215***	2.697**	2.201*	2.857**	2.350*
	(0.424)	(0.449)	(0.426)	(0.450)	(1.147)	(1.283)	(1.141)	(1.275)
Year	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Maturity	X	X	X	X	X	X	X	X
Pseudo R^2	0.392		0.391		0.488		0.487	
Observations	825		825		432		432	

Table 3.11: The effect of competition on the absolute size of the first revision of the initial rating of a bond issue

Table 3.11 presents the slope coefficients from tobit regressions bounded at 1 (smallest revision) and 12 (largest revision). The sample period is from 2001 through Q2 2007. The dependent variable is the absolute value of the first revised rating less the initial rating made on a bond issue by the same rating agency. CR is the two-firm concentration ratio and HHI is the Herfindahl-Hirschman Index, both of which are calculated within industry-year clusters. For the rating agency fixed effects, Fitch is the base. Year represents yearly fixed effects, industry represents controls for NAICS, Maturity represents the time, in months, until the bond matures, and Time to Revision represents the time, in months, until the first revision was made by an agency on their initial rating. Heteroskedastic-robust standard errors are shown in parentheses. ***, **, * show significance at the 1%, 5% and 10% levels, respectively.

	All Bonds	All Bonds	Exclude NAICS 52	Exclude NAICS 52
CR	-15.319**		-12.173**	
	(7.480)		(4.966)	
HHI		-46.979*		-29.194*
		(26.661)		(17.598)
S&P	-1.300*	-1.322*	-0.51	-0.606
	(0.744)	(0.740)	(0.482)	(0.475)
Moody's	-2.364**	-2.381**	-1.949**	-1.977**
	(1.186)	(1.198)	(0.831)	(0.840)
2nd Rater	-0.549	-0.52	-1.289***	-1.242***
	(0.748)	(0.743)	(0.468)	(0.466)
3rd Rater	0.267	0.252	-1.254***	-1.298***
	(0.520)	(0.516)	(0.325)	(0.319)
Year	X	X	X	X
Rating Level	X	X	X	X
Industry	X	X	X	X
Maturity	X	X	X	X
Time to Revision	X	X	X	X
Direction of Revision	X	X	X	X
Pseudo R^2	0.144	0.144	0.237	0.232
Observations	722	722	433	433

CHAPTER 4: INCENTIVES AND CREDIT RATINGS

Credit rating agencies (CRAs) are constantly assessed on their ability to provide accurate ratings on bond issues. Although an ongoing debate exists as to whether reputation or profit guides the rating decisions of CRAs, if bond issuers are providing incentives to rate in a certain manner, then the true driver of rating decisions may lie in the hands of the bond issuers themselves. While the current literature focuses on both the reasons for attaining a third rating on a bond issue and the relative level of ratings for that third rating, this chapter instead looks to decipher what happens to the third rating agency's stream of future ratings coverage following their issuance of a rating. By focusing on the issue from the *ex post* perspective, the underlying incentive structure for the third rating agency to rate a particular bond issue can be revealed.

A couple of contributions from this paper add to the growing literature on CRAs. First, the third rating agency is more likely to be rewarded with future business when they rate above the lower of the other two rating agencies. This provides evidence that bond issuers are both shopping for ratings and rewarding those CRAs who rate higher. Second, the third rating agency is used for certification at the investment grade line. After providing an investment grade rating on a previously split-rated bond (one rating above investment grade and one rating below investment grade), the third rater is less likely to rate the next bond issue by that same issuer (unless that next issue needs certification again). Finally, the results suggest that finance industry issuers may provide different underlying incentives to the third rating agency than do the non-finance industry issuers.

4.1 Literature Review

There are two papers most closely related to this paper. First, Kronlund (2012) finds that firms are more likely to obtain ratings from CRAs which have provided a higher rating to the firm in the past. The author focuses on bond issues with only one or two ratings and examines whether this choice is biased towards those CRAs likely to rate the bond issue favorably. He finds that, if an issuer solicits only one CRA to rate a new bond, the CRA which on average rated an issuer's prior bonds higher is more likely to rate a new bond for that issuer. We instead focus on the relationship between the rating provided by the third rater, relative to the first two raters, and whether that specific issuer chooses the third rater to rate their next bond issue.

Second, Bongaerts et al. (2012) find the likelihood of getting a Fitch rating is strongly related to Moody's and Standard & Poor's having rated on opposite sides of the investment grade line, a result consistent with ratings shopping. Unlike Bongaerts et al. (2012), we look at whether certification at the investment grade line impacts the likelihood of rating the next issue by the same issuer.

The literature on ratings shopping, or the ability to choose amongst multiple CRAs, is also related to this paper. Both the theory of Skreta and Veldkamp (2009) and the empirical tests of Kronlund (2012) find ratings shopping is more prevalent on complex products, whereas simple products have less dispersion amongst ratings and thus provide little incentive to shop for ratings. The model of Sangiorgi, Sokobin, and Spatt (2009) shows that ratings shopping is more prone to occur when there is more heterogeneity amongst the rating agencies views. Finally, Spatt (2009) discusses how firms can only shop when they choose who gets to rate them. For instance, essentially all taxable corporate bond issues are rated by Moody's and Standard & Poor's, and thus the potential advantages from ratings shopping is mitigated.

Research has also suggested that the third rating agency tends to rate higher than the first two raters. Cantor and Packer (1997) find the most important determinants in the decision to get a third rating are a firm’s age and size. By testing for differences between rating scales of CRAs, i.e., testing for whether default risks associated with a particular rating are different across CRAs, Cantor and Packer (1997) also provide evidence that the tendency for a third rating agency to assign a higher rating is only partially driven by sample selection bias (only approach a third agency to rate if they are expected to provide a higher rating). Becker and Milbourn (2011) find that when bonds have a Fitch rating, S&P and Moody’s ratings are slightly lower, *ceteris paribus*.

4.2 Data

Using the Mergent FISD database, bond characteristics, bond ratings, and issuer industry information are merged to form a comprehensive data set. Bond characteristics include the issuer type (e.g., corporate, agency). Bond ratings data include the rating dates, initial ratings, rating revisions, and rating agency for each unique bond issue. Issuer industry information includes the NAICS code for the issuer.

Our sample period is 2001 through 2010. In order to assure that results are not driven by the bulk downgrades of privately issued mortgage-backed securities, regressions are also estimated on a trimmed sample period where the third rating had to take place before mid-2007. We start in 2001 for two reasons. First, Bongaerts et al. (2012) note the incompleteness in the Mergent FISD coverage of Standard & Poor's ratings until the middle of 2000. Second, because Fitch acquired Thomson BankWatch and Duff & Phelps in 2000, starting in 2001 accounts for Fitch's organic growth. We end in December 2010 in order to allow enough time for subsequent bond issues to be rated by a third rating agency.[37]

The bond characteristics are used to eliminate any bond that is not a U.S. corporate bond issue. After this elimination, bond ratings are converted from an alphabetic to a numeric scale using the following classifications for Fitch and S&P ratings (Moody's), 21 for AAA (Aaa), 20 for AA+ (Aa1), 19 for AA (Aa2), 18 for AA− (Aa3), 17 for A+ (A1), 16 for A (A2), 15 for A− (A3), 14 for BBB+ (Baa1), 13 for BBB (Baa2), 12 for BBB− (Baa3), 11 for BB+ (Ba1), 10 for BB (Ba2), 9 for BB− (Ba3), 8 for

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[37] The median time until the third rating took place was approximately 8 months.

B+ (B1), 7 for B (B2), 6 for B− (B3), 5 for CCC+ (Caa1), 4 for CCC (Caa2), 3 for CCC- (Caa3), 2 for CC (Ca), and 1 for C (C).[38]

After the ratings are classified, they are then sorted within each unique bond issue by the date on which they are rated. If a third rating agency rates a particular bond issue, as long as it is chronologically after the first two rating agencies, the first time which that rating agency rates that particular issue is identified as the third rater's rating. All ratings on that unique issue that take place after that third rating are eliminated from the data set. Working backwards in time from the date on which the third rating took place, we take the most up-to-date rating provided by the first and second rating agencies to rate that unique bond issue and label them as such.

We next sort the data to create a time series of each type of bond issue by each issuer (e.g., debentures, medium-term notes, etc.).[39] For each bond issue having a third rating, we identify the next available bond issue of the same bond type by that same issuer for which the third rating agency had a chance to provide a rating. An indicator variable, Future Gains, is created and takes the value 1 if the third rating agency provides a rating on the next possible issue of the same bond type and a 0 otherwise. The final data set includes 4,589 bond issue credit ratings in which a rating agency has a chance to rate the next issue of the same bond type by the same issuer.

Summary statistics are provided in Table 4.1. The Future Gains variable shows that, of the bond issues rated by a third rating agency, 84.1% of the next available issues of the same bond type by that same issuer were rated by that third rating agency. The

[38] These numerical ratings are similar to those used by Cantor and Packer (1997), Depken and LaFountain (2006), and Bongaerts et al. (2012).

[39] Sorting within bond type is done in order to get rid of any potential specialization effect. The results are robust to sorting within each issuer (regardless of bond type); however there are fewer observations within that sort.

third rating agency rated above the lowest of the most recent ratings by the first two rating agencies 45.0% of the time (Rating Diff). Within the sample, approximately 60% of the bonds which had split ratings at the investment grade line were certified, or rated above-the-line, by the third rating agency (Certifies at IG). Slightly over half of the bond issues were in the financial services NAICS industry code. Further, 54.7% of the third ratings were provided by Fitch. A larger number of third ratings occur in the years 2004-2007. Also, corporate debentures and corporate medium-term notes account for over 80% of the bond issues. Finally, third ratings were provided within three months of the most recent first and second CRA's ratings approximately 60% of the time, within 6 months approximately 70% of the time, and within a year approximately 80% of the time.

4.3 Methodology and Results

To test whether the third rater gains future business based on the relative level of their rating, we use the following regression specification:

(1) Future Gains = f (Rating Diff, Certifies IG, Fitch, Bond Type, Rating Level, Time Lag, Industry, Year)

where Future Gains is an indicator variable which takes the value 1 when the third rating agency rates the next issue of the same bond type by the same issuer, and 0 otherwise; Rating Diff is an indicator variable taking the value 1 when the third rater rates the prior issue above the lowest rating of the first two rating agencies, and 0 otherwise; Certifies at IG is an indicator variable taking the value of 1 if the third rater rates the prior issue above the investment grade line and the first two ratings on that issue are on opposite sides of the investment grade line, and 0 otherwise.[40] Controls are also added for the year which the third rating takes place, the industry of the issuer, the type of the bond, the rating provided by the third rating agency, and the time lag, in months, between the most recent rating by either the first or second rating agency and the third rating agency. The type of the bond can include debentures, medium-term notes, convertibles, zeros, etc.

Controlling for the time lag between the third rating and the most recent rating by another rater is a way to identify the issuers rationale for attaining a third rating. If more time has passed between ratings, it is possible that the issuer has decided to add a third rater with no intentions of seeking a higher rating. However, if minimal time elapsed between ratings, it may be that the third rater is used for certification or ratings shopping

[40] Not certifying, or rating at or below the lower of the two existing ratings, is not significant towards gaining or losing the next rating in any specification.

purposes. Within each of the tables, separate regressions are estimated to control for different time lags between ratings. As suggested above, we hypothesize that the shorter time lag will be associated with ratings shopping.

Table 4.2 presents results for all industries pooled together. When looking at all industries, we find that the third rating agency gains future business by rating higher than the other two raters. Also, the empirical evidence shows that certifying at investment grade is associated with a lower probability of rating the next issue. Moreover, if the third rater is Fitch, then they are less likely to rate the next issue. The finding that a higher rating is associated with a larger probability of rating the next issue of the same type by the same issuer is robust across all time lags. In other words, the evidence suggests that CRAs have an incentive to inflate ratings.

The last column of Table 4.2 illustrates a regression estimated for third ratings made by Fitch within three months of the prior rating. The negative coefficient estimate for Certifies IG suggests that the likelihood that Fitch rates the next bond issue decreases when Fitch certifies the previous bond by that same issuer at the investment grade line. After being certified by the third rater, over two-thirds of the next bond issues by that same issuer had a first rating which was already above investment grade. Basically, Fitch previously certified the issuer, and so the next time around Fitch is no longer needed. This finding is in line with Bongaerts et al. (2012), in that Fitch is used as a certification tiebreaker at the investment grade line.

Table 4.3 looks at all those issuers not in the finance industry. The results within this table appear to be driving the results of Table 4.2. Issuers outside of the finance industry reward the third rating agency who rates higher, a finding in support of ratings shopping. Also, as in Table 4.2, when the third rating agency is certifying an issuer at the investment grade line, the third rater is less likely to rate the next bond issue by that issuer. Further, non-financial firms utilize Fitch as a certification tiebreaker, as illustrated by the negative coefficient on the Certifies IG variable.

Table 4.4 looks at bond issuers classified within NAICS 52, or the finance industry. Segmentation on financial firms is performed since financial firms issue a large share of the corporate bonds and these bonds may be fundamentally different from non-financial firms' bonds. The only variable which is significant in any of the specifications is the indicator variable for Fitch, which remains negative and highly significant. All other variables are no longer significant.[41] This result suggests that, within the finance industry, bond issuers do not reward and/or punish the third rater for rating above the other rating agencies or for certifying an issue at the investment grade line. Hence, within the finance industry, the decision to utilize a third rating agency may be an attempt to provide more information to the market, rather than to shop for a higher rating or to certify an issue.

As a robustness check, we test to see whether the ratings provided by a third rater are statistically different in distribution from the previous CRAs' ratings. Ratings which do not follow the same distribution would allude to a systematic, not a relative, difference in the level of ratings provided by the third rater. If the difference is systematic, the results are potentially spurious. In looking at the first CRAs' rating, second CRAs' rating, and third CRAs' rating, the Kolmogorov-Smirnov test fails to reject the null that they are drawn from the same distribution. In other words, the results in Tables 4.2, 4.3, and 4.4

[41] For NAICS 52, within 6 and within 3 months, the certifying variable perfectly predicts success, i.e., those rating firms who certified the issue rated the next issue by that same issuer 100% of the time.

are not spurious. Further, in comparing the third rating to the rating(s) on the next issue, the Kolmogorov-Smirnov test fails to reject that the third rating is from the same distribution of either the first or second rating on the next issue.

Perhaps interestingly, the Kolmogorov-Smirnov test rejects the null that the third rating and the next issues' third rating are from the same distribution. Figures 4.1 and 4.2 illustrate the third rating and the next issues' third rating. The next third rating has a larger percentage of ratings directly at investment grade, which provides support for Bongaerts et al. (2012) certification hypothesis. This suggests that the initial third rating certifies and another third rating is now only needed when certification at the investment grade line is necessary.[42]

[42] Approximately 80% of the next bond issues receive a third rating. Of those, only 80% are a unique third rating in terms of it being released after the first two ratings.

4.4 Conclusions

Regardless of whether credit rating agencies are profit maximizers or reputation maximizers, it is important to understand the underlying incentives which they face when providing ratings. If ratings accuracy were all that mattered in terms of acquiring future business from issuers, than the relative level of ratings should have no statistically significant effect on future business. The results of this paper show that future business acquisition for credit rating agencies is not necessarily purely focused on the accuracy of prior ratings. Instead, credit rating agencies are rewarded business when they rate higher than the other rating agencies.

Ratings shopping is widely discussed in the current academic literature. This paper adds to that literature with evidence that issuers outside of the finance industry not only shop around for higher ratings, but also utilize the third rating agency as a certifier at the investment grade line. The results that CRAs issuing higher ratings are rewarded with future business, and that a third rater is used to certify at the investment grade line, suggest that the underlying incentives provided by bond issuers for credit rating agencies may be causing some of the bond rating inaccuracy. Or, in other words, the ability for a bond issuer to shop for ratings may be contributing to ratings inflation.

Table 4.1: Summary statistics

Table 4.1 presents summary statistics for the sample. There are 4,589 observations in which a rating agency has a chance to rate the next issue of the same bond type by the same issuer. All variables are indicator variables where 1 represents a bond issue falls within the variable category, and a 0 if it does not.

Variable	Mean
Future Gains	0.8413
Rates Above Lowest	0.4502
Certifies at IG	0.0142
Does Not Certify at IG	0.0096
NAICS 52	0.5217
Fitch is Third Rater	0.5470
2001	0.0656
2002	0.0748
2003	0.0990
2004	0.1293
2005	0.1319
2006	0.1302
2007	0.1155
2008	0.0750
2009	0.0927
2010	0.0861
Corporate Debentures	0.5651
Corporate Medium-Term Notes	0.2716
Third Rating within 3 Months	0.6257
Third Rating within 6 Months	0.7142
Third Rating within 12 Months	0.8082

Table 4.2: The relationship between future ratings coverage and the third raters' rating relative to first and second raters' ratings

Table 4.2 presents the slope coefficients from probit regressions. The sample period is from 2001 through 2010. The dependent variable is an indicator variable representing whether the third rater rates the next bond issue of the same bond type by the same issuer. Rating Difference is the difference in rating level between the third rating and the lowest of the first two ratings, where a value of 1 represents a higher third rating, 0 is the same third rating. Certifies at IG is an indicator variable taking the value of 1 if the third rater rates above the lower of the first two raters when the bond had split ratings at the investment grade line, and 0 otherwise. Fitch is an indicator variable taking the value 1 when Fitch is the third rater, 0 otherwise. Year represents yearly fixed effects, industry represents controls for NAICS, Bond Type represents controls for the type of bond, i.e. U.S. Corporate Debenture, U.S. Corporate Medium Term Note, U.S. Corporate Zero, etc., Rating Level controls for the numerical rating, and Time Lag represents the time elapsed between the first rating and the third rating. Heteroskedastic-robust standard errors are calculated and shown in parentheses. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

	All Data		Within 1 Year		Within 6 Months		Within 3 Months	
	All	Fitch Only	All	Fitch Only	All	Fitch Only	All	Fitch Only
Rating Diff	0.155***	0.191***	0.123*	0.141	0.141*	0.193*	0.187**	0.199
	(0.057)	(0.074)	(0.069)	(0.097)	(0.076)	(0.113)	(0.084)	(0.127)
Certifies IG	-0.588**	-0.456*	-0.382	-0.306	-0.586	-0.569	-0.567	-1.044**
	(0.241)	(0.245)	(0.320)	(0.324)	(0.357)	(0.397)	(0.388)	(0.445)
Fitch	-0.535***		-0.425***		-0.431***		-0.435***	
	(0.060)		(0.069)		(0.076)		(0.085)	
Year	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Bond Type	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Time Lag	X	X	X	X	X	X	X	X
Pseudo R^2	0.2426	0.2368	0.1939	0.1879	0.1826	0.1771	0.1501	0.1332
Observations	4469	2442	3595	1767	3103	1390	2658	1104

Table 4.3: The relationship between future ratings coverage and the third raters' rating relative to first and second raters' ratings - excluding financials

Table 4.3 presents the slope coefficients from probit regressions. The sample period is from 2001 through 2010. The dependent variable is an indicator variable representing whether the third rater rates the next bond issue of the same bond type by the same issuer. Rating Difference is the difference in rating level between the third rating and the lowest of the first two ratings, where a value of 1 represents a higher third rating, 0 is the same third rating. Certifies at IG is an indicator variable taking the value of 1 if the third rater rates above the lower of the first two raters when the bond had split ratings at the investment grade line, and 0 otherwise. Fitch is an indicator variable taking the value 1 when Fitch is the third rater, 0 otherwise. Year represents yearly fixed effects, industry represents controls for NAICS, Bond Type represents controls for the type of bond, i.e. U.S. Corporate Debenture, U.S. Corporate Medium Term Note, U.S. Corporate Zero, etc., Rating Level controls for the numerical rating, and Time Lag represents the time elapsed between the first rating and the third rating. Heteroskedastic-robust standard errors are calculated and shown in parentheses. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

	All Data		Within 1 Year		Within 6 Months		Within 3 Months	
	All	Fitch Only	All	Fitch Only	All	Fitch Only	All	Fitch Only
Rating Diff	0.332***	0.271**	0.353***	0.303**	0.402***	0.330*	0.554***	0.501**
	(0.094)	(0.106)	(0.124)	(0.144)	(0.147)	(0.178)	(0.171)	(0.217)
Certifies IG	-0.605**	-0.39	-0.475	-0.28	-0.869**	-0.7	-1.009**	-1.543***
	(0.256)	(0.265)	(0.355)	(0.372)	(0.388)	(0.445)	(0.435)	(0.578)
Fitch	-0.604***		-0.509***		-0.558***		-0.632***	
	(0.120)		(0.148)		(0.168)		(0.182)	
Year	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Bond Type	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Time Lag	X	X	X	X	X	X	X	X
Pseudo R^2	0.2422	0.2109	0.1488	0.1168	0.1603	0.1503	0.1928	0.2071
Observations	2111	1313	1589	896	1301	655	1076	467

Table 4.4: The relationship between future ratings coverage and the third raters' rating relative to first and second raters' ratings - financials only

Table 4.4 presents the slope coefficients from probit regressions. The sample period is from 2001 through 2010. The dependent variable is an indicator variable representing whether the third rater rates the next bond issue of the same bond type by the same issuer. Rating Difference is the difference in rating level between the third rating and the lowest of the first two ratings, where a value of 1 represents a higher third rating, 0 is the same third rating. Certifies at IG is an indicator variable taking the value of 1 if the third rater rates above the lower of the first two raters when the bond had split ratings at the investment grade line, and 0 otherwise. Fitch is an indicator variable taking the value 1 when Fitch is the third rater, 0 otherwise. Year represents yearly fixed effects, industry represents controls for NAICS, Bond Type represents controls for the type of bond, i.e. U.S. Corporate Debenture, U.S. Corporate Medium Term Note, U.S. Corporate Zero, etc., Rating Level controls for the numerical rating, and Time Lag represents the time elapsed between the first rating and the third rating. Heteroskedastic-robust standard errors are calculated and shown in parentheses. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

	All Data		Within 1 Year		Within 6 Months		Within 3 Months	
	All	Fitch Only	All	Fitch Only	All	Fitch Only	All	Fitch Only
Rating Diff	0.03	0.038	0.025	-0.056	0.065	0.046	0.101	0.021
	(0.073)	(0.110)	(0.084)	(0.141)	(0.091)	(0.156)	(0.099)	(0.172)
Certifies IG	-0.429	-0.922	-0.676	-0.761	.	.	.	.
	(0.615)	(0.669)	(0.539)	(0.659)	.	.	.	.
Fitch	-0.499***		-0.402***		-0.413***		-0.376***	
	(0.073)		(0.083)		(0.091)		(0.101)	
Year	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X
Bond Type	X	X	X	X	X	X	X	X
Rating Level	X	X	X	X	X	X	X	X
Time Lag	X	X	X	X	X	X	X	X
Pseudo R^2	0.2493	0.2594	0.1988	0.2218	0.1756	0.2008	0.1358	0.1335
Observations	2351	1124	1964	855	1740	714	1520	573

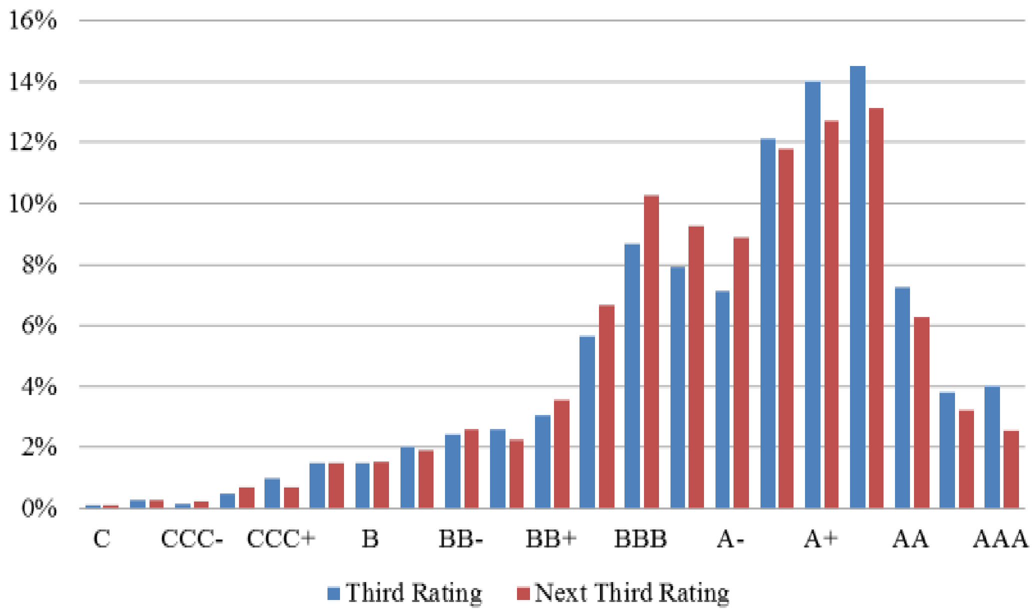

Figure 4.1: Third rating versus next third rating

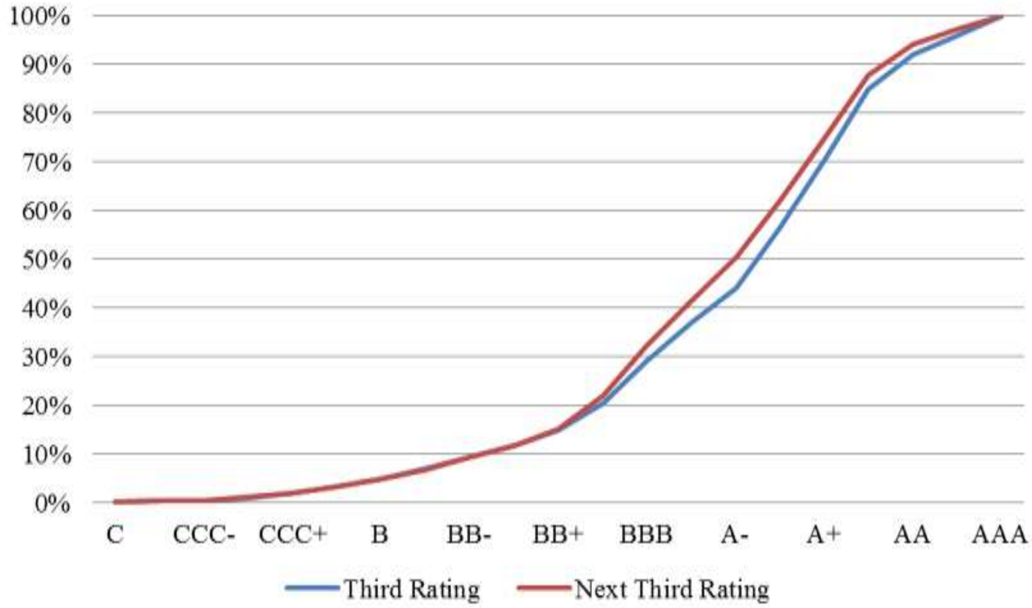

Figure 4.2: Cumulative frequency distribution of third rating and next third rating

CHAPTER 5: CONCLUSION

Why were the credit ratings so often fundamentally misrepresentative? This dissertation set out to study this overarching question by analyzing the reputational dynamic, competitive environment, and incentive structure for credit rating agencies.

The first chapter provided a historical overview of the environment in which the credit rating agencies operate and also discussed a few of the reasons posited as a cause for the inaccuracy of the raters. Also, a couple of proposed changes to the regulatory and competitive environment were discussed, such as those offered by Richardson and White (2009) and Stolper (2009). Finally, to illustrate why the public should care about credit rating agencies, the work of White (2010) was summarized.

The second chapter analyzed the link between reputation and ratings accuracy. The results suggested that if credit rating agencies are truly reputation maximizers, then reputational concerns alone are unlikely to improve ratings accuracy. Also, when a CRA acts as a reputation maximizer, a competitive environment reflects an accuracy level that is at least as high as that of a monopoly. Further, given the proper mix of reputational incentives and reputational punishments, competition may help to improve ratings accuracy.

The third chapter studied the impact of competition on ratings stability. The results provided evidence that competition improves the quality of only the first rating agency to rate a specific bond issue. Also, competition appears to be counterproductive when a rating agency has the ability (as the second or third rater) to determine the rating utilized for regulatory purposes. Additionally, we find evidence that the third rater is a regulatory certifier, i.e., the rating issued by the third rater can determine investment grade status.

The fourth chapter examined the underlying incentives faced by the third credit rating agency to rate a particular bond issue. The results suggested that ratings shopping is prevalent amongst bond issuers. Also, the third rater is rewarded with future business for rating above the first two rating agencies to rate a particular bond issue. These results illustrate that a credit rating agency has the incentive to inflate ratings, an action which is associated with ratings inaccuracy.

The conclusions of this dissertation suggest that ratings accuracy is negatively affected by both a lack of competition associated with the first credit rating agency to rate a particular bond issue and an incentive structure provided by the issuers which rewards credit rating agencies for inflated ratings. Further, a more competitive environment leads to ratings inflation by the second and third rating agencies to rate a bond issue. Finally, in order for competition to improve ratings quality, there must exist a sufficiently large ratio of reputational incentives to reputational punishments.

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