Three Essays on Credit Ratings

Leo Tang

A dissertation submitted to the
Graduate School - Newark
Rutgers, the State University of New Jersey
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy
Graduate Program in Management
Written under the direction of
Professor Bikki Jaggi
and approved by

____

Dr. Bikki Jaggi

____

Dr. Valentin Dimitrov

____

Dr. Dan Palmon

____

Dr. Gary Kleinman

Newark, New Jersey
May 2016

Abstract

In this dissertation, I examine several forces which impact credit ratings. One driver of credit ratings is recent legislation from the Dodd-Frank Wall Street Reform and Consumer Protection Act. This sweeping regulatory reform moderated the incentives of credit rating agencies (CRAs) to issue upwardly biased ratings by significantly increasing CRAs' exposure to litigation and regulatory risk. The first essay examines how the impact of this legislation affected rating properties. Another driver behind credit rating is access to soft information. Utilizing proximity between rating agencies headquarters and firm headquarters, the second essay analyzes how access to soft information impacts the accuracy of ratings. The third essay examines market participant's degree of reliance on credit ratings. The 2010 recalibration of municipal bonds provides an opportunity to test investors' reactions to rating changes which incorporate no new information and which were done irrespective of changes in credit quality. Reaction to the implementation of recalibration may imply that market participants over-rely on ratings and "fixate" on them.

Acknowledgements

I would like to gratefully acknowledge the contributions and guidance of the members of my dissertation committee, Bikki Jaggi, Valentin Dimitrov, Dan Palmon and Gary Kleinman. I would like to specially thank Dr. Jaggi and Dr. Dimitrov for their mentorship during my time at Rutgers University. I would like to specially thank my family for their support and encouragement.

TABLE OF CONTENTS

List of Tables

Essay 1

Essay 2

Essay 3

List of Figures

Chapter 1: Introduction

Credit rating agencies (CRAs) provide ratings that assess the credit worthiness of a specific debt obligation. The principal CRAs in this industry are the three major credit ratings agencies (Moodys, Standard & Poors, and Fitch Ratings). The history of this industry began in the early twentieth century with ratings of railroad debt. In the early 1930s, bank regulators, insurance companies and pension funds began using ratings to limit the riskiness of assets held. Regulators also required insurance company capital charges based on current ratings and limited the credit quality of assets for certain funds. Although ratings were becoming more accepted in the market place during this time, the rarity of defaults caused ratings to be perceived as relatively insignificant. The economic turbulence of the 1970s changed this perception and by 1975, the Securities and Exchange Commission (SEC) began to recognize certain firms as NRSROs (nationally recognized statistical ratings organizations) and in effect required ratings for anyone selling debt.

Credit ratings are represented as a letter grade and accompanied with commentary (report). At the major CRAs, ratings are typically analyst driven and involve analysis of both qualitative and quantitative inputs depending on the issuance[1]. The process of determining ratings first begins with a lead analyst who gathers information, meets with management of the issuer, and develops a recommended rating. These recommendations are then brought before a rating committee which is composed of senior employees with voting privileges. The rating rationale of the lead analyst is discussed and a final rating is assigned which may or may not differ from the initial recommendation.

---

[1] Frost (2007) notes that the major rating agencies use significant amount of qualitative information along with analysis-driven approaches to develop credit ratings.

Given the importance of credit ratings, the literature is abundant with studies that examine various aspects of credit ratings. An abundant literature has examined the informativeness of credit ratings, possible conflicts of interest and various rating properties and characteristics. This dissertation is motivated by the literature on credit ratings and consists of three essays on this topic.

The first essay examines the impact of Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) on corporate bond ratings issued by credit rating agencies (CRAs). One key motivation of Dodd-Frank was to temper the incentives of CRAs to issue upwardly biased ratings by significantly increasing CRAs' exposure to litigation and regulatory risk. Among other things, the reforms specifically increased litigation risk by amending previous rules which effectively shielded CRAs from expert and civil lawsuits. A new SEC office was also created with the power to suspend or revoke a CRA's license for noncompliance with the new regulatory structure. This essay examines two specific hypotheses on the impact of Dodd Frank. Under the first hypothesis, Dodd-Frank achieves its goal of making credit ratings more accurate and informative by imposing higher legal and compliance penalties on CRAs. This is called the *disciplining hypothesis*. Alternatively, Dodd-Frank may have an adverse effect on credit ratings by making CRAs significantly more concerned with their reputation for issuing biased ratings. Morris (2001) suggests that increased reputational concerns may lead to a loss of information in a cheap talk game that is descriptive of the interaction between CRAs and market participants. CRAs may respond to Dodd-Frank by becoming more conservative in their ratings in an attempt to avoid being perceived by market participants as being upwardly biased. As CRAs try to counteract their perceived rating bias, market participants rationally discount the downgrades issued by CRAs. This second hypothesis is called the *reputation hypothesis*.

The second essay examines how access to soft information impacts the accuracy of credit ratings. The accuracy of credit ratings affects the reputation of rating agencies (e.g. Strausz, 2005; White, 2002) and also plays an important role in stock pricing, firm valuation, contracts, and regulations (e.g. Beaver, Shakespeare and Soliman, 2006). In order to achieve higher accuracy for credit ratings, the major rating agencies use quantitative as well as qualitative information (Fitch 2007; Moody's 2002; Standard & Poor's 2008), which is also referred to as hard and soft information. Using proximity as a proxy for access to soft information (Coval and Moskowitz, 1999; Huberman, 2001; Malloy, 2005; Uysal, Kedia and Panchapagesan, 2008; Kedia and Rajgopal, 2011), this essay examines how proximity between the rating agencies and rated firms impacts credit ratings. Consistent with the geographic proximity literature, we hypothesize that proximity facilitates access to soft information for rating analysts through common professional, social, and cultural contacts. Proximity may also relax certain time and distance constraints and allows analysts to visit firms for obtaining information through face-to-face meetings.

The third essay examines market participant's reliance on credit ratings. Because of the importance of credit ratings in firm valuation, contracts and regulations, early research has established that investors react to ratings (Grier and Katz, 1976; Brooks and Copeland, 1983; Holthausen and Leftwich, 1986). While credit ratings are an important channel of information, their importance may also cause certain investors to focus on the ratings too much. Over reliance on ratings implies that certain investors may react to the ratings themselves rather than the information that they convey and implies a sort of "fixation" on credit ratings. Utilizing Moody's 2010 recalibration of municipal bonds, I attempt to show that investors fixate on credit ratings. Since the recalibration process was separated into two stages, this allows me to test investor reactions on announcement of recalibration which contained information on how the ratings would be adjusted, followed by the actual implementation of rating adjustments which in light of the announcement contained no additional information. If investors fixate on credit ratings, I expect investors to react only on implementation date which incorporates no new information and was done irrespective of changes in issuer credit quality.

The remainder of the dissertation is organized as follows. Chapter 2 presents a review of the relevant literature. Chapter 3 presents the first essay, which examines how Dodd-Frank has influenced credit ratings. Chapter 4 presents the second essay, which examines how soft information influence rating accuracy. Chapter 5 addresses whether investors fixate on credit ratings. Chapter 6 concludes the dissertation.

Chapter 2: Literature Review

2.1. Credit Ratings and Informativeness

CRAs play several major roles in the market. First, by assessing the credit quality of a debt issue, ratings represent a dissemination of information to market participants. Credit ratings also play an important role in contracts and regulations (e.g. Beaver, Shakespeare and Soliman, 2006). Rating based regulation typically appears in loan agreements, bond covenants, and in-house investment rules. For instance, Rule 2a-7 under the Investment Company Act (1940) limits money market funds to investing only in high-quality short term instruments, where the minimum quality investment standards are based on ratings published by CRAs.

Due to the important market role that ratings play, early research in the area examine the informativeness of ratings about the prospects of the rated firms. Grier and Katz (1976) find that average monthly bond prices react to changes in corporate credit ratings. However, Weinstein (1977) also examine monthly bond prices and finds little reaction to ratings changes. Ingram, Brooks and Copeland (1983) examine monthly changes in municipal bond yields and find significant bond price reactions to rating changes. Holthausen and Leftwich (1986) study the market reaction to 1,104 announcements of credit rating changes over the 1977-1982 period and find that credit rating downgrades are associated with an average stock price reaction of -2.66%. They do not find a significant stock price reaction to upgrades. Hand, Holthausen, and Leftwich (1992) extend this earlier sample and find that both bond and stock prices of the issuing company change in the expected direction when Moody's or S&P publish an actual or potential rating change. More recent work by Dichev and Piotroski (2001) confirms that both credit upgrades and credit downgrades result in significant stock market reaction over the entire 1970-1997 period. Still, the reaction is significantly larger for downgrades than for upgrades, possibly because the market perceives positive ratings as more likely to be optimistically biased. Ederington and Goh (1988) trace the stock price reactions to rating changes to subsequent changes in earnings and conclude that ratings changes are informative about subsequent operating performance. Kao and Wu (1990) show that ratings are informative about credit risk and are positively correlated with bond yields. Kliger and Sarig (2000) utilize a natural experiment and study Moody's refinement in credit ratings which was done irrespective of changes in firm conditions. They find that the market does value credit ratings and reacts positively (negatively) when the refinement leads to a higher (lower) rating modifier.

2.2. Credit Ratings and Conflicts of Interest

Since 1975, the major CRAs have adopted an issuer-pays model[2]. Since credit ratings have been shown to affect both pricing and contracts, this creates an incentive for CRAs to accommodate their clients and issue optimistic ratings (e.g. Kraft, 2011). IOSCO (2003a) states that "perhaps the single greatest concern facing CRAs is identifying and addressing potential and actual conflicts of interest that may inappropriately influence the rating process." Several papers study the differences between solicited and unsolicited ratings to test if economic benefits influence ratings

[2] The issuer-pays model was introduced in part because of the adoption of copying machines, which made it easy for investors to copy existing CRA reports. At the same time, demand for credit ratings increased substantially in 1975 following the SEC requirement that public debt issues are rated by "Nationally Recognized Statistical Organizations" (NRSROs). Subscription fees were no longer sufficient to cover the cost of evaluating credit quality on such a scale. See Jiang, Stanford, and Xie (2012) for a detailed analysis of the decision to switch to the issuer-pays model.

levels. Poon (2003) uses cross sectional data of 265 firms in 15 countries from Standard & Poor's and finds the unsolicited ratings are lower. Poon and Firth (2005) use an international sample of bank ratings and find similar results. Jiang, Stanford and Xie (2012) study rating properties before and after S&P switched to the issuer-pays model in 1974 as a way to test if economic influence ratings. They find that S&P assigned higher bond ratings after it switched to the issuer-pays model, and that this result is particularly strong for bonds with higher expected fees or lower credit quality. Strobl and Xia (2012) show that S&P assigns higher ratings than the Egan-Jones Rating Company, which uses an investor-pays model. However, the argument that economic incentives may bias credit ratings is not undiputed. While CRAs may have an incentive to cater to clients, there are also reputational incentives to maintain accurate ratings (e.g. Strausz, 2005; White, 2002). Covitz and Harrison (2003) measure the timeliness of downgrades as a way to test the conflict of interest hypothesis. They find that downgrades appear timelier for bond issues which generate more publicity. This finding seems to suggest that CRAs seek accurate ratings when it has an impact on their reputation.

The collapse of AAA-rated structured finance products during the recent financial crises has created renewed attention on the possible bias in credit ratings. Skreta and Veldkamp (2009) develop an equilibrium model of the market for structured credit ratings and show that a combination of asset complexity and ratings shopping can produce rating inflation. Mathis, McAndrews and Rochet (2009) find that rating inflation can also occur when it becomes a major source of income. Opp, Opp, and Harris (2013) focus on the interaction of the existing issuer-pays model and the regulatory use of ratings within a rational-expectations framework. The model shows that the mere existence of a regulatory advantage for highly rated securities may lead to inflated ratings. Griffin and Tang (2011) find that CRA analysts use more optimistic assumptions when their pay is more directly linked to bringing in new rating business. Griffin and Tang (2012) find that CRAs frequently made subjective positive adjustments in the CDO market prior to 2007 that were difficult to explain by economic determinants. He, Qian, and Strahan (2012) find that CRAs apparently issued more favorable ratings to larger issuers in the mortgage-backed securities (MBS) market during the boom market from 2004 to 2006. Similar biases are also apparent in the corporate credit market. These findings suggest that the bias in credit ratings can be traced to the economic incentives of CRAs.

2.3. Credit Ratings and Competition

While a substantial stream of literature focuses on the conflict of interest in credit ratings, ratings may also be influenced by increased competition among different CRAs. In Bolton, Freixas, and Shapiro (2012), competition among CRAs facilitates ratings shopping by issuers and results in excessively high reported ratings, especially when there is a large clientele of investors who take ratings at face value. Becker and Milbourn (2011) study the impact of Fitch's growing market share and argue that increased competition from Fitch lowers the importance of reputation of incumbent CRAs (Moody's and Standard and Poor's (S&P)) by lowering expected future rents in the industry. They find that the emergence of Fitch in the corporate bond rating market results in Moody's and S&P issuing higher credit ratings with lower quality.

2.4. Regulatory Reform and Credit Ratings

Blume, Lim, and MacKinlay (1998) examine the period from 1978 through 1995 and find that credit rating standards are becoming more stringent over time. Baghai, Servaes, and Tamayo (2012) show a similar trend over the period 1985 to 2009. Holding firm characteristics constant, they find that average ratings have dropped by 3 notches over that time period. Alp (2013) shows a divergent pattern between investment-grade and speculative-grade rating standards from 1985 to 2002 as investment-grade standards tighten and speculative-grade standards loosen. She also shows a structural shift towards more stringent ratings in 2002, possibly as a response to the increased regulatory scrutiny and investor criticism following the collapse of Enron and WorldCom. The increased conservatism in ratings beginning in 2002 parallels our finding of lower credit ratings following the passage of Dodd-Frank. Jorion, Liu, and Shi (2005) find that the information content of both credit rating downgrades and upgrades is greater following the passage of Regulation Fair Disclosure (FD) in 2000. Similarly, Cheng and Nemtiu (2009) find that CRAs issue more timely downgrades, increase rating accuracy, and reduce rating volatility following the passage of the Sarbanes-Oxley Act in 2002. They attribute their findings to the threat of increased regulatory intervention and/or reputational concerns. However, they do not test directly whether either of these factors contribute to their findings. Cathcart, El-Jahel, and Evans (2010) analyze the credit default swaps market immediately following the 2008 financial crisis and find that corporate credit ratings are viewed as less credible.

Chapter 3: The Impact of Dodd-Frank on Credit Ratings

3.1. Introduction

This essay examines how recent Dodd-Frank legislation has influence credit ratings. The Dodd-Frank Act was passed in July 2010 in response to the events of the financial crisis. Many believe that inflated credit ratings were one cause of the financial crisis (see, for e.g., Blinder (2007), Stiglitz (2008), and Brunnermeier (2009)).

Dodd-Frank attempted to address the issue of inflated ratings through several key provisions. First, Dodd-Frank significantly increased CRAs' exposure to litigation and regulatory risk. Specifically, Dodd-Frank amends previous rules which effectively shielded CRAs from expert and civil lawsuits. Second, Dodd-Frank sought to improve the internal controls of CRAs. In particular, new provisions require CRAs to establish internal controls to monitor adherence to rating policies and procedures, submit annual compliance reports to the SEC, maintain an independent board of directors, and establish procedures to evaluate possible conflicts of interest related to former employees. Lastly, Dodd-Frank established a new SEC office which oversees the CRAs. This office monitors CRAs and has the power to suspend or revoke a CRA's license for noncompliance with the new regulatory structure.

This essay examines two predictions regarding how Dodd-Frank may influence the corporate bond ratings issued by CRAs. According to the first prediction, which we call the *disciplining hypothesis,* Dodd-Frank achieves its goal of making credit ratings more accurate and informative by imposing higher legal and compliance penalties on CRAs. Such penalties make it costlier for CRAs to issue optimistically biased ratings. Alternatively, Dodd-Frank may have an adverse effect on credit ratings by making CRAs significantly more concerned with their reputation for issuing biased ratings. We call this second hypothesis the *reputation hypothesis*. We use the model of Morris (2001) to hypothesize that increased reputational concerns may lead to a loss of information in a cheap talk game that is descriptive of the interaction between CRAs and market participants. Specifically, CRAs may respond to Dodd-Frank by becoming more conservative in their ratings in an attempt to avoid being perceived by market participants as being upwardly biased. As CRAs try to counteract their perceived rating bias, market participants rationally discount the downgrades issued by CRAs.

The reputation hypothesis makes three empirical predictions: (1) all else equal, CRAs issue lower credit ratings following Dodd-Frank; (2) all else equal, there are more false warnings (i.e., speculative grade rated issues that do not default within a year) following Dodd-Frank; and (3) all else equal, credit rating downgrades become less informative following Dodd-Frank. In contrast, the disciplining hypothesis predicts that credit ratings become more accurate and more informative following Dodd-Frank, directly opposing predictions (2) and (3) of the reputation hypothesis.

Using a comprehensive sample of corporate bond credit ratings from 2006 to 2012, we find results that provide strong support for the reputation hypothesis. First, we find that bond ratings are lower, on average, in the post-Dodd-Frank period (defined as the period from July 2010 to May 2012). The odds that a corporate bond is rated as non-investment grade are 1.19 times greater after the passage of Dodd-Frank, holding all else constant. Second, we find more false warnings in the post-Dodd-Frank period, where false warnings are defined as speculative grade rated issues that do not default within one year. The odds of a false warning are 1.84 times greater after the passage of Dodd-Frank, holding all else constant. Third, we find that the bond market responds less to rating downgrades in the post-Dodd-Frank period. Prior to the passage of Dodd-Frank, bond prices decrease on average by 1.023% following a rating downgrade; this compares to a decrease of 0.654% following the passage of Dodd-Frank. In contrast, the bond market's response to rating upgrades remains the same. Fourth, we find that the stock market also responds less to rating downgrades in the post-Dodd-Frank period. Stock prices decrease by 2.461% following a rating downgrade in the pre-Dodd-Frank period; in the post-Dodd-Frank period, the decrease is only 1.248%. Taken together, these results show that rating downgrades are less informative in the post-Dodd-Frank period as the market discounts the actions of CRAs meant to protect their reputation. It appears that the reputation effect outweighs the disciplining effect of Dodd-Frank in the market for corporate bond credit ratings.

We provide additional evidence in support of the reputation hypothesis by examining whether the above results vary with variations in the CRAs' ex-ante reputation costs. Becker and Milbourn (2011) show that CRAs invest more in reputation when they face less intense competition. Using Fitch's entry into the CRA market as a competitive shock, Becker and Milbourn (2011) show that increased competition from Fitch coincides with lower quality ratings from the incumbent CRAs (Moody's and Standard and Poor's).[3] By decreasing expected rents in the industry, competition decreases incumbents' incentives to invest in reputation for accurate ratings. Based on the results of Becker and Milbourn (2011), we expect that following the passage of Dodd-Frank, ratings are lower,

[3] Becker and Milbourn (2011) show convincingly that Fitch's market share within an industry is exogenous to industry characteristics and the quality of credit ratings. For example, Fitch's market share in an industry is unrelated to credit growth in the industry, to industry profitability, and to the difficulty of predicting default within the industry. Fitch's market share is also unrelated to the coverage provided by Moody's and S&P, who rate virtually all corporate issues.

less accurate, and less informative in industries where Fitch has lower market share. When Fitch's market share is lower, legal and regulatory penalties have higher expected costs in terms of lost future rents. Showing that the results are stronger when Fitch's market share is lower ties our main findings to CRAs' reputation incentives.

Consistent with the reputation hypothesis, we find that all four results are stronger for industries where Moody's and S&P enjoy larger market share relative to Fitch. Within industries in the bottom quartile of Fitch market share, the passage of Dodd-Frank lowers the odds of an investment grade rating 2.27 times, increases the odds of a false warning 8.24 times, reduces the reaction of bond prices to downgrades by 1.083%, and reduces the reaction of stock prices to downgrades by 2.976%. These results are both statistically and economically significant. CRAs issue lower, less accurate, and less informative credit ratings following Dodd-Frank when their reputation costs are greater.

We perform a number of robustness tests. First, it is possible that the results are driven in part by the economic recession of 2007-2009 rather than the passage of Dodd-Frank. However, our results remain similar after controlling for macroeconomic variables such as market valuation, market returns, firm-specific returns, perceived profitability, and GDP. We also find no changes in credit ratings around the 2001 economic recession within industries with low Fitch market share. Second, we find that credit ratings become progressively more conservative and less informative as the uncertainty surrounding Dodd-Frank's passage is reduced. This finding establishes a closer link between Dodd-Frank's passage and changes in credit ratings. Third, we find no evidence that the lower ratings in the post-Dodd-Frank period reflect deteriorating issuer quality.

Taken together, our findings show that Dodd-Frank has had unintended consequences in the market for corporate bond ratings.[4] We focus on the ratings of corporate bonds because corporate bonds are a homogeneous asset class, the properties of corporate credit ratings have been studied extensively in the literature, and data on ratings, pricing, and characteristics of corporate bond issuers are readily available. Our findings may not apply to credit ratings of structured finance products. The structured finance market has experienced significant changes following 2008, including the continued involvement by the Federal Reserve, the collapse of the private residential mortgage-backed securities market, and the placement of Fannie and Freddie Mac, two of the largest underwriters, in conservatorship. These developments make it challenging to attribute any recent changes in the properties of structured finance credit ratings to the passage of Dodd-Frank.

This paper can help guide policy as regulators continue to debate the best way to restructure the credit ratings industry. Our results for corporate bond ratings suggests that further attempts to increase the costs to CRAs for issuing biased ratings are likely to be ineffective and could result in a loss of information. The common wisdom is that increasing the penalties for biased ratings will make CRAs provide higher quality ratings. However, as we show in this paper, CRAs respond to the increased regulatory pressure by issuing lower, less informative corporate bond ratings to protect their reputation. Any regulatory scheme for CRAs should carefully consider the trade-off between these two effects.

---

[4] Prior studies show unintended consequences of various regulations, including mandatory seat belt laws (Peltzman (1975)), teacher compensation (Jacob and Levitt (2003)), historic landmark designations (Schaeffer and Millerick (1991)), and predatory lending laws (Bostic et al. (2012)).

3.2. Legislative Background

In this section we take a closer look at the provisions of Dodd-Frank that relate to the CRA market. We identify the provisions that are ex-ante most likely to affect corporate credit ratings, and discuss the timeline for their implementation. We also identify the provisions that are least relevant for our findings. Subtitle C of Dodd-Frank, "Improvements to the Regulation of Credit Rating Agencies," contains nine separate sections (Sec. 931 through Sec. 939) and several subsections. The provisions relate to litigation, internal controls, disclosure, and regulatory oversight. A summary of the provisions is provided in Appendix A.

Liability Provisions

Arguably the most significant set of provisions within Dodd-Frank are those that increase CRAs' potential liability for issuing erroneous (or biased) credit ratings (Coffee (2011)). Traditionally, CRAs have been successful in claiming that credit ratings constitute opinions protected as free speech under the First Amendment. This defense requires plaintiffs to prove that CRA defendants issued ratings with knowledge they are false or with reckless disregard for their accuracy, effectively preventing most cases from proceeding to trial.[5] In contrast, Section 933 of Dodd-Frank explicitly lessens the pleading requirement in private actions under Rule 10b-5 of the Securities and Exchange Act of 1934, whereas plaintiffs must now only prove that CRA defendants knowingly or recklessly failed to conduct a *reasonable investigation* of the rating security. This change is likely to result in more lawsuits surviving CRA defendants' motion to dismiss, leading

[5] See Alicanti (2011) for a thorough review of case law applicable to credit rating agencies.

to potentially damaging revelations during pre-trial discovery. Section 933 takes effect immediately with the signing of Dodd-Frank into law.[6]

Another immediate change in CRAs' liability for issuing erroneous ratings comes from Section 939G, which makes CRAs liable as experts under Section 11 of the Securities and Exchange Act of 1934 for material misstatements and omissions in registration statements filed with the SEC. Prior to Dodd-Frank, CRAs were effectively shielded from such liability by Rule 436(g), which allowed CRAs to avoid consenting to being "experts" for the purpose of Section 11. Section 939G expressly overrules Rule 436(g). The reaction of CRAs to this change has been swift; CRAs refused to consent to having their ratings included in the registration statements for both structured finance products and corporate bonds (Coffee (2011)). The result was that the market for asset-backed securities froze, leading the SEC to suspend Section 939G for structured finance products (but not for corporate bonds). The refusal of CRAs to provide any ratings for new corporate bond issues eliminates CRAs' potential liability under Section 939G, making this section less relevant for our findings. However, it is worth noting that CRAs' actions in response to Section 939G show how imposing strict penalties on CRAs can lead to a complete loss of CRAs' information in the market for new corporate bonds.

Regulatory Penalties

The second set of provisions of Dodd-Frank that ex-ante are likely to have an effect on the CRA market in general, and on corporate credit ratings in particular, concerns SEC's expanded role in the CRA market. Section 933 states that the enforcement and penalty provisions of federal securities law apply to the statements made

[6] More subtle is the change in language adopted in Section 932(a), requiring that CRAs "file" rather than "furnish" statements with the SEC. This provision makes CRAs liable for filing false reports under Section 18 of the Securities and Exchange Act of 1934.

by CRAs to the same extent as these provisions apply to registered public accounting firms or securities analysts. Furthermore, Section 933 specifically states that CRAs' statements are no longer considered forward-looking for the purpose of the safe provisions of the Securities and Exchange Act of 1934. These changes in the law make it easier for the SEC to bring claims against CRAs for material misstatements and fraud.

The increase in mandated disclosures under Section 932 of Dodd-Frank further increases the risk of regulatory penalties. According to Section 932, CRAs must file annual reports on internal controls with the SEC, disclose their rating methodologies, make third-party due-diligence reports public, and disclose the accuracy of past credit ratings. Section 932 also mandates that SEC establish Office of Credit Ratings to better monitor CRAs' compliance with the new rules. While many details regarding the disclosures are yet to be finalized by the SEC, CRAs have already begun to provide additional data to regulators (and investors). Annual reviews of the CRAs by the SEC have been taking place since 2010, and the Office of Credit Ratings was established in 2012.

In addition to bringing claims against CRAs for material misstatements and fraud, the SEC now has the power under Section 932 to revoke or suspend the registration of a Nationally Recognized Statistical Rating Organizations (NRSRO) with respect to a particular class of securities if the NRSRO's ratings are deemed inaccurate.[7] In other words, if a NRSRO is perceived to issue erroneous or biased ratings of corporate bonds,

[7] NRSROs' credit ratings are used in federal and state legislation and in financial regulations in the United States. Under current practice, CRAs must apply to the Securities and Exchange Commission (SEC) to be recognized as an NRSRO. According to the SEC, "The single most important factor in the Commission staff's assessment of NRSRO status is whether the rating agency is 'nationally recognized' in the United States as an issuer of credible and reliable ratings by the predominant users of securities ratings" (SEC (2003)).

it may lose its market share of the corporate bond market.[8] Given that CRAs are rarely accused of being overly conservative in their ratings, Section 932 can be interpreted as imposing regulatory costs for issuing upwardly biased (or overly optimistic) ratings. This provision takes effect immediately with the signing of Dodd-Frank into law.

Regulatory Reliance on Ratings

Sections 939 & 939A require each federal agency to review its regulation, identify any references to credit ratings, and remove any reference to or requirement of reliance on credit ratings. Section 939A also directs federal agencies, including the SEC and the Office of the Comptroller or the Currency (OCC), to make appropriate substitutions using alternative measures of credit-worthiness. The intent is to eliminate any sense that ratings carry a government imprimatur (see Congressional Research Service R41503). The de-emphasis of credit ratings in regulatory filings may lead to less demand for the ratings of the big three CRAs as investors turn to alternative sources of information on corporate bond issues. However, Sections 939 & 939A do not become effective with the passage of Dodd-Frank. Originally, agencies were given one year to complete the changes. However, establishing rules on alternative measures of credit-worthiness has taken longer than anticipated, and most rules come into effect as of January 2013 (which falls outside of our sample period). This delay limits the potential effect of Section 939 and 939A on our findings.

Internal Controls

Several broad guidelines with respect to CRAs' internal controls also become effective with the signing of Dodd-Frank into law. These include Section 932(a)(2),

[8] Previously, the SEC had the authority to revoke a CRAs' registration as a NRSRO if it deemed that the CRA does not have adequate resources to perform its duties as stipulated under the Credit Ratings Agency Reform Act of 2006.

requiring that NRSROs establish internal controls over the ratings process; Section 932(a)(8), prescribing requirements for NRSROs' board of directors; Section 935, requiring NRSROs to consider credible information about an issuer from third parties; and Section 938, requiring NRSROs to establish, maintain, and enforce written policies and procedures with regards to determining default probabilities and the meaning and definition of rating symbols. Observers have questioned whether such internal controls will do much to alter the functioning of credit rating agencies. Coffee (2011) points out that financial institutions failed during the financial crisis despite having similar control structures in place. Furthermore, many important details concerning internal controls and governance provisions are yet to be finalized. The SEC proposed rules mandated under Sections 932, 936, and 938 in May 2011, but has not finalized the rules as of the writing of this paper. Given that internal control and corporate governance rules are yet to be finalized, their effects on credit ratings are likely to be limited.

Other Provisions

The remaining provisions are ex-ante unlikely to affect corporate bond credit ratings. Section 931 contains the legislative intent of Congress. Sections 934 requires CRAs to report suspected violations of law by the issuer to the authorities, which increases the litigation risk of the issuer and not of the CRAs. Section 937 concerns the timeframe for the issuances of final rules by the SEC. Sections 939C, 939D, & 939E merely mandate studies by the SEC and the GAO of the credit-rating industry. Section 939F (the Franken Amendment) deals exclusively with structured finance products and not corporate bonds. Section 939B (eliminating CRAs' exemption from Regulation FD) is unlikely to affect credit ratings because CRAs entered into confidentiality agreements with the issuers. Section 939H contains the Sense of Congress.

Summary

Our reading of the law and its coverage in the press and in academia suggest that the most immediate and relevant changes in the CRA market due to Dodd-Frank are the significant increase in CRAs' liability for issuing inaccurate ratings and the strengthening of SEC's mandate to levy penalties against CRAs. Both of these changes take effect immediately with the passage of Dodd-Frank on July 2010. This is why we use July 2010 as our main event date. The removal of references to ratings in federal regulations may ultimately prove to be significant, but the effect may not be apparent for several years because many of the changes become effective in January 2013. Internal control and corporate governance reform may have a more limited effect because many of the final rules are yet to be determined.

3.3. Sample

Sample selection

We obtain all credit rating announcements during the period from January 2006 to May 2012 from Mergent's Fixed Investment Securities Database (FISD). The sample begins in 2006 to avoid any ongoing market adjustments to the 2002 Sarbanes-Oxley Act (see, for e.g., Cheng and Neamtiu (2009)). The sample includes U.S. domestic corporate bonds rated by Moody's, S&P, or Fitch, and excludes Yankee bonds and bonds issued through private placement. Ratings of D (indicating default) are excluded because these ratings are assigned ex-post. We require that each bond issuer is covered by Compustat and has market value data on CRSP (Center for Research in Security Prices) for the most recent quarter prior to the respective credit rating announcement. For cases in which more than one CRA issues a credit rating on the same date for the same bond, we keep the observation with the greatest rating change. We exclude bonds rated only by Moody's. Moody's does not provide default ratings and hence it is not possible to determine whether a bond rated only by Moody's is currently in default. We also exclude bond issuers from the financial industry. The resulting sample consists of 26,625 credit rating upgrades, credit rating downgrades, initial ratings, and ratings that are reaffirmed.

Variable measurement

Table 1 summarizes the variables used in the study and their measurement. We discuss the main variables below. Rating levels are the numerical transformation of the alphanumerical rating codes issued by CRAs, from 1 to 22 (AAA to D), as detailed in Appendix B. Following Cheng and Neamtiu (2009) and Bonsall (2014), we define a rating's Type II error (or false warning) as a dichotomous variable which equals one for a BB+ or lower rated issue that does not default within one year, and zero otherwise.

Announcement bond returns are calculated as the percentage change in bond prices from trades surrounding rating announcements.[9] Bond prices are obtained from FINRA's Trade Reporting and Compliance Engine (TRACE) database. The bond price before the rating announcement is the volume-weighted trade price on the day closest and prior to the rating announcement date. The bond price after the rating announcement is the volume-weighted trade price on the day closest to and following the rating announcement date. We measure announcement bond returns only for bond issues with

[9] Because of the different maturities, credit quality, and characteristics of the various bond issues in the sample, there is no readily available benchmark for announcement bond returns. Hence, we examine raw announcement bond returns in our analysis in Section 5.3. The contrast between credit rating upgrades and credit rating downgrades, and between industries with high and low Fitch market share, alleviates concerns that market-wide movements in interest rates might account for our findings.

at least one trade during the five days before, and the five days after, the rating announcement date.

Stock prices are obtained from CRSP and are used to calculate CAPM beta, return volatility, and excess stock returns surrounding announcements of rating changes. Announcement stock returns are calculated as buy-and-hold stock returns over the three-day period centered at the rating announcement date minus the corresponding return on the CRSP value-weighted index. We measure announcement stock returns only for issuers with non-missing returns on all three days. CAPM beta is estimated using the CRSP value-weighted index as the market index and daily returns over the most recent fiscal quarter ending prior to the rating announcement date. Idiosyncratic stock return volatility is the standard deviation of the residual from the CAPM model. Total stock return volatility is the standard deviation of daily returns over the most recent fiscal quarter ending prior to the rating announcement date.

The remaining variables are described in detail in Table 1. All financial ratios are measured for the most recent fiscal quarter ending prior to the rating announcement date. Variables with large outliers are winsorized at the 1% and the 99% level.

< Table 1 >

Summary statistics

Table 2 reports summary statistics for the variables used in the study. We refer to the period from January 2006 to July 21, 2010 as the pre-Dodd-Frank period, and the period from July 22, 2010 to May 2012 as the post-Dodd-Frank period. There are 18,606 corporate bond credit rating announcements during the pre-Dodd-Frank period and 8,019 announcements during the post-Dodd-Frank period. There are fewer observations for announcement bond returns (7,120 during the pre-Dodd-Frank period and 3,715 during the post-Dodd-Frank period) because many bond issues have no trade data around the rating announcement date. The average credit rating increases from 10.85 before Dodd-Frank to 10.125 after Dodd-Frank, corresponding to a change in S&P rating from BB+ to BBB-. The incidence of false warnings (type II rating errors) decreases from 0.448 during the pre-Dodd-Frank period to 0.392 during the post-Dodd-Frank period. The increase in credit ratings and the reduction in false warnings correspond to an improvement in market conditions following the passage of Dodd-Frank. Return on assets (ROA) and operating margins are higher after Dodd-Frank. Firms' balance sheets also strengthen after Dodd-Frank. For example, the long-term debt-to-assets ratio is 0.316 during the pre-Dodd-Frank period and 0.304 during the post-Dodd-Frank period. The other leverage measures show similar improvement. Both total and idiosyncratic volatility are lower during the post-Dodd-Frank period than during the pre-Dodd-Frank period. In the next section, we examine whether credit ratings are higher and false warnings are lower during the post-Dodd-Frank period holding firm characteristics fixed.

<Table 2>

3.4. Findings

In this section, we test whether the data are consistent with the reputation hypothesis or the disciplining hypothesis. Section 5.1 examines whether credit ratings are lower during the post-Dodd-Frank period than during the pre-Dodd-Frank period. Section 5.2 examines the incidence of false warnings before and after Dodd-Frank. Section 5.3 examines the information content of credit rating changes using bond returns data and stock returns data. Section 5.4 presents the results of several robustness tests.

We report results for the full sample and for subsamples based on Fitch's market share in each industry.

Before turning to our main results, we confirm that Fitch's market share is a meaningful proxy for reputation concerns during our sample period. First, we find that Fitch's market share varies significantly across industries and time within our sample. The average Fitch market share across the 11 Fama-French industries in 2006 is 37%, and that number increases to 53% by 2012.[10] In 2006, Fitch's market share varies from a low of 28% for consumer durables to a high of 50% for utilities. In 2012, Fitch's market share varies from 28% for business equipment to 75% for telecoms. Second, we confirm that Moody's and S&P continue to issue higher credit ratings in industries with higher Fitch market share after 2006. This result is consistent with Becker and Milbourn (2011)'s findings for the period from 1995 to 2006. It indicates that Moody's and S&P are less concerned with their reputation and hence more likely to inflate ratings in industries with high Fitch market share.[11]

Credit rating levels before and after Dodd-Frank

In this section we examine how credit rating levels change after the passage of Dodd-Frank using the credit rating model of Blume et al. (1998). Blume et al. (1998) estimate an ordered logit model of credit ratings using operating margin, interest coverage, long-term debt-to-assets, total debt-to-assets, market value of equity, stock beta,

[10] We exclude Financials from the original list of 12 Fama-French industries. The results are similar when we group firms into industries based on two-digit North American Industry Classification System (NAICS) codes.

[11] These results are available from the authors upon request.

and idiosyncratic stock return volatility as explanatory variables.[12] We augment the original model to differentiate between ratings issued by Moody's, S&P, and Fitch, and include a dummy variable for the post-Dodd-Frank period (After Dodd-Frank). Because a single firm can have multiple rating announcements in the sample, we cluster standard errors by firm.

The results of the estimation are reported in Model 1 of Table 3. We find that credit ratings are significantly lower in the post-Dodd-Frank period. The coefficient on the After Dodd-Frank dummy is 0.171, with a z-statistic of 2.14. The economic magnitude is large. After the passage of Dodd-Frank, the odds that a corporate bond is rated as non-investment grade are 1.19 times greater than before the passage of Dodd-Frank, holding all else constant. This result is consistent with the reputation hypothesis, whereas CRAs issue lower credit ratings to protect their reputation following the increase in legal and regulatory costs in the post-Dodd-Frank period. The result is also consistent with the disciplining hypothesis, whereas the increase in legal and regulatory penalties motivates CRAs to issue less optimistically biased ratings following Dodd-Frank

We next examine how the results vary with ex-ante reputational costs. Becker and Milbourn's (2011) show that Moody's and S&P are more protective of their reputation in industries where Fitch's market share is lower. We measure Fitch's market share in each industry for the year prior to the ratings announcement, and divide the sample into two subsamples – rating announcements in industries within the lowest 25th percentile of Fitch market share, and rating announcements in industries within the highest 75th percentile of Fitch market share. Model 2 includes a dummy variable for

---

[12] This has become the standard model in the literature. Our results are similar when we augment Blume et al. (1998)'s model with industry fixed effects.

rating announcements in industries with the lowest Fitch market share (Fitch market share), and an interaction of After Dodd-Frank with the Fitch market share. If reputation concerns drive CRAs to lower their ratings, we expect to find that the coefficient on the interaction variable is positive and significant (i.e., ratings are lower in the post-Dodd-Frank period in industries with low Fitch market share). The disciplining hypothesis makes the opposite prediction: any reduction in the optimistic bias of credit ratings as a result of Dodd-frank should be greater in industries with high Fitch market share because the optimistic bias in these industries is greater prior to Dodd-Frank (Becker and Milbourn (2011)).

The results are reported in Model 2 of Table 3. As in Becker and Milbourn (2011), the sample is restricted to rating announcements made only by Moody's or S&P. Consistent with the reputation hypothesis, we find that credit ratings are lower in the post-Dodd-Frank period in industries with low Fitch market share. The coefficient on the interaction of After Dodd-Frank with Fitch market share is 0.908 with a z-statistic of 3.39. Within industries in the bottom quartile of Fitch market share, the passage of Dodd-Frank lowers the odds of an investment grade rating 2.27 times (calculated as $e^{0.908-0.090}$). In contrast, within industries in the top three quartiles of Fitch market share, the passage of Dodd-Frank does not significantly affect credit ratings. These results indicate that CRAs lower their ratings after Dodd-Frank when their reputation is more valuable.

< Table 3 >

Incidence of false warnings before and after Dodd-Frank

In this section, we analyze whether the lower credit ratings following Dodd-Frank are warranted by subsequent outcomes. In our sample there are no defaults of corporate bonds within a year of an investment-grade rating (type I error). Hence, we focus on the incidence of false warnings (type II errors). If the lower ratings following Dodd-Frank are warranted, we should observe either that the incidence of false warnings following Dodd-Frank either decreases or remains the same. In contrast, if CRAs lower credit ratings to protect their reputation (and not necessarily because credit quality has deteriorated), we should observe that the incidence of false warnings is higher following the passage of Dodd-Frank. Furthermore, the effect should be stronger for industries with higher expected reputation concerns.

The regression specification for false warnings includes controls for firm characteristics (ROA, interest coverage, long-term debt-to-assets, book-to-market, log of market value, years to maturity, and total stock return volatility), and for recent bond market conditions as captured by the return on the 30-year Treasury bond index over the calendar year prior to the rating announcement date. The model also differentiates between ratings issued by Moody's, S&P, and Fitch, and includes a dummy variable for the post-Dodd-Frank period (After Dodd-Frank).

< Table 4 >

The results are reported in Model 1 of Table 4. We find a significant increase in the incidence of false warnings in the post-Dodd-Frank period. The coefficient on the After Dodd-Frank dummy is 0.607, with a z-statistic of 4.77. After the passage of Dodd-Frank, the odds of a false warning are 1.84 times greater than before the passage of Dodd-Frank, holding all else constant. Hence, the lower ratings following the passage of Dodd-Frank are not warranted ex-post. The results are consistent with the reputation hypothesis, wherein CRAs lower ratings to protect their reputation. As a result, the usefulness of ratings for predicting actual defaults is reduced.

The results for Model 2 in Table 4 provide further support for the reputation hypothesis. We find that the effect of Dodd-Frank on false warnings is significantly larger in industries where Moody's and S&P have stronger reputation concerns. The interaction between After Dodd-Frank and Fitch market share is 1.810 with a z-statistic of 4.21. Within industries in the bottom quartile of Fitch market share, the passage of Dodd-Frank increases the odds of a false warning 8.24 times (calculated as $e^{1.810+0.299}$). In contrast, within industries in the top three quartiles of Fitch market share, the passage of Dodd-Frank increases the odds of a false warning only 1.35 times. The larger the economic rents at stake, the more protective the CRAs are of their reputation as evidenced by the lower assigned ratings.

The definition of a false warnings in the above tests is admittedly stringent given that actual defaults are rare in the data. We examine the robustness of the results with respect to the definition of false warnings in by defining false warnings as speculative grade rated issues (BB+ or lower) that do not default within two years. We also define false warnings as B+ or lower rated issues that do not default within two years. In both cases, we find no change in our results.[13]

Information content of credit rating changes

---

[13] We also considered using ex-ante default probabilities such as distance-to-default to test whether the lower credit ratings following Dodd-Frank are warranted. The problem with this approach is that the correct ex-ante default probability associated with a given credit rating is not known. Without a correct mapping between credit ratings and ex-ante default probabilities, it is difficult to interpret the change in the default probability of a credit rating from the pre- and post-Dodd-Frank period. If there is a decline in the default probability of speculative grade bonds after Dodd-Frank, it is not clear if this change indicates a greater likelihood of false warnings or a better mapping between credit ratings and default probabilities.

In this section, we examine the effect of Dodd-Frank on the informativeness of credit ratings by comparing the reaction of investors to rating changes before and after the passage of Dodd-Frank. We examine the reaction of both the bond market and the stock market. The advantage of using bond data is that bond prices are more directly affected by changes in default probabilities, which credit ratings ostensibly measure. However, bonds are relatively illiquid and many bonds do not trade around rating changes. Using stock price data allows us to capture investors' reaction to nearly all credit rating changes, albeit with the caveat that stock prices are less sensitive to changes in default probabilities.

The disciplining and reputation hypotheses make different predictions about the effect of Dodd-Frank on the informativeness of credit rating changes. According to the disciplining hypothesis, Dodd-Frank improves the quality of credit ratings, making both upgrades and downgrades more informative. According to the reputation hypothesis, rating downgrades are less informative following Dodd-Frank because CRAs issue downgrades partly to protect their reputation. In contrast to downgrades, rating upgrades following Dodd-Frank are more costly because they expose CRAs to legal and regulatory penalties. To avoid the perception of biased ratings, CRAs could expand greater effort when issuing an upgrade, making upgrades potentially more informative. Nevertheless, the effect of Dodd-Frank on upgrades could be less apparent in the data because rating upgrades are significantly less timely than rating downgrades (see Holthausen and Leftwich (1986), Hand, Holthausen, and Leftwich (1992), and Dichev and Piotroski (2001)).

The distribution of rating changes over the sample period is shown in Panel A of Table 5. The frequency of upgrades is noticeably higher after Dodd-Frank, which corresponds to the improving economic conditions following the financial crisis. We also find that CRAs are more cautious after Dodd-Frank in the sense that ratings change by fewer notches.

Panel B.1 of Table 5 reports rating announcement bond returns for the full sample of credit rating downgrades and credit rating upgrades. Consistent with the reputation hypothesis, we find that the informativeness of credit rating downgrades is significantly lower after Dodd-Frank. Specifically, mean bond returns around rating downgrades are -1.023% before Dodd-Frank but only -0.654% after Dodd-Frank.[14] The difference of 0.369% is significant at the five percent level. In contrast, there is no change in the informativeness of credit rating upgrades; mean bond returns around rating upgrades are very similar before and after Dodd-Frank.

< Table 5 >

Panel B.2 & B.3 of Table 5 report rating announcement bond returns for two subsamples based on Fitch market share. The subsamples are limited to ratings of Moody's and S&P. The effect of Dodd-Frank on the informativeness of rating downgrades is significantly stronger in industries with the lowest Fitch market share. In Panel B.2, mean bond returns around rating downgrades are -1.485% before Dodd-Frank but only -0.402% after Dodd-Frank. The difference of 1.083 is significant at the five percent level. In contrast, Dodd-Frank has no effect on the informativeness of ratings downgrades in industries with high Fitch market share (Panel B.3 of Table 5). Overall,

[14] Both our hypotheses make predictions in terms of mean returns. Medians are reported along with means for completeness.

the evidence indicates that the loss of information in rating downgrades following Dodd-Frank is due to the heightened reputation concerns of CRAs.

Table 6 reports the results for the stock market's reaction to credit rating changes before and after Dodd-Frank. When there are rating changes for multiple bonds by the same company on the same date, we keep the observation with the greatest rating change. As a result, there are significantly fewer observations in Panel A of Table 6 than in Panel A of Table 5. Still, the results in Panel B of Table 6 parallel those in Panel B of Table 5. In Panel B.1 of Table 6, we find that mean stock returns around rating downgrades are -2.461% before Dodd-Frank but only -1.248% after Dodd-Frank. The difference of 1.212% is significant at the ten percent level. In Panel B.2 of Table 6, we find that the negative effect of Dodd-Frank on the informativeness of credit rating downgrades is significantly stronger in industries with lower Fitch market share. In this case, Dodd-Frank leads to a reduction in the reaction to credit rating downgrades of 2.976% (significant at the five percent level). These results are even more notable considering the small number of observations involved.

There is preliminary evidence in Table 6 that rating upgrades might be more informative following Dodd-Frank. In Panel B.1 of Table 6, we find that mean stock returns around rating upgrades are 0.062% before Dodd-Frank and 0.369% after Dodd-Frank. However, the difference of 0.308% is statistically insignificant. Furthermore, this effect is absent in industries with lower Fitch market share (Panel B.2 of Table 6), and is absent for bond returns (Table 5). Based on these results we conclude that Dodd-Frank has not had a significant effect on credit rating upgrades.

< Table 6 >

One potential concern with the stock market tests is that equity values at the time of Dodd-Frank's passage were abnormally low relative to historical values. If equities were priced for a worst-case scenario, then any bad news may be less value relevant during the post-Dodd-Frank period.[15] We address this potential concern in two ways. First, we note that equity prices and valuations are not different between the pre- and post-Dodd-Frank periods. Equity prices reached their lowest levels following the recession on March 6, 2009, with the S&P closing at 683. By the time Dodd-Frank become law in July 2010, S&P had recovered drastically, closing the month at 1,100. When we compare the level of the S&P during the periods before and after Dodd-Frank, we find similar average levels: 1,225 during the pre-period and 1,297 during the post period. S&P's earnings-to-price ratios are also similar during the two periods. The comparable levels of the S&P before and after Dodd-Frank, and the fast ascend of the market following March 2009, suggest there was ample room for equities to fall during the post-Dodd-Frank period.

Second, we include S&P 500's level and earnings-to-price ratio as control variables in a regression of stock returns around rating downgrades on a dummy variable for the post-Dodd-Frank period. Consistent with our results in Table 6, we find that the stock market responds significantly less to downgrades following the passage of Dodd-Frank within industries where Fitch has the lowest market share. These results are not tabulated but are available from the authors.

In summary, the results are consistent with the prediction of Morris (2001) and Goel and Thakor (2011) that imposing large asymmetric penalties on CRAs may lead to a loss of information in equilibrium.

---

[15] We thank the referee for pointing this out.

Business cycle effects

Dodd-Frank's passage takes place during the early stages of U.S.' recovery from the financial crisis. In this section, we examine whether our results can be explained by business cycle dynamics rather than the passage of Dodd-Frank. First, we augment the regression models in Table 3 and Table 4 with variables that vary with the business cycle. These include log of GDP, past one year market returns (using the S&P 500 Index), S&P 500 Index level, perceived firm profitability (calculated as analysts' forecasted earnings per share for the next fiscal year divided by price per share), and the firm's lagged quarterly stock returns. We find that the results in Table 3 and Table 4 are not sensitive to the inclusion of these additional controls.

Second, we perform a placebo test around the recession of 2001. We focus on the relatively mild 2001 recession because Fitch was not a significant competitor in the corporate bond ratings market during the more severe but earlier recessions of 1991-1992 and 1981-1982. Consistent with Alp (2013), we find that rating levels are significantly lower and more conservative (i.e., there are more false warnings) in the post-recession period. However, there is no evidence that the increased conservatism in the post-recession period is related to reputation concerns. Furthermore, there is no significant difference in the stock market reaction to credit rating downgrades (or upgrades) during the pre- and post-recession period. Overall, the results indicate that our findings in support of the reputation hypothesis are unlikely to be driven by the business cycle alone.

Evolution of Dodd-Frank

Dodd-Frank underwent several major changes prior to becoming law. In July 2009, the first version of the legislation was introduced in the House of Representatives.

It contained limited CRA provisions, primarily related to regulatory reliance on ratings. In December 2009, revised versions were introduced in the House of Representatives by Financial Services Committee Chairman Barney Frank, and in the Senate Banking Committee by Chairman Chris Dodd. These versions contained the outlines of the CRA provisions that were eventually included in the final bill. Further negotiations from December 2009 until the law's final passage in July 2010 altered many of the original provisions. We expect that the uncertainty surrounding the passage of the bill is reduced as the legislative process moves closer to the final signing of the bill by President Obama. The initial introduction of the bill may have a muted effect on credit ratings, but the effect should strengthen as uncertainty is reduced.

< Table 7 >

In Table 7, we redefine the post-Dodd-Frank period to start in July 2009, December 2009, or May 2011, respectively. We then reestimate the regression specifications for rating levels and false warnings for each of the alternative starting dates. Panel A of Table 7 reports the results for regression specifications corresponding to the results in Table 3 for rating levels; Panel B of Table 7 reports the results for regression specifications corresponding to the results in Table 4 for false warnings. For brevity, we only show the coefficients on the two relevant variables – the After Dodd-Frank dummy from Model 1, and the interaction of the After Dodd-Frank dummy with Fitch market share dummy from Model 2. We also report the original results for comparison. We find that our results for credit rating levels and false warnings get stronger as the uncertainty surrounding the passage of Dodd-Frank is reduced. For example, in Panel A, the coefficient on the interaction of the Dodd-Frank dummy with the Fitch market share dummy increases from 0.342 for the July 2009 date, to 0.754 for the December 2009 date, and to 0.908 for the July 2010 date. The pattern is similar in Panel B.[16] We also find that results do not change notably following May 2011, when the SEC issued proposed rules on CRAs' internal controls and corporate governance. This finding reinforces our conclusion that the CRAs' response to Dodd-Frank is mostly driven by the legal and regulatory penalties stipulated under Dodd-Frank.

[16] Given the small samples in Tables 5 and 6, we do not find any significant variation in the effect of Dodd-Frank on the informativeness of rating downgrades as we alter the starting date of the post-Dodd-Frank period.

Chapter 4: Geographic Location of the Firm and Credit Rating Accuracy

4.1. Introduction

It is well documented in the literature that credit ratings play an important role in stock pricing, firm valuation, contracts, and regulations (e.g. Beaver, Shakespeare and Soliman, 2006), and their accuracy has an impact on the reputation of rating agencies (e.g. Strausz, 2005; White, 2002). In order to achieve higher accuracy for credit ratings, the major rating agencies use quantitative as well as qualitative information[17] (Fitch 2007; Moody's 2002; Standard & Poor's 2008), which is also referred to as hard and soft information.[18] In this study, we focus on soft information[19] and provide evidence that proximity of geographic location of firms, i.e. distance between the offices of firms and rating agencies, is an important source for soft information, which leads to higher accuracy for bond ratings and improves the timeliness of downgrades. These findings thus document that geographic proximity is an important determinant of bond ratings.

Several studies have previously examined the role of geographic proximity in the decision making process in different areas. Kang and Stulz (1997) and Huberman (2001) have examined the role of proximity in investment decisions, and they document that investors invest more in firms that are close to their home because they have better information about these firms (also see Coval and Moskowitz, 1999), and they refer to it as a "home bias" hypothesis. In this regard, Huberman (2001) argues that informational

---

[17] Frost (2007) notes that the major rating agencies use significant amount of qualitative information along with analysis-driven approaches to develop credit ratings.

[18] For discussion on the role of hard versus soft information in the decision making process refer to Petersen (2004), and Stein (2002).

[19] The term soft information can be used for different types of non-quantitative information. Kraft (2012) presents that soft information may capture assessment of management quality, aggressive accounting, governance risk, industry structure, and financial policy. In this study, we focus on soft information that is obtained by the credit analysts through informal information channels and face-to-face meetings with management.

advantages motivate investors to favor nearby investments. Kedia and Rajgopal (2011) have evaluated the role of geographic distance to test the "differentially informed criminal" hypothesis and they document that "counties closer to the SEC are associated with significantly lower misreporting deviations". They interpret their results to support "the differentially informed criminal hypothesis" that firms have heterogeneous information about regulatory oversight. Malloy (2005) documents the role of geographic proximity in terms of informational advantages which improve the accuracy of analysts' forecasts.

We extend the geographic proximity argument to the ratings of bonds that are issued by three major rating agencies, i.e. Moody's, Standard and Poor's (S&P), and Fitch. We argue that proximity of a firm's headquarters to the credit rating agency's (CRA) headquarters provides an opportunity to the bond rating analysts to obtain soft information through common professional, social, and cultural contacts, which enables them to make more accurate ratings. The geographic proximity argument also suggests that certain time and distance constraints are relaxed for the rating analysts to visit firms for obtaining information that is difficult to codify and transmit, but can be obtained through face-to-face meetings. Thus, convenient geographic location makes it easier for the rating analysts to obtain soft information through house calls instead of waiting for conference calls (e.g. Malloy 2005). It is further argued that information obtained from the face-to-face meetings is generally of higher quality compared to that obtained from conference calls or surveys (e.g. Graetz et al., 1998; Baltes et al., 2002; Alge et al., 2003). Furthermore, information obtained through non-verbal means is considered even more useful than information obtained through verbal means. Mehrabian (1972) argues that as much as 93 percent of information communicated through non-verbal channels is useful.[20] These arguments lead us to hypothesize that availability of soft information as a result of geographic proximity will enable the rating analysts to achieve higher accuracy for credit ratings. Because headquarters of all CRAs covered in this study are located in New York City (NYC), [21] our hypothesis implies that the rating errors are positively associated with geographic distance, meaning that the rating errors are higher for firms that are located away from NYC compared to the firms with headquarters in NYC or close to NYC.

Additionally, we evaluate whether the positive association between rating errors and geographic distance are influenced by firm complexity and analyst following. With regard to firm complexity, we argue that availability of soft information is especially useful to enhance accuracy of ratings for complex firms because it will enable the credit analysts to have a better understanding of the complicated business models and intricate business operations of complex firms (e.g. Scherer, 1965; Churchill and Lewis, 1983). Thus, availability of soft information obtained through visits to firms will assist the credit analysts to develop better ratings for these firms. Conversely, firm complexity will aggravate the ratings analysts' lack of understanding of the firms that are located far away from NYC and suffer from non-availability of soft information. Based on these arguments, we hypothesize that the rating accuracy of firms away from NYC will even be

---

[20] Though any kind of information can be obtained through face-to-face meeting, but this type of information is especially emphasized in the psychology literature (e.g. Mehrabian, 1972; Knapp, 1972).

[21] New York City may exhibit a unique mix of industries and borrower characteristics. For instance, the concentration of large multinational firms in NYC may make them more complex and difficult to rate. We control for this effect on credit ratings with a NYC dummy.

lower if they are complex and are located away from NYC. We use product lines as a proxy for firm complexity (e.g. Bushman et al., 2004).

With regard to analyst coverage, findings of extant research indicate that firms with more analyst coverage have lower information asymmetry and higher visibility (Frankel and Li, 2004; Uysal, Kedia and Panchapagesan, 2008). Cheng and Subramanyam (2008) argue that coverage of firms by security analysts also has an impact on monitoring of managerial behavior and actions, which result in lower information asymmetry. Based on this evidence, we argue that higher coverage of firms by security analysts will reduce information asymmetry, which will in turn reduce importance of soft information for bond ratings. On the other hand, a lower analyst following will enhance the need for soft information to compensate for lower firm visibility and higher information asymmetry. These arguments lead us to hypothesize that the positive association between geographic distance and error ratings will be stronger for firms with low analyst following.

We use the U.S. firms rated from 1992 through 2010 to examine the accuracy of their bond ratings by the three largest credit rating agencies (CRAs). We evaluate the rating accuracy of bonds and the timeliness of downgrades prior to the default of bonds (for discussion on downgrades refer to Cheng and Neamtiu, 2009), and we define rating accuracy in terms of missed defaults, measured by type 1 error, and false warnings, measured as type 2 error. We conduct logistic regressions to test our hypotheses on the rating accuracy and OLS regressions to evaluate the timeliness of downgrades.

Our findings show that there is a significantly positive association between the rating errors and geographic distance. The rating errors increase as distance between

NYC and location of firm headquarters increases. The likelihood of missed defaults (Type 1 error) increases by 5.2 percent and the likelihood of false warnings (Type 2 error) increases by 2.1 percent for every 100 kilometers the firm is located away from NYC. The results also show that the timeliness of downgrades improves with lower geographic distance.

With regard to complexity, the findings show significantly higher missed defaults and lower timeliness of downgrades for complex firms with offices located away from NYC. These findings show that access to soft information is more important for complex firms located far away from NYC. Thus, our findings confirm that the complex and multifaceted nature of diverse firms make the availability of soft information more important for developing accurate credit ratings, especially when the firms are located away from NYC. The results for type 2 error, however, do not show any significant impact on the association between the rating errors and geographic distance, indicating that there is no incremental effect of complexity on false warnings.

With regard to the impact of analyst coverage, our findings show that the positive association between geographic distance and missed defaults and geographic distance and less timely downgrades is weaker for the firms with higher analyst coverage, suggesting that high analyst coverage moderates the association between rating errors and distance. The results thus show that the impact of soft information is more valuable for firms located away from NYC when information asymmetry is high, i.e. analyst following is low. The results for type 2 errors, however, show that there is no significant impact of analyst following. This indicates that there is no significant differential impact of analyst following on developing false warnings.

We test the robustness of our findings by including industry fixed effects to control for the possibility that certain industries may be harder to rate, and also include time fixed effects in the regression analyses to control for variation within the sample time period. The results show that our main findings remain unchanged when fixed effects are included in the analyses.

We conduct additional analysis to evaluate whether easy accessibility of firm headquarters to NYC will make it easier for the credit rating analysts to visit companies for face-to-face meetings and obtain soft information. We use the availability of direct flights from NYC to the firm headquarters as a proxy for easy access to the firm. We expect that firms headquartered in cities without direct flight access from NYC will comparatively be less accessible to the rating analysts and thus we expect their rating errors to be comparatively higher. The results of this analysis show that the rating accuracy as well as the timeliness of downgrades is lower for the firms that are located in cities without direct flights from NYC. This finding thus suggests that the rating analysts are less likely to conduct site visits for face-to-face meetings for the firms that have headquarters in location with less accessibility from NYC.

We also evaluate how rating analysts react to geographic distance which may result in lower availability of soft information. We examine whether analysts are motivated to rate bonds optimistically because that may be more beneficial to the firm and to them, especially when their contracts are tied to credit ratings (e.g. Kraft, 2011). Our findings show that the rating analysts rate the bonds lower when geographic distance is greater. We interpret this finding to suggest that analysts protect themselves and their agencies against any potential risk associated with higher ratings, and thus they assign lower ratings to firms located farther away from NYC (e.g. see Goel and Thakor, 2011 for theoretical arguments).[22] Our analyses, however, also indicate that the lower ratings given to these firms do not result in lower type 1 errors and there is no improvement in the timeliness of downgrades. Thus, this finding suggests that lower ratings do not fully compensate for missing soft information.

Our findings have important implications for market participants in the $8.1 trillion U.S. corporate bond market[23], and they make the following contributions to the literature. First, the findings add to the literature on the importance of soft information for evaluation of risk associated with credit ratings (e.g. Kraft, 2011; Kraft, 2012; Butler and Cornaggia, 2012). The existing literature also emphasizes that credit ratings plays an important role in evaluating bond risk (Grier and Katz, 1976; Hand, Holthausen and Leftwich, 1992; Hite and Warga, 1997). We contribute to this debate by documenting that geographic proximity is an important factor to determine the availability of soft information, which can be used in evaluating bond risk.

Second, our findings document geographic proximity is an important determinant of credit rating accuracy. Thus, our findings add to the literature that shows that geographic proximity provides useful information for different types of decisions. They especially supplement the findings on the role played by proximity in the monitoring process by a regulatory agency (e.g. Kedia and Rajgopal, 2011). Our findings provide additional evidence on the importance of geographic distance for decision making, such as monitoring by regulatory agencies, investment decisions, etc.

---

[22] Goel and Thakor (2011) present a theoretical argument that the rating agencies may be more conservative when risks and uncertainty are high. Our empirical findings support their argument.
[23] According to the Securities Industry and Financial Markets Association (SIFMA), as of Q1 2012.

Finally, our findings provide support to the CRAs' views that soft information is important for rating decisions, which is especially emphasized by S&P and Fitch. The S&P emphasizes the importance of soft information in their statement that credit analysts are likely to "weigh qualitative information" more than the model-driven credit ratings which are based solely on evaluation of financial information (Standard and Poor's, 2010). Similarly, the Fitch Rating Agency emphasizes that qualitative information is responsible in "roughly equal measure" for the changes in credit ratings (Fitch, 2007).

4.2. Hypotheses

Association between Rating Errors/Timeliness and Geographic Distance

It is well documented in the literature that geographic distance plays a significant role in providing soft information that helps investors to make investment decisions as reflected by stock returns (e.g. Coval and Moskowitz, 2001; Uysal, Kedia and Panchapagesan, 2008; Stotz, 2011). Findings show that, consistent with the "home bias" argument, investors invest more in firms that are close to their home because they have better information about these firms (e.g. Coval and Moskowitz, 1999). Additionally, Kedia and Rajgopal (2011) present that consistent with the notion that firms in counties closer to the SEC are associated with significantly lower misreporting deviations. Malloy (2005) documents that geographic proximity provides informational advantages to analysts which results in higher forecast accuracy. Based on the evidence that geographic location provides an important input to the decision making process, we argue in this study that soft information, proxied by geographic proximity, also plays an important role in the rating decisions on corporate bonds. We expect the proximity of firm location to the rating analysts' headquarters to provide an opportunity to the rating analysts to obtain soft information that will enable them to achieve higher accuracy and more timely downgrades for their ratings, and we present the following arguments in support of our expectation.

First, it is argued that geographic proximity of the firm to the rating agency will enable the rating analysts to obtain information that is difficult to codify but can only be obtained through shared and common professional, social and cultural relations. Thus, the rating analysts will have additional information for firms that are located in close proximity of their headquarters, i.e. in NYC or close to NYC, compared to the firms which are located far away from their offices.

Second, it is argued that there is a certain type of information that cannot be codified and transmitted, but can be communicated through face-to-face meetings, especially through non-verbal means (e.g. Malloy 2005). It is argued that information obtained through non-verbal means in the face-to-face meetings can especially be more useful than that obtained through verbal means (e.g. Mehrabian, 1972). The rating analysts will be more likely to obtain this value relevant information from the geographic proximity as it will relax the time and distance constraints for meetings with firm managers. This will make it feasible for the rating analysts to obtain information through direct contacts. Thus, meetings with managers will enable the rating analysts to have a better understanding of the firms which will improve the overall quality of information available to analysts for developing their ratings.

The above arguments thus suggest that the rating errors are expected to be lower and downgrades more timely for firms with lower geographic distance from the CRAs' headquarters, compared to the firms that have headquarters with higher geographic distances. In contrast to this argument, there is an alternative explanation for the difference in the rating errors of firms away from NYC compared to the firms located in NYC or its vicinity. It is argued that differences in the rating errors of the two groups may primarily be due to inefficient processing of hard information. This argument suggests that the reliability of hard information rather than non-availability of soft information has an impact on accuracy (e.g. DeFranco et al., 2011; Kim et al., 2012). The validity of this alternative explanation is, however, considered questionable because the negative effect of inefficient processing of hard financial information on the rating errors can be mitigated by making certain adjustments to hard information, which reflect the underlying economic value of assets and liabilities (e.g. S&P, 2008; Moody's, 2006).[24] Moreover, it is argued that comparability of hard information across firms is more likely to differ because of the difference in the nature of the firm's business (industry) rather than geographic distance. An empirical study is therefore needed to evaluate the validity of expectations formulated in this study and alternative explanations. The results of this study will provide useful information on the role of soft information in providing higher accuracy to bond ratings.

We develop the following hypothesis to test the impact of soft information obtained through shared professional, social and cultural relations and direct contacts with management, on the accuracy of credit ratings and timeliness of downgrades:

> **H1: There is a positive relation between the rating errors and geographic distance of firm and CRA Headquarters and negative relation between the timeliness of downgrades and geographic distance of firm and CRA Headquarters.**

---

[24] CRAS make adjustments to financial statements with respect to defined benefit pensions, operating leases, hybrid securities, securitizations, capitalized interest, and etc. For instance, operating leases are capitalized and securitizations that do not fully transfer risk are treated as collateralized borrowings. Furthermore, inventory is adjusted to a FIFO basis for all firms.

Impact of Firm Complexity and on the Rating Errors/Downgrade Timeliness and Geographic Distance

Next, we examine whether firm complexity has an impact on the association between geographic proximity and credit rating accuracy[25] and timeliness of downgrades. We use product lines as a proxy for firm complexity. It is argued that firms with less product lines are less complex, have simpler business models, and their operations are generally straightforward (e.g. Bushman et al, 2004). Thus, it is easier for credit analysts to analyze these less complex firms. On the other hand, firms with more products develop a corporate structure that increases the firm's complexity, which would require more coordination among product divisions. Moreover, addition of more product lines will make the firms more diverse and complex, which would require more detailed analyses and comprehensive information by rating analysts. Thus, highly complex firms will require extra effort to collect information, and soft information will especially become more useful for developing accurate credit ratings (e.g. Butler and Cornaggia, 2012).

The above discussion suggests that firm complexity will aggravate the lack of information for firms which are located far away from NYC. The business complexity will make availability of soft information more important for the rating analysts to develop accurate ratings. We, therefore, hypothesize that business complexity will increase the rating errors of firms that are located far away from NYC. Similarly, the

[25] Skreta and Veldkamp (2009) argue that complexity affects credit ratings. They further state that "an increase in the complexity of recently-issued securities could create a systematic bias in the disclosed rating (abstract)"

timeliness of downgrades will be adversely affected for these firms. We develop the following hypothesis to test the impact of firm complexity.

H2: The positive relation between rating errors and geographic distance and negative relation between the timeliness of downgrades and geographic distance will be stronger for complex firms.

Impact of Analyst Coverage on the Association between Rating Errors/Downgrade Timeliness and Geographic Distance

The extant literature on analysts' earnings forecasts suggests that coverage of a firm by a higher number of security analysts results in a broader coverage that reduces information asymmetry and enhances visibility of firms (e.g. Frankel and Li, 2004; Uysal et al., 2008). It is argued that reduction in information asymmetry as a result of a wider coverage of firms is achieved because it impacts disclosure policies of firms, such as disclosure of earnings guidance, management of earnings forecasts, and earnings quality (Cheng and Subramanyam 2008). In this study, we examine whether higher following by analysts will have an impact on the association between rating accuracy/timeliness of downgrades and geographic distance of firm headquarters. Based on the existing evidence, we argue that lower analyst following, which increases information asymmetry, will especially aggravate the positive association between rating errors and geographic distance.

Our argument is based on the expectation that the rating analysts will need more detailed and reliable information for developing accurate ratings for firms with low analyst following because of higher information asymmetry. But higher information asymmetry as a result of low analyst following will not be problem for firms located in NYC or its vicinity because soft information will become easily available, which will compensate for higher information asymmetry. Based on the arguments that access to soft information will be especially important for firms with low analyst forecast and located away from NYC, we develop the following hypothesis:

> **H3: The positive relation between rating errors and geographic distance and negative relation between timeliness of downgrades and geographic distance will be stronger for firms with low analyst following.**

4.3. Sample

Data

We use the *Mergent Fixed Investment Securities Database (FISD)* to obtain both bond ratings and default information from 1992 through 2010 (different steps in the data selection process are provided in Appendix C). We focus on the ratings from the three largest rating agencies, i.e. Moody's, S&P and Fitch. The firms must be rated at least by one of the three rating agencies to be included in the sample. If the same entity is rated by three different agencies, we treat each rating as a separate observation. It is important to note that these ratings are predictions and therefore they are assigned ex-ante, i.e. before any default takes place. There is, however, another set of ratings of DDD/DD/D which are assigned in the event of an actual default, and we use these ratings to define bond default. We cross validate the measure of default with bankruptcies indicated on the UCLA-LoPucki Bankruptcy Research Database. We also assign numerical codes from 1 through 22 to each ratings expressed in alpha code (AAA through D) (details on converting alpha to numerical are provided in Appendix B).

We obtain data on quarterly financial information and on firm product lines from the *Compustat* database; data on market values are extracted from *the Center for Research in Securities Prices* (CRSP), and we use the *I/B/E/S summary history database* to obtain information on the number of analysts following a firm. While each rating agency has many regional U.S. offices, corporate analysts have a limited presence in them.[26] For example, Moody's U.S. corporate analysts are only stationed in NYC.[27] One commonality among the three agencies is that they all are headquartered in NYC. Therefore, we define distance from the rating agency as the distance from NYC. Because of non-availability of market value data on *CRSP and Compustat* for the most recent quarter prior to the respective credit rating announcement for some observations, the final sample consists of 96,271 observations.

To estimate distance between cities, we use the latitude and longitude of cities available from the U.S. Census Bureau Gazetteer, and use the Haversine Formula for this purpose[28]. We obtain information on fight routes to NYC from online searches, and we include three major airports in the NYC metropolitan area in determining the flights to NYC, i.e. LaGuardia Airport, John F. Kennedy International Airport, and Newark Liberty International Airport.

Methodology

Rating Accuracy and Timeliness

Consistent with Cheng and Neamtiu (2009), we measure the rating accuracy in terms of two rating errors, i.e. the rating error for missed default (type 1 error) and the

---

[26] Information on the rating agency offices are obtained from online searches. Details on analysts disclosed by Moody's provide exact analyst count for each office location, whereas S&P and Fitch only provide general office and headquarter information.

[27] See http://www.moodys.com/Page/findanalyst.aspx (As of 2012 all corporate analysts were exclusively in NYC).

[28] The Haversine Formula calculates the shortest distance over the earth's surface:

$$a = \sin^2(\Delta lat/2) + \cos(lat1).\cos(lat2).\sin^2(\Delta long/2)$$
$$c = 2.\text{atan2}\,(\sqrt{a}, \sqrt{(1-a)})$$
$$d = R.c$$

where R is earth's radius (mean radius = 6,371km) rating error for false warning (type 2 error)[29]. We use the investment grade boundary and a two-year time horizon to define Type 1 and Type 2 errors. If a firm has a rating of an investment grade or higher and it defaults within 2 years of the rating date, we consider it as rating error of type 1[30]. In other words, if the rating analyst does not predict default and it defaults within two years after the rating was assigned, it is considered as type 1 error. On the other hand, if the firm is rated below investment grade (which is considered as speculative grade), and the firm does not default within two years, it will be considered as type 2 rating error. In other words, the rating analyst provided false warnings for default potential.

We do not consider boundaries below the investment grade level because Moody's ratings will typically factor in an "expected recovery"[31], which is a predicted probability of how much principal may be ultimately paid to the bondholders in the event of default.

The timeliness of downgrades is defined by the number of days between the downgrade date and the default date for each bond issue. The event window for downgrades is limited to a two-year period prior to default to gauge the timeliness of downgrades within a close period of possible future default[32]. For instance, if a bond is

---

[29] Although we examine both type 1 and type 2 errors to determine overall accuracy, we deem a missed default (type 1 error) to be more serious because it results in greater losses to investors. Holthausen et al. (1986) and Goel and Thakor (2011) also note that missed downgrades may have greater reputational costs than missed upgrades.
[30] Alternatively, we also use different rating horizons in our sensitivity analyses, such as 1, 3 and 5 years. The results are presented in the subsection on additional analyses.
[31] Moody's ratings factor in "expected recovery". Therefore, a bond which is in default will still have an ex-ante rating which anticipates recovery rates. These recovery rates are based on a prediction of how much principal a bond holder may ultimately recover in the event of a default. However, ratings with a high "expected recovery" will not have an investment grade rating.
[32] We also examine alternative events windows of 1 year prior to default and all downgrades prior to default. Our results are robust to these specifications.

downgraded 100 days prior to default, that particular downgrade would be assigned a value of 100.

Logistic Regression Models to Evaluate Rating Accuracy

We use a logistic model to test the effect of geographic proximity on the error measures, i.e. type 1 and type 2 errors. Because each firm may have multiple bond ratings that are tracked through time, the use of a normal logistic model will incorrectly underestimate the standard error of regressors. In order to correct the underestimation problem, we use a logistic regression clustered by both a firm ID (GVKEY) and time (fiscal quarter). Petersen (2009), Thompson (2011), and Cameron et al. (2011) argue that the approach that clusters along the dimensions of firm and time corrects for correlations among different firms in the same year and different years in the same firm. The logistic model clustered by GVKEY and fiscal quarter is as follows:

$$\begin{aligned}\text{ErrorMeasure}=\beta_0 &+\beta_1\text{Distance\_to\_NYC}+\beta_2\text{Moodys\_Rating}+\beta_3\text{Fitch\_Rating}+\\ &\beta_4\text{Maturity}+\beta_5\text{NYC\_dummy}+\beta_6\text{Financial\_Crisis}+\beta_7\,\text{2001\_Recession}+\\ &\beta_8\text{ROA}+\beta_9\text{Log\_Market\_Value}+\beta_{10}\text{Interest\_Coverage}+\beta_{11}\text{Return\_Volatility}+\\ &\beta_{12}\text{Book\_to\_Market}+\beta_{13}\text{Debt\_Equity\_ratio} \qquad (1)\end{aligned}$$

We provide description of variables used in the analyses in Table 1.

<Table 1>

The dependent variable of "ErrorMeasure" can be type 1 or type 2 error, and we conduct separate tests on these two measures. The bond that has the rating of an "investment grade" and defaults within 2 years, it is considered to be rated incorrectly and in this case, the type 1 error is coded as"1", otherwise "0". The type 2 error is coded as "1" if a bond receives a speculative grade rating and does not default within 2 years, and it is coded as "0" if it defaults.

OLS Regression Model to Evaluate Timeliness of Downgrades

We evaluate the impact of geographic location on the timeliness of downgrades by using OLS regression with the dependent variable of DAHEAD, which is defined as the number of days between a downgrade date and a default date. DAHEAD measures the timeliness of downgrades and if the firm is downgraded several times before an eventual default, there is more than one value for the downgrades and this result in more observations. A lower DAHEAD value would indicate lower timeliness because bonds are downgraded closer to a default date. We use equation (1) with dependent variable of DAHEAD instead of ErrorMeasure.

Test and Control Variables

The test variable of distance to NYC is measured by the number of kilometers that a company's headquarters is away from NYC. We also include dummy variables for Moody's and Fitch rating and also for NYC firms. To control for exogenous shocks that may have an impact on rating accuracy, we include dummy variables for the 2001 recession and the financial crisis. We also include other control variables which may affect the timeliness and accuracy of ratings (Cheng and Neamtiu, 2009). Additionally, we control for the return on assets (Compustat Quarterly data68/date44), interest coverage (Compustat Quarterly data8/data22), debt to equity ratio (Compustat Quarterly data51/data59), volatility of returns (lagged quarterly standard deviation of daily returns calculated from the CRSP daily stock file), and the book to market ratio (Compustat Quarterly data59/(data12*data61)). Because the degree to which a rating agency monitors a bond issue influences the accuracy of its rating, we control for the characteristics that may influence the monitoring activity and also have an impact on the error measure. We use the maturity of the bond issue and log of market value (Compustat Quarterly data12*data61) as additional control variables.

We winsorize all variables at the 1st and 99th percentiles to mitigate the outlier effect, except for the variable of distance, variables with logarithmic values, and dummy variables.

4.4. Findings

Descriptive Statistics

Descriptive Statistics are provided in Table 2. The average distance of firms from NYC is 1,322 kilometers. Occurrences of Type 1 rating errors are 0.8% of the entire sample, while type 2 rating errors are 29.6% of the sample. The average number of days between downgrades and defaults during a two year window prior to default is 199 days.

<Table 2>

Regression Results

Results on the association between Distance and Rating Errors

Test Results on Missing Defaults (Type 1 error)

We first examine the rating errors for missed defaults by conducting logistic regression tests with type 1 error as the dependent variable. As mentioned earlier, if a bond rating is investment grade and the firm defaults within two years, the ErrorMeasure is coded as 1, otherwise zero. The results are presented in Table 3.[33]

< Table 3>

The results for Model 1 show that the coefficient of "Distance to NYC" is positive and significant at the 1 per cent level, indicating that as the distance between the firm headquarters and NYC increases, type 1 error increases. This result suggests that bonds

[33] The coefficients of logistic regressions are presented as log odds ratios.

rated with investment grade ratings are more likely to default if the firm is located further away from NYC compared to the NYC firms or firms located close to NYC. More specifically, the results show that for each 100 kilometers the firm moves away from NYC, the likelihood of type 1 error increases by 5.2 percent.[34] The results also show that Moody's ratings are less likely to miss defaults compared to S&P ratings, which is indicated by the negative and significant coefficient for Moody's. Separate F-test results on the coefficients show that type 1 errors are significantly different between the Moody's and S&P ratings, but there is no significant difference in the type 1 errors between Moody's and Fitch (untabulated). The results on a comparatively lower error for Moody's are consistent with Livingston et al.'s (2010) results, which indicate that Moody's is more conservative relative to S&P.

Test Results on False Warnings (Type 2 error)

We conduct logistic regression with type 2 error as the dependent variable to evaluate the rating errors for false warnings. The rating error is coded 1 if the bond rating is speculative but the bond does not default within two years, and zero otherwise. The results are presented in Table 4.

<Table 4 >

The results for Model 1 show that the coefficient for "Distance to NYC" is positive and significant at the 1 per cent level. This result suggests that as distance of firms from the rating agency headquarters increases, there is a higher probability of false warnings. The results specifically show that for every 100 kilometers the firm moves

[34] To compute the percentage increase in error rate, we take the difference in the exponentials between 100 kilometers as [exp (100*.00048)-exp (.00048)] =0.052 or 5.2 percent.

away from NYC, the likelihood of false warnings increases by 2.1 per cent[35]. This result indicates that lack of access to soft information as a result of longer distance between the headquarters of CRAs and firms leads to less accurate ratings.

Test Results on the Timeliness of Downgrades

We examine the timeliness of downgrades by conducting an OLS regression test with DAHEAD as the dependent variable. The results are presented in Model 1 of Table 5.

<Table 5 >

The results show that the variable of "Distance to NYC" is negative and significant at the 5 per cent level, indicating that downgrades for firms with longer distance from NYC occur with delay and closer to the default dates, suggesting that downgrades are less timely for the firms that are further away from the rating analysts.

Discussion on Control Variables

Bonds with higher years to maturity are likely to command greater attention from CRAs and this leads to more accurate ratings, which is indicated by the negative coefficient both for type 1 and type 2 errors. These coefficients are consistent with our expectations. The variables for recession, return on assets, return volatility, debt/Equity ratio, and book-to-market ratio are especially significant. Amato and Furfine (2004) present that the stability of credit ratings over the economic cycles may result in ratings which are relatively high during recessions and low during economic booms. Consistent with this argument, we find that type 1 errors are higher during recessions while type 2 errors are lower. The stock return volatility and debt to equity ratio, which capture

[35] To compare distance to NYC, we take the difference in the exponentials between 100 kilometers as [exp (100*.00021)-exp (.00021)] =0.021 or 2.1 percent.

riskiness and firms which may be more difficult to rate, are positive for type 1 and type 2 errors.

Overall Results on Hypothesis H1

Overall, the results show that the likelihood of missed defaults, false warnings, and less timely downgrades increases as the distance of firms from NYC increases. These results are thus consistent with our hypothesis H1 that the rating errors/lower timeliness increase as the geographic distance of the firm headquarters from the rating agency headquarters increases.

Impact of Firm Complexity on the Association between Rating Errors and Geographic Proximity

The impact of firm complexity on the association between distance and type 1 error is examined by identifying product diversification of firms, indicated by the number of product segments mentioned in the *Compustat* database. We conduct this test on the total sample as well as on the high and low subsamples classified based on firm complexity[36]. The variable Complexity, is coded as 1 (higher complexity) for firms with segments above the median of all firms, and otherwise 0. The interaction term between Complexity and Distance to NYC will indicate whether firm complexity has an incremental effect on rating errors. We also conduct two sensitivity tests by using alternative classification criteria for Complexity. First, we measure Complexity based on quartiles. The variable of Complexity for observations in the quartile with highest complexity is coded as 4, and observations in the median and bottom quartiles are coded as 3, 2 and 1, respectively. Second, we use Complexity as a continuous variable in the

[36]For the subsample tests, the sample is divided based on the median of segment numbers of all firms.

test. Because the results of all three tests are not significantly different, we tabulate the results based on the median number of product segments in Table 6.

< Table 6 >

The results for Model 1 in Table 13 show that the coefficient of the interaction term between Distance and Complexity is positive and significant, indicating that type 1 error is higher for more complex firms that have headquarters away from NYC. Thus, these findings are consistent with hypothesis H2 that the positive relation between rating errors and geographic distance is stronger for firms with higher complexity. These findings suggest that soft information is especially valuable to credit analysts for complex firms located away from NYC.

The results on type 2 error are presented in Model 2 (Table 13). The results show that the coefficient of the interactive term is positive but insignificant. This result indicates that complexity has no significant impact on the association between false warnings and geographic proximity, which is inconsistent with our hypothesis 2. Type 2 errors represent speculative ratings for firms which do not default. These results thus imply that firm complexity does not have an incremental effect on the association of type 2 errors and geographic distance.

The results on the timeliness of downgrade (Model 3, Table 13) show that the interaction term is significantly negative, indicating that analysts' performance with regard to the timeliness of downgrades is even worse for complex firms that have headquarters away from NYC. This finding also supports our hypothesis H2 that the negative association between downgrades and geographic distance is stronger for complex firms.

We also conduct regression tests separately on the subsamples of high complexity and low complexity observations. Consistent with the results based on the total sample for type 1 error and timeliness of downgrades, the results (untabulated) for these tests show that the coefficient for "Distance to NYC" is statistically significant for the group with high complexity, whereas it is insignificant for the group with low complexity. Consistent with the findings for the total sample, the results for type 2 errors show the association between type 2 errors and geographic distance is significant for both high complexity and low complexity firms.

Impact of Analyst Following on the Association between Error Rate and Geographic Proximity

We test the effect of "analyst following" by including an interaction variable between "analyst following" and "Distance to NYC" in our regression model. The results are presented in Table 7.

< Table 7 >

The results for Model 1 on type 1 error show that coefficient of the interaction term between Distance and Analyst Following is negative and significant at 10% per cent level. This result indicates that the positive association between the rating error and distance is moderated by lower information asymmetry, proxied by higher analyst following. In other words, higher rating errors for firms with longer distance from NYC is reduced if analyst following is high which results in lower information asymmetry. Conversely, the rating error is especially high for firms with longer distance from NYC when information asymmetry is high because of low analyst following.

Regression results on type 2 errors, i.e. false warning, are presented under Model 2 in Table 7. The results show that coefficient of the interaction term is positive but insignificant. This finding suggests that analyst following has no significant impact on the association between false warnings and geographic distance. Similar to the explanation for the firm complexity, the results thus imply that analyst following does not add to the error rate for false warnings.

The results on the timeliness of downgrades are presented under Model 3 in Table 7. The results show that coefficient for the interaction term is significantly positive. This finding indicates that a higher coverage by analysts that reduces information asymmetry moderates the negative association between the timeliness of downgrades and geographic proximity.

We also conduct regression tests separately on the subsamples of observations with high analyst following and low analyst following. The high and low analyst following is identified based on the median of analyst following for the total sample. Consistent with the results for type 1 error based on total sample, the results show that the coefficient for "Distance to NYC" is statistically significant for the subsample with high analyst following, whereas it is insignificant for the subsample with low analyst following. The results for type 2 error show that there is no significant impact of analyst following on the association between type 2 error and geographic distance.

Robustness Tests

We conduct robustness tests to evaluate the validity of our findings and the results of these are discussed below.

Industry and Year Fixed Effect

We test the robustness of our findings by including industry and year fixed effects in the analyses. We define industries in accordance with the Fama-French 12 industry classification. The results on the industry and year fixed effects are presented in models 2 and 3 of Table 3 for type 1 error, Table 4 for type 2 errors, and Table 5 for the timeliness of downgrades. The results show that the coefficient of variable "distance to NYC" remains significant even after industry and year fixed effects are included in the analyses.

Tests based on different Time Horizons for Error Rates

The above analyses are based on the rating errors determined for the time horizon of 2 years. In other words, Type 1 errors are determined when an investment grade rated bond defaults within two years from the time of its rating. Similarly, Type 2 errors are determined when a speculative bond does not default within 2 years. We conduct additional analyses by defining the time horizon for rating errors with 1, 3, and 5 years as time horizons, meaning that type 1 errors can occur within 1, 3, or 5 years from default, and type 2 errors can occur for speculative ratings which do not default within 1, 3, or 5 years, respectively. The results (untabulated) of all tests are consistent with our main results.

Results on the Error Measure for different Rating Agencies

Our measure of NYC as the location of rating analysts is based on the assumption that corporate rating analysts are primarily based in the NYC offices of the rating agencies. While both S&P and Fitch are headquarters in NYC, their corporate analysts may also have a presence at other locations. Since Moody's headcount shows that their corporate rating analysts are primarily based in NYC[37], we rerun tests using Moody's ratings only. The results (untabulated) show that there is a positive association between the error measures and geographic distance, and a negative association between

---

[37] See http://www.moodys.com/Page/findanalyst.aspx (As of 2012 all corporate analysts were exclusively in NYC).

DAHEAD and geographic distance. Thus, these results are consistent with our main results reported earlier.

As an additional robustness, we focus only on S&P and Fitch rating and define type 1 and type 2 errors using a different rating boundary of triple C (rating code 17). This analysis is done because Moody's is the only CRA which incorporates an expected recovery into their credit ratings. Therefore, it would be inaccurate to assume that non-investment grade ratings are erroneous prior to default because these ratings may take into account higher recovery rates. We address this issue for our main results by defining missed defaults as only the ratings that are investment grade prior to default. As additional analysis, we exclude Moody's ratings and examine a different rating boundary for type 1 and type 2 errors at the triple C rating boundary. The results (untabulated) are similar to our main results.

Additional Analysis

Accessibility of Location

Easy accessibility to a firm location will encourage the rating analysts to obtain soft information from face-to-face meetings. Because all ratings agencies covered in this paper are located in NYC, we examine whether easy access to the firm headquarters from NYC will have an impact on the association between rating errors/downgrade timeliness and geographic distance. We use direct flights to the firm headquarter location as a proxy for easy accessibility.

We argue in this paper that absence of easy access will not motivate analysts to obtain soft information for developing their ratings. This will aggravate the information asymmetry situation and thus make it even more difficult for analysts to make accurate ratings forecasts. Thus, we expect the positive relation between rating errors and geographic distance and negative relation between timely downgrades and geographic distance to be stronger for firms with no direct flight access to rating agency headquarters.

We create a dummy variable of "Non-direct", which is coded as 1 if there is no direct flight to the location of the firm headquarters from NYC, and zero otherwise[38]. We expect the coefficient of the interaction term between the variables of "Non Direct" and "Distance to NYC" to be positive for rating errors, indicating higher rating errors for lower accessibility. Additionally, we expect the interaction term between the variables of timeliness and "Non-direct" to be negative, indicating less timely downgrades in relation to the default dates.

The results (untabulated) for type 1 error show that the firms with lower access from NYC, proxied by no direct flights, are associated with higher type 1 error and less timely downgrade. Firms located in cities with less ease of access to rating analysts have ratings that are more likely to be associated with missed defaults and downgrades closer to defaults.

Adjustment of Ratings by Analysts as a result of Geographic Distance

We also examine whether the rating analysts adjust their ratings lower to compensate for lack of soft information as a result of distance of the client firm from their offices. In order to evaluate this, we conduct an ordered logit test using the ratings as a dependent variable and "distance to NYC" as the main independent variable.[39] We convert "alpha" ratings to numerical ratings by assigning numbers to different ratings

[38] Cities considered as having direct flight access must be at least 100 kilometers away from NYC. In robustness tests where direct flight access is defined for cities at least 200 and 300 kilometers away from NYC, our results are consistent.
[39] We employ control variables from Blume et al. (1998)

given by the rating analysts. The highest rating is coded as 1, whereas the lowest rating is coded as 21. The details on the coding system are provided in appendix B. The regression results are contained in Table 8.

<Table 8>

The results for Model 1 show that the coefficient of "Distance to NYC" is positive and significant, indicating that the ratings are lower as the distance between firm headquarters and CRA headquarters increases. The results for Model 2 show that the coefficient does not change when industry and year fixed effects are included. These results thus show that the ratings are significantly lower as firms move further away from NYC. This finding thus suggests that the rating analysts recognize that they may be missing on soft information for the firms that are further away from their headquarters and they adopt a conservative approach to compensate for this lack of soft information.

Although the ratings for distant firms are lower, our results suggest that distant firms are still associated with higher missed defaults and less timely downgrades. Therefore, these findings suggest that lower ratings do not fully compensate for missing soft information.

Chapter 5: Do Investors Fixate on Credit Ratings

5.1. Introduction

"We need to reduce the mechanical reliance on ratings."
Mario Draghi, Chairman of the Financial Stability Board[40]

Investors taking ratings at face value have been attributed as a leading cause for the recent financial crisis (see, for e.g., Blinder (2007), Stiglitz (2008), and Brunnermeier (2009)). Recent legislative and regulatory efforts have attempted to address this issue by reducing the importance of ratings through Dodd-Frank legislation which has removed statutory references to credit ratings by federal regulations. The underlying premise behind these efforts is that investors mechanically rely on credit ratings. However, providing evidence that investors mechanically rely on credit ratings is difficult as the optimal degree of reliance on credit ratings is unclear. Identifying mechanical reliance is also confounded by the fact that ratings reflect information. It is therefore uncertain whether investors who react to ratings are mechanically reacting to ratings or responding to the information that it conveys. In this paper, I provide evidence of mechanical reliance by identifying a situation where investors fixate and react to ratings which contain no new information.

On April 16th, 2010, Moody's began the process of recalibrating its municipal bond scale. In order to better align municipal bond ratings with ratings with other asset classes, Moody's recalibration resulted in upward shifts to most municipal ratings. However, for most bonds, the implementation of recalibration presented no new information and was not accompanied by any issuer specific rating reports. The announcement and report detailing the recalibration process occurred a month earlier.

---

[40] Statement following G20 meeting in Seoul, Korea during 2010. Concerns of mechanical reliance on ratings are also formally reported by the Financial Stability Board (FSB, 2010; FSB 2012).

A report titled "Recalibration of Moody's U.S. Municipal Ratings to its Global Rating Scale", published on March 16th, 2010 had already explained the purpose of recalibration which was to make future default probabilities conveyed by municipal credit ratings more comparable with corporate and sovereign bonds. The information content regarding the purpose of recalibration is questionable because Moody's already noted as early as 2002 that municipal ratings would be higher if rated on a corporate scale[41]. Specifically, Moody's (2002, page 11) reports that if municipal bonds were rated on the corporate scale, nearly all general obligation bonds would be rated double A or higher.

However, the earlier announcements did not provide a detailed algorithm showing how Moody's plans to adjust municipal ratings[42]. Any particular assessments on how ratings should be adjusted are also time-varying. Therefore, the announcement on March of 2010 did provide new information regarding Moody's *current assessment* of how much certain types of municipal bonds would be upwardly adjusted. A detailed algorithm showing bond type and the amount of upward shift are noted in the report[43]. The announcement and its details were also covered by the press and institutions[44]. In light of the information contained in the announcement report and earlier commentaries,

[41] Subsequent commentaries in June of 2006 and March of 2008 also confirm this point.
[42] Without a detailed algorithm, it would not be possible to differentiate market reaction to particular bonds on these announcement dates.
[43] The algorithm is shown on page 2 in "Recalibration of Moody's U.S. Municipal Ratings to its Global Rating Scale", published on 3/16/2010 (also shown in figure 3). An implementation date of mid-April 2010 is indicated on page 6.
[44] The announcement of Moody's recalibration is also reported by the Bond Buyer, "Moody's to Recalibrate Muni Ratings in Mid-April", by Lynn Hume, published 3/16/2010. Available online at http://www.bondbuyer.com/news/-1009571-1.html. Janney Fixed Income also references the algorithm published by Moody's and the report is available online at http://www.janney.com/File%20Library/Marketing%20Material/Rating%20Changes.pdf.

the actual implementation of the rating changes presents no new information[45]. In other words, the actual implementation of recalibration is merely a mechanic change in ratings which reflects information conveyed earlier.

In this paper, I examine market reaction to the recalibration process. I focus on a sample of general obligation bonds for the U.S states whereby rating shifts on implementation date followed the announcement date indications *exactly*. I find positive market reactions on the implementation date. Why did investors react on the implementation of recalibration even though the informational content behind recalibration was conveyed earlier? This puzzling reaction in the absence of new information could be explained by the fact that institutions face ratings-based financial regulation and investment policies. For instance, institutions such as mutual funds are required to maintain certain credit grades for their portfolios (Cornaggia, Cornaggia and Hund, 2013). Therefore, institutions may be restricted from purchasing certain bonds until the actual implementation date because that is the point where the credit ratings of bonds come into compliance with regulations and investment policies. As the credit ratings of bonds come into compliance with investment policies on implementation date, greater demand by institutions could explain the positive market reactions.

Institutions that are restricted by ratings based regulation and investment policies are unlikely to drive positive implementation date returns for several reasons. First, Moody's recalibration did not involve any bonds crossing the crucial investment grade boundary which some institutions focus on. Second, institutions such as banks and insurance companies are not restricted from owning lower rated bonds and merely have

[45] For most bonds, there was no uncertainty surrounding the rating changes on implementation date. A detailed discussion is provided in section 3.

to set aside more capital for riskier investments. However, while banks are not prohibited from owning lower rated bonds, the added cost of setting aside capital could cause banks to wait till the implementation date to purchase bonds.

As additional evidence that institutions are not driving positive reactions on the implementation date, I restrict the sample to bonds likely held by retail investors and find similar results. Retail investors, who are not subject to ratings-based financial regulation and investment policies, reacted positively to the implementation of recalibration.

Next, I examine reactions on the announcement of recalibration. If investors also reacted on the announcement date, positive implementation date returns could represent a continued trend of investors gradually updating their beliefs to new information. I find that investors did not react on the announcement date.

Why did investors react exclusively to the implementation of rating changes? One explanation for this behavior is that investors have limited attention and processing power and did not pay attention to the news surrounding recalibration. Given that time and attention are costly, being inattentive may be reasonable behavior (Hirshleifer and Teoh, 2003). In this setting related to credit ratings, being inattentive can make sense because credit ratings are a substitute for costly credit analysis and information processing. The municipal bond market, in particular, is an appropriate setting because it is dominated by households who have limited skills and resources to conduct credit analysis[46]. For these naïve investors, the existence of credit ratings allows easy access to information and negates the need to process other sources of information.

[46] Retail investors hold approximately 75% of municipal bonds outstanding. Federal Reserve Flow of Funds Accounts of the United States, December 8, 2011. This figure comprises securities held directly by individual investors (51 percent) or through investment management companies such as mutual funds,

Reliance on ratings may also be evident in the $3.7 trillion municipal bond market[47] due to the fact that financial information about municipal bond issuers is less available, less reliable, less comparable cross-sectionally, and less timely than information about corporate issuers (Ingram et al. 1983; Cole et al. 1994). More specifically, financial information about municipalities often is not prepared in accordance with generally accepted accounting principles (GAAP) and may not be audited. Each municipality may design its own financial reporting format and release financial statements with lags of up to nine months after fiscal year-end. Furthermore, municipalities are exempt from many disclosure and registration requirements that apply to other security issues. Thus, the unavailability of reliable alternative sources of information provides investors in the municipal bond market another reason to pay sole attention to credit ratings.

Inattention to information implies a form of functional fixation (Hirshleifer and Teoh, 2003). In this instance, investors did not respond to the information conveyed earlier but reacted on the implementation date. Even though the implementation of recalibration did not convey any new information, investors continued to believe that rating changes convey information. This inattentive behavior implies a fixation on credit ratings. In psychology, Duncker (1945) popularized the hypothesis that an individual's prior use of an object prevents them adjusting their beliefs about alternative uses for that object. Ijiri, Jaedicke, and Knight (1966) applied this concept to accounting and found that users also do not change their decision process regarding the use of accounting figures after changes in accounting assumptions. While many subsequent papers have

---

money market mutual funds, closed-end funds, and exchange-traded funds (24 percent). Insurance companies and commercial banks hold most of the remaining securities.

[47] Federal Reserve Flow of Funds Accounts of the United States, December 8, 2011.

examined fixation as related to accounting numbers (Dyckman et al., 1982; Bloom et al., 1984; Hand, 1990; Harris and Ohlson, 1990; Sloan, 1996; Vergoosen, 1997; Chen and Schoderbek, 2000; Arunachalam and Beck, 2002; Hirshleifer, Hou and Teoh, 2004), this paper is the first to extend the theory of fixation to credit ratings. This paper shows that investors in the municipal bond market appear to be inattentive to the information behind rating changes and fixate on ratings by continuing to react to rating changes which contain no new information.

Moody's municipal bond recalibration in 2010 was not the first time that a major rating agency modified its rating scale. Notably, in 1982, Moody's refined its corporate ratings by attaching rating modifiers of "1", "2" and "3" to base rating categories. This refinement was not tied to changes in issuer characteristics and effectively expanded corporate credit rating categories from 9 to 19. Several papers utilized this natural setting to examine investor responses to this refinement (Liu, Seyyed and Smith, 1999; Kliger and Sarig, 2000; Tang, 2009). However, the 1982 refinement is inherently different from the 2010 recalibration because it was *not anticipated or preceded by earlier announcements*. Therefore, the implementation of rating refinement in 1982 does represent *a release of information* to market participants. This study is unique because the 2010 recalibration was preceded by earlier information which absorbs any information that may be contained in the rating changes during implementation.

Cornaggia, Cornaggia and Israelsen (2014) also examine the price impact of the 2010 recalibration. However, their paper focuses on the long term impact of the actual implementation of recalibration and reaffirms that credit rating agencies (CRAs) are relevant intermediaries (Holthausen and Leftwich, 1986; Cornell et al., 1989; Hite and

Warga, 1997; Kliger and Sarig, 2000; Agarwal, Chen and Zhang, 2015)[48]. Adelino, Cunha and Ferreira (2015) examine the economic effects of the recalibration and find that municipalities increase expenditures and employment. This paper is an event study comparing the announcement of recalibration to its implementation. My findings suggest that not only are credit ratings important but that investors fixate on them.

The evidence in this study is important for several reasons. First, the premise that investors fixate on credit ratings implies that investors take credit ratings at face value and are mechanically relying on credit ratings. Recent Dodd-Frank legislation has attempted to address these concerns by removing statutory references to credit ratings by federal regulations. This paper suggests that regulators should also focus on improving disclosure requirements across municipal issuers. Improving transparency in the municipal market may reduce mechanistic reliance on ratings and further regulatory efforts to protect investors. Second, this paper suggests that ratings have real effects for issuers. In July 2008, the Attorney General of the State of Connecticut filed a lawsuit against the major CRAs alleging that harsh ratings resulted in higher interest costs imposed on taxpayers. The premise of this lawsuit is that credit ratings may have an undue influence on interest costs. The evidence of this paper supports this contention by showing that investors fixate and market prices may reflect ratings which do not contain new information.

5.2. Recalibration Background

The discrepancy between corporate and municipal bond default rates has long been noted by market participants and CRAs. Moody’s noted in 2002 that in terms of

[48] See Frost (2007) for a comprehensive review on CRAs.

default probabilities, municipal bond ratings were much harsher relative to corporate bonds. Similarly, Fitch performed two comprehensive default studies of municipal debt in 1999 and 2003. The universe for these studies consisted of all municipal bond defaults, not just those that were rated by Fitch or other bond rating agencies. Since the 2003 default study, only a few Fitch-rated municipal bonds have defaulted. Most defaults were limited to health providers. In terms of general obligation bonds which are backed by an unlimited tax pledge of the municipality, investors are usually repaid in full even in the unlikely event of a default. Out of more than 8,600 general obligation credits rated by Moody's, only 3 defaults have been observed since 1970, none which was state level debt[49]. The last state level default in U.S. history occurred during the Great Depression when the State of Arkansas defaulted but eventually repaid investors 100 percent of their investment.

As a result of low default rates, CRAs typically rate municipal bonds on average higher than corporate bonds. Also, municipal bonds tend to be concentrated at the A and AA rating levels while corporate bonds are much more widely dispersed as a result of high variance in default probability. Below is the 2010 default study by Moody's which compares corporate ratings with municipalities.

<Figure 1>

While municipal bonds tend to concentrate at high investment grade levels, the market nonetheless continues to price municipal bonds according to their difference in ratings because *past default rates are not fully indicative of probabilities of future default*.

[49] As of 2011, two were counties (Jefferson County, Al and Baldwin County, AL). One was a special district (Sierra Kings Health Care). Bondholders for Baldwin County bonds ultimately recovered 100% of their investment. Another notable default was Orange County, Ca which was a general obligation bond with a limited tax pledge. Bondholders for Orange County also eventually recovered their full investment.

Market data from any sample clearly reveals this fact. Below shows the municipal bond yields for different ratings and maturities as of May 17th, 2010, available on Bloomberg.

<Figure 2>

To allow for better comparison of municipal ratings with corporate and sovereign ratings, both Moody's and Fitch implemented the recalibration of municipal credits in 2010[50]. Specifically, Moody's recalibration of its municipal ratings was announced on March 16, 2010. Rating implementation was realized in stages beginning on April 16th and ending on May 10th. For U.S. states, ratings were recalibrated during market hours on April 19th.

5.2. Sample

Rating changes for U.S. states during the recalibration process is available and reported by the Bond Buyer[51]. Figure 3 shows the indicated change in ratings given on the announcement date on March 16th, 2010. I focus on general obligation bonds for U.S. states which show the most variation in terms of change in scale, ranging from zero to three notches. I exclude from my sample states originally rated Aa1 because the announcement of recalibration did not specify which would actually have an improvement in rating levels. Note that for general obligation bonds originally rated Baa3, the indicated change in scale may range from two to three notches. I include these bonds in the main analysis because while the level of change is uncertain, there is certainty in that the ratings will be recalibrated higher. In robustness tests (see section 4.3.3), I exclude these bonds as well and find similar results. Table 1 shows all U.S. state

---

[50] This study only focuses on Moody's recalibration process. Fitch has a lower coverage of state general obligation bonds.

[51] See "Moody's Lifts Up 34 States", by Dan Semour, the Bond Buyer, 4/19/2010. Available online at http://www.bondbuyer.com/issues/119_323/moodys_recalibration-1011076-1.html.

rating changes as a result of Moody's recalibration on implementation date. For state general obligation bonds, the actual recalibration on implementation date followed the announcement date indications exactly. Note that there are three states unrated by Moody's[52]. Also, seven states already had triple A and stable ratings and did not change from the recalibration process[53] while nine states originally rated Aa1 received either a new stable outlook or a one notch improvement in rating levels[54]. The difference column shows the difference in notches pre and post recalibration. New York State typically issues very few general obligation bonds as most of bonds are revenue in nature and issued through the Empire State Development Corporation, the Dormitory Authority of the State of New York, and New York State Thruway Authority. Since New York City and New York shared the same ratings pre and post recalibration, I include them together.

<Table 1>

Bond prices in the secondary market are provided by the Municipal Securities Rulemaking Board's (MSRB). The MSRB pricing data contain the data fields such as date and time of each trade, maturity date, the par amount traded, and the price at which the par amount is traded. I calculate a volume weighted trade price per bond per date[55]. Following Bessembinder et al. (2009), this volume weighted approach produces statistical tests which are better specified and more powerful than using end-of-day prices. Volumes weighted trade prices are calculated separately for retail investor samples based

---

[52] Moody's does not maintain general obligation bond ratings for Nebraska, South Dakota, and Wyoming.
[53] Moody's maintained triple A and stable ratings for Maryland, Missouri, North Carolina, South Carolina, Utah, Vermont and Virginia prior to recalibration.
[54] Of the nine states originally rated Aa1, four states received a stable outlook while five states improved by one notch. As noted earlier, I exclude these original Aa1 rated states because the announcement of recalibration did not specify which would actually have an improvement in rating levels and only noted that original Aa1 rated general obligation bonds may improve by one or zero notches (figure 3).
[55] This method uses all trades on a given day for a particular bond and estimates the daily price as the volume-weighted average price.

on trade size. The proxy for retail held bonds come from a comprehensive report conducted by the United States Government Accountability Office (GAO) in 2012 which examines the municipal bond market. In this report, the GAO interviewed broker-dealers, investors and other market participants and conclude that retail investors typically trade in amounts of less than $250,000 (GAO, 2012 pg. 5). Bonds held by retail investors are restricted to issues that only trade in amounts less than $250,000 during the period surrounding the recalibration process.

I identify trade prices which are only associated with state general obligation bonds and match these by cusip to the pre and post recalibrated ratings shown in table 1. I exclude bonds which are pre-refunded or insured because these bonds are secured by and maintain the ratings of treasury bonds and bond insurers, respectively. Following Downing and Zhang (2004), the following criteria are also imposed. First, in order to eliminate the possibility of bid-ask bounce effects, I restrict transactions to only include customer initiated buy orders. Second, bonds maturing in less than one year are also discarded[56].

Bond returns are calculated as the percentage change in bond prices from trades surrounding the announcement and implementation of recalibration. The bond price before the announcement or implementation is given by the volume-weighted trade price on the day closest and prior to the announcement or implementation date. The bond price after the announcement or implementation is given by the volume-weighted trade price on the day closest to and following the announcement/implementation date. I measure bond returns only for bond issues with at least one trade during the five days before and

[56] Defined as maturing on April 2011 or earlier.

the five days after the announcement or implementation date (Dimitrov, Palia, and Tang, 2014).

Bond returns are calculated as raw returns where P_{t+1} is the weighted average price on the closest business trading date within five trading days following the event date and P_{t-1} is the weighted average price on the closest business trading date within five trading days before the event date[57].

$$\text{Bond Return}_{\text{raw}} = \frac{P_{t+1} - P_{t-1}}{P_{t-1}}$$

I employ a one sample mean comparison test to see if each event generates a return greater than zero. In addition, I use the Wilcoxon matched pairs signed rank test to test whether median returns are greater than zero. Separately, I also test whether returns are significantly different from the Bloomberg Fair Market Value General Obligation AAA 20 year benchmark[58]. I use a benchmark of triple A municipal bonds because these bonds already have the highest possible bond rating and should not be affected by the recalibration process. Therefore, this benchmark should not be contaminated by the announcement or implementation of recalibration and serves as a reasonable point of reference for bond prices during recalibration. Using a municipal bond benchmark also has certain advantages over other benchmarks such as treasuries. First, liquidity differences may weaken the relationship between municipal bonds and treasuries (Downing and Zhang, 2004). Second, the muni-treasury relationship may also break

---

[57] Moody's announcement of recalibration occurred on March 16th, 2010. The pre-announcement window ranges from March 9th to March 15th while the post announcement window ranges from March 17th to March 23rd. Moody's implementation date occurred on April 19th. The pre implementation window ranges from April 12th to April 16th while the post implementation window ranges from April 20th to April 26th.

[58] Benchmark returns during announcement and implementation are matched to the trades for the entire sample. The average benchmark return during announcement/implementation was negative 0.035 and positive 0.002 percent, respectively.

down during economic cycles, as was particularly evident during the post financial crisis years after 2008[59].

5.2. Findings

Response by investors on implementation date

The purpose of recalibration which was to make future default probabilities conveyed by municipal credit ratings more comparable with corporate and sovereign bonds was conveyed as early as 2002. Additionally, a report titled "Recalibration of Moody's U.S. Municipal Ratings to its Global Rating Scale", published on March 16th, 2010 also expressed this idea and provided a detailed algorithm highlighting exactly how certain bonds would be upwardly adjusted. In light of this information, the actual implementation of the rating changes presents no new information because these rating changes *only occur* as a reflection of the information conveyed earlier. If investors understand the recalibration process, there should be no market reaction on the implementation date.

However, I find that for the entire sample, there are positive market reactions which vary with the magnitude of rating change (Table 2, panel A). The overall results are unlikely to be driven by institutions that are restricted by ratings based regulation and investment policies. Moody's recalibration did not involve any bonds crossing the crucial investment grade boundary which some institutions focus on. Also, institutions such as banks and insurance companies are not restricted from owning lower rated bonds

[59] See "Crisis Upends Muni-Treasury Relationship", by Dan Semour, the Bond Buyer, 12/2/2008. Available online at http://www.bondbuyer.com/issues/117_229/-297063-1.html. See "Muni-Treasury Relationship Trouble", by Dan Semour, the Bond Buyer, 4/29/2009. Available online at http://www.bondbuyer.com/issues/118_81/-302789-1.html.

and merely have to set aside more capital for riskier investments. However, the added cost of setting aside capital could cause banks to wait till the implementation date to purchase bonds. To rule out ratings-based investment and regulation policies as an explanation for positive implementation date returns, I restrict the sample to bonds held by retail investors.

Panel B shows that positive implementation date returns persist when restricted to a sample of bonds held by retail investors. Retail investors who are not restricted to ratings based investment policies reacted positively with mean returns of 0.605 (panel B). These reactions are slightly greater than the overall sample (panel A) and also vary with the magnitude of rating change. The positive returns for retail held bonds are greatest at 1.095 percent when rating levels improved by 3 notches during implementation, followed by 0.362 percent for a 1 notch improvement. Furthermore, I separate out states which were originally rated triple A and hence did not change as a result of recalibration. The results show that for zero notches (original triple A issuers), investors did not react positively. These results suggest that the positive market reactions are not being driven by demand from institutions that face ratings based investment policies.

<Table 2>

Response by investors on announcement date

The results earlier suggest that positive implementation date returns are not being driven by demand created by ratings-based regulation and investment policies from institutions. Reactions on the implementation date could also be preceded by positive reactions on the announcement date. If investors also reacted on the announcement date, positive implementation date returns could represent a continued trend of investors gradually updating their beliefs to new information.

The findings in panel A of table 3 do not show significant positive returns for the overall sample. Both mean and medium returns are not significantly positive for all states or when segmented based on the indicated recalibrated improvements in ratings. The results are similar when restricted to bonds held by retail investors (panel B).

<Table 3>

Additional analysis

Results Adjusted by Municipal Benchmark

I reexamine the main findings by adjusting for returns based on a triple A municipal bond benchmark. As noted earlier, this benchmark is uncontaminated by the recalibration process and allows for a test of abnormal bond price reactions during announcement and implementation dates. The average benchmark returns during announcement and implementation dates are negative 0.035 and positive 0.002 percent, respectively[60]. Adjusting for these benchmarks does not change the significance of the earlier reported results (untabulated).

Regression Analysis

In this section, I examine the main results controlling for factors which may influence the magnitude of investor reactions on the announcement and implementation dates. I test the following model:

$$\text{Bond Return} = \beta_0 + \beta_1\text{RatingDiff} + \beta_2\text{YTM} + \beta_3\text{Amount} + \varepsilon$$

[60] Based on Bloomberg Fair Market Value triple A 20 year index. I also try state specific triple A indices such as Maryland, North Carolina, Georgia and Virginia general obligation bonds. The results are robust to these alternative specifications.

(1)

Bond returns are the raw returns surrounding the announcement and implementation dates as explained earlier in the paper. Rating Diff is defined as the difference between a new recalibrated rating and the old rating and is categorized as notches of three, two, one or zero. This is the main variable of interest and is expected to be positive and significant if investors react according to the level of rating adjustment. YTM is the number of years to maturity for a particular bond. It is expected that longer maturity bonds are at greater risk of losses and are more likely to be traded. Amount is the outstanding amount of a particular bond and is expected to be positively correlated with trading activity. YTM and amount figures are collected from Mergent.

The results in table 4 show that the coefficient for Rating Diff is positive and significant on the implementation date. The coefficient for Rating Diff is insignificant on the announcement date, supporting the inference that investors did not react on the announcement date. The results are consistent when restricted to bonds held by retail investors.

<Table 4>

Uncertainty Surrounding the Implementation Date

The March 2010 announcement published an algorithm indicating how the ratings of certain bonds will be recalibrated. Within certain rating categories, Moody's indicated one or two different possible outcomes. For these categories, Moody's indicated that individual reviews will take place to determine the appropriate outcome. In terms of general obligation bonds, ratings which may have different possible outcomes belonged to the Aa1 and Baa3 categories. Bonds originally rated Aa1 may move by zero or one notch while Baa3 rated bonds may move by either two or three notches. Moody's ultimately decided that for general obligation bonds of U.S. states, bonds which had a stable outlook would shift by the higher of two indicated outcomes on the announcement date. For instance, Aa1 rated states with a stable outlook would shift to Aaa while those with a negative outlook would remain Aa1. Baa3 rated bonds with a stable outlook would shift by three notches to A3.

Rating categories with two different possible outcomes does represent uncertainty which would only be resolved on the implementation date. I deal with this issue in two ways. First, as noted earlier, my main analysis excludes all bonds originally rated Aa1. In robustness tests, I also exclude bonds originally rated Baa3. I find that the remaining sample of bonds recalibrated three notches remains significant with average returns of 0.873 and 1.276 percent for the overall and retail sample, respectively. Note that these returns are actually greater than the main results which include Baa3 rated bonds which were recalibrated to the more positive of two outcomes indicated on the announcement date.

Second, I compare the bonds which received the more positive outcome on implementation date (bonds rated Aa1 or Baa3 which shifted by 1 or 3 notches rather than 0 or 2 notches, respectively) with my sample of bonds which also shifted by these exact amounts as indicated on the announcement date. If uncertainty is driving positive reactions on the implementation date, the reaction of bonds which received a positive outcome should be greater than bonds for which there was no uncertainty. The results in table 5 show that average returns on implementation date for bonds with a positive outcome *are less* than those without indicated uncertainty on the announcement date. It is unlikely that uncertainty drives positive reactions on the implementation date.

<Table 5>

Discussion

Investors reacted significantly to the implementation of recalibration even though the information content of these ratings changes was conveyed earlier. I find that this puzzling reaction cannot be explained by demand from institutions created by regulation and investment based policies. I also find that investors did not react on the announcement date, suggesting that there was not a gradual price discovery process beginning on the announcement date.

This puzzling behavior could be explained by the idea that investors have limited attention. Inattention can be rational when time and attention are costly (Hirshleifer and Teoh, 2003). In this case, reliance on credit ratings allows for easy access to information and negates the need to process other sources of information. This reliance on ratings may be particularly evident in the municipal bond market given less timely disclosures and a lack of reliable alternative sources of information when compared to corporate issuers (Ingram et al. 1983; Cole et al. 1994).

Reliance on credit ratings while being inattentive to other information implies a fixation on credit ratings. In this instance, investors did not respond to the information conveyed on announcement but reacted on the implementation date. Even though the implementation of recalibration did not convey any new information, investors continued to believe that rating changes convey information. Duncker (1945) theorizes that fixation results when an individual's prior use of an object prevents them from adjusting their beliefs about alternative uses for that object. In this instance, investors in the municipal bond market fixate on ratings by continuing to react to rating changes which contain no new information.

This study has several important implications. First, the idea that investors fixate on credit ratings suggests that they are over relying on credit ratings. The underlying premise behind recent Dodd-Frank legislation which has removed statutory references to credit ratings by federal regulations is that investors rely excessively on ratings. This paper provides evidence which supports this contention by showing that investors react to ratings which do not contain new information. This paper also suggests that regulators should focus on improving disclosure requirements across municipal issuers. Improving transparency in the municipal market may reduce mechanistic reliance on ratings and further regulatory efforts to protect investors. Second, this paper shows that ratings have real effects for issuers. In July 2008, the Attorney General of the State of Connecticut filed a lawsuit against the major CRAs alleging that harsh ratings resulted in higher interest costs imposed on taxpayers. The premise of this lawsuit is that credit ratings may have an undue influence on interest costs. The evidence of this paper supports this contention by showing that market prices may reflect ratings which do not contain new information.

Chapter 6: Conclusions

In this dissertation, I examine several forces which impact credit ratings. In response to the recent financial crisis, Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act in July 2010 to temper the incentives of CRAs to issue upwardly biased ratings. Using a large sample, we find no evidence that Dodd-Frank encourages CRAs to provide corporate bond ratings that are more accurate and informative. Instead, we find that following Dodd-Frank CRAs issue lower ratings, give more false warnings, and issue downgrades that are less informative (i.e., the stock market and the bond market react less to corporate bond rating downgrades). These results are consistent with the reputation model of Morris (2001), and suggest that CRAs in the post-Dodd-Frank period are more protective of their reputation.

In the next essay, we examine the effect of geographic distance on the accuracy of corporate bond ratings. We document in this study that lack of soft information as a result of longer distance between firm headquarters and rating agency headquarters results in higher rating errors, proxied by type 1 and type 2 errors for missed defaults and false warnings, respectively. Our results show that for each 100 kilometers a firm is away from the rating agency headquarters in New York City (NYC), the likelihood of missing defaults (type 1 error) increases by 5.2 percent, and the likelihood of false warnings (type 2 error) increases by 2.1 percent. Additionally, our analyses show that downgrades are also less timely for firms that are further away from the rating agency headquarters.

Lastly, I examine whether investors fixate on credit ratings. I examine market reaction to the recalibration process and find a puzzling positive reaction on the implementation date. This positive reaction on the implementation date is still present when restricted to bonds held by retail investors who do not face ratings based regulation or investment policies. I also find that investors do not react on the announcement date. Additionally, I provide evidence against uncertainty as a reason for positive reactions on implementation date. These results suggests that investors appear to be inattentive to the information behind rating changes and instead fixate on rating changes even when they contain no new information.

References

Adelino, Manuel and Cunha, Igor and Ferreira, Miguel A., (2015). The Economic Effects of Public Financing: Evidence from Municipal Bond Ratings Recalibration. Unpublished working paper, Duke University and Nova School of Business and Economics.

Agarwal, S., Chen, V, & Zhang, W., (2015). The Information Value of Credit Rating Action Reports: A Textual Analysis. Management Science, Forthcoming.

Alge, B. J., Wiethoff, C., & Klein, H. J. (2003). When does the medium matter? knowledge-building experiences and opportunities in decision-making teams. Organizational Behavior and Human Decision Processes, 91(1), 26-37.

Alicanti, S. P., (2011). A pattern of unaccountability: Rating agency liability, the Dodd-Frank act, and a financial crisis that could have been prevented. Unpublished working paper. Emory University.

Alp, A., (2013). Structural shifts in credit rating standards. Journal of Finance, 68(3), 2435-2470.

Amato, J. D., & Furfine, C. H. (2004). Are credit ratings procyclical? Journal of Banking & Finance, 28(11), 2641-2677.

Arunachalam, V., & Beck, G. (2002). Functional fixation revisited: The effects of feedback and a repeated measures design on information processing changes in response to an accounting change. Accounting, Organizations and Society, 27(1–2), 1-25.

Baghai, R., Servaes, H., & Tamayo, A., (2012). Have rating agencies become more conservative? Implications for capital structure and debt pricing. Unpublished working paper. Stockholm School of Economics, London Business School, and London School of Economics & Political Science.

Baltes, B. B., Dickson, M. W., Sherman, M. P., Bauer, C. C., & LaGanke, J. S. (2002). Computer-mediated communication and group decision making: A meta-analysis. Organizational Behavior and Human Decision Processes, 87(1), 156-179.

Beaver, W. H., Shakespeare, C., & Soliman, M. T. (2006). Differential properties in the ratings of certified versus non-certified bond-rating agencies. Journal of Accounting and Economics, 42(3), 303-334.

Becker, B., & Milbourn, T., (2011). How did increased competition affect credit ratings? Journal of Financial Economics, 101(3), 493-514.

Bessembinder, H., Kahle, K. M., Maxwell, W. F., & Xu, D. (2009). Measuring abnormal bond performance. Review of Financial Studies, 22(10), 4219-4258.

Blinder, A., (2007). Six fingers of blame in the mortgage mess. *New York Times*, September 30.

Bloom, R., Elgers, P. T., & Murray, D. (1984). Functional fixation in product pricing: A comparison of individuals and groups. Accounting, Organizations and Society, 9(1), 1-11.

Blume, M. E., Lim, F., & Mackinlay, A. C., (1998). The declining credit quality of U.S. corporate debt: Myth or reality? Journal of Finance, 53(4), 1389-1413.

Bolton, P., Freixas, X., & Shapiro, J., (2012). The credit ratings game. Journal of Finance, 67(1), 85-112.

Bonsall, S. B. IV, (2014). The impact of issuer-pay on corporate bond rating properties: Evidence from Moody's and S & P's initial adoptions. Journal of Accounting and Economics.

Bostic, R., Chomsisengphet, S., Engel, K. C., McCoy, P. A., Pennington-Cross, A., & Wachter, S., (2012). Mortgage product substitution and state anti-predatory lending laws: Better loans and better borrowers? Atlantic Economic Journal, 40(3), 273-294.

Brunnermeier, M. K., (2009). Deciphering the liquidity and credit crunch 2007–2008. Journal of Economic Perspectives, 23(1), 77-100.

Bushman, R., Chen, Q., Engel, E., & Smith, A. (2004). Financial accounting information, organizational complexity and corporate governance systems. Journal of Accounting and Economics, 37(2), 167-201.

Butler, A. W. & Cornaggia, K. R. (2012). Rating Through the Relationship: Soft Information and Credit Ratings. Unpublished working paper. Rice University and American University.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. Journal of Business & Economic Statistics, 29(2), 238-249.

Cathcart, L., El-Jahel, L., & Evans, L., (2010). The credit rating crisis and the informational content of corporate credit ratings. Unpublished working paper. Imperial College Business School.

Chen, K. C., & Schoderbek, M. P. (2000). The 1993 tax rate increase and deferred tax adjustments: A test of functional fixation. Journal of Accounting Research, 23-44.

Cheng, M., & Subramanyam, K. (2008). Analyst following and credit ratings. Contemporary Accounting Research, 25(4), 1007-1044.

Cheng, M., & Neamtiu, M., (2009). An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility. Journal of Accounting and Economics, 47(1–2), 108-130.

Churchill, N. C., & Lewis, V. L. (1983). The five stages of small business growth. Harvard Business Review, 61(3), 30.

Coffee, J. C., (2011). Ratings reform: The good, the bad, and the ugly. Harvard Business Law Review, 1, 236-278.

Cole, C. S., Liu, P., & Smith, S. D. (1994). The issuer effect on default risk insured municipal bond yields. Journal of Economics & Finance, 18(3), 331.

Cornaggia, J., Cornaggia, K. R., & Israelsen, R. D. (2014). Credit ratings and the cost of municipal financing. Unpublished working paper, Georgetown University, American University and Indiana University.

Cornaggia, J., Cornaggia, K. R., & Hund, J. (2013). Credit ratings across asset classes: A ≡ A? Unpublished working paper, Georgetown University, American University and Rice University.

Cornell, B., Landsman, W., & Shapiro, A. C. (1989). Cross-sectional regularities in the response of stock prices to bond rating changes. Journal of Accounting, Auditing & Finance, 4(4), 460-479.

Coval, J. D., & Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. Journal of Finance, 54(6), 2045-2073.

Coval, J. D., & Moskowitz, T. J. (2001). The geography of investment: Informed trading and asset prices. Journal of Political Economy, 109(4), 811.

De Franco, G., Kothari, S., & Verdi, R. S. (2011). The benefits of financial statement comparability. Journal of Accounting Research, 49(4), 895-931.

Dichev, I. D., & Piotroski, J. D., (2001). The long-run stock returns following bond ratings changes. Journal of Finance, 56(1), 173-203.

Dimitrov, V., Palia, D., & Tang, L. (2014). Impact of the dodd-frank act on credit ratings. Journal of Financial Economics (JFE), Forthcoming.

Dodd–Frank Wall Street Reform and Consumer Protection Act, One hundred and eleventh congress of the United States (2010).

Downing, C., & Zhang, F. (2004). Trading activity and price volatility in the municipal bond market. Journal of Finance, 59(2), 899-931.

Duncker, K. (1945). The structure and dynamics of problem-solving processes. Psychological Monographs, 58(5), 1-112.

Dyckman, T. R., Hoskin, R. E., & Swieringa, R. J. (1982). An accounting change and information processing changes. Accounting, Organizations and Society, 7(1), 1-11.

Ederington, L. H., & Goh, J. C., 1998. Bond rating agencies and stock analysts: Who knows what when? Journal of Financial and Quantitative Analysis, 33(4), 569-585.

Financial Stability Board. (2010). Principles for reducing reliance on CRA ratings.

Financial Stability Board. (2012). Roadmap and workshop for reducing reliance on CRA ratings.

Fitch Ratings. (2007). Special report: Default risk and recovery rates on U.S. municipal bonds.

Fitch Ratings. (2007). Inside the ratings: What credit ratings mean.

Frankel, R., & Li, X. (2004). Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders. Journal of Accounting and Economics, 37(2), 229-259.

Frost, C. A. (2007). Credit rating agencies in capital markets: A review of research evidence on selected criticisms of the agencies. Journal of Accounting, Auditing & Finance, 22(3), 469-492.

Goel, A., & Thakor, A., (2011). Credit ratings and litigation risk. Unpublished working paper. Navigant Economics and Washington University, Saint Louis.

Goel, A., & Thakor, A., (2013). Why are credit ratings coarse? Unpublished working paper. Navigant Economics and Washington University, Saint Louis.

Graetz, K. A., Boyle, E. S., Kimble, C. E., Thompson, P., & Garloch, J. L. (1998). Information sharing in face-to-face, teleconferencing, and electronic chat groups. Small Group Research, 29(6), 714-743.

Grier, P., & Katzf, S. (1976). The differential effects of bond rating changes among industrial and public utility bonds by maturity. Journal of Business, 49(2), 226.

Griffin, J. M., & Tang, D. Y., (2011). Did credit rating agencies make unbiased assumptions on CDOs? American Economic Review, 101(3), 125-130.

Griffin, J. M., & Tang, D. Y., (2012). Did subjectivity play a role in CDO credit ratings? Journal of Finance, 67(4), 1293-1328.

Hand, J. R. M., Holthausen, R. W., & Leftwich, R. W., (1992). The effect of bond rating agency announcements on bond and stock prices. Journal of Finance, 47(2), 733-752.

Hand, J. R. M. (1990). A test of the extended functional fixation hypothesis. The Accounting Review, 65(4), 740-763.

Harris, T. S., & Ohlson, J. A. (1990). Accounting disclosures and the market's valuation of oil and gas properties: Evaluation of market efficiency and functional fixation. The Accounting Review, 65(4), 764-780.

He, J. J., Qian, J. Q., & Strahan, P. E., 2012. Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities. Journal of Finance, 67(6), 2097-2137.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics, 36(1), 337-386.

Hirshleifer, D., Kewei Hou, Teoh, S. H., & Yinglei Zhang. (2004). Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics, 38, 297-331.

Hite, G., & Warga, A. (1997). The effect of bond-rating changes on bond price performance. Financial Analysts Journal, 53(3), 35-51.

Holthausen, R. W., & Leftwich, R. W., (1986). The effect of bond rating changes on common stock prices. Journal of Financial Economics, 17(1), 57-89.

Huberman, G. (2001). Familiarity breeds investment. Review of Financial Studies, 14(3), 659.

Ijiri, Y., Jaedicke, R. K., & Knight, K. E. (1966). The effects of accounting alternatives on management decisions. Graduate School of Business, Stanford University.

Ingram, R. W., Brooks, L. D., & Copeland, R. M. (1983). The information content of municipal bond rating changes: A note. Journal of Finance, 38(3), 997-1003.

Jacob, B. A., & Levitt, S. D., (2003). Rotten apples: An investigation of the prevalence and predictors of teacher cheating. Quarterly Journal of Economics, 118(3), 843-877.

Jiang, J, Harris Stanford, M., & Xie, Y., (2012). Does it matter who pays for bond ratings? Historical evidence. Journal of Financial Economics, 105(3), 607-621.

Jorion, P., Liu, Z., & Shi, C., (2005). Informational effects of regulation FD: Evidence from rating agencies. Journal of Financial Economics, 76(2), 309-330.

Kao, C., & Wu, C., (1990). Two-step estimation of linear models with ordinal unobserved variables: The case of corporate bonds. Journal of Business & Economic Statistics, 8(3), 317-325.

Kang, J. K., & René M. S. (1997). Why is there a home bias? an analysis of foreign portfolio equity ownership in japan. Journal of Financial Economics 46 (1) (10): 3-28.

Kedia, S., & Rajgopal, S. (2011). Do the SEC's enforcement preferences affect corporate misconduct? Journal of Accounting & Economics, 51(3), 259-278.

Kim, S., Kraft, P., & Ryan, S. G. (2012). Financial statement comparability and credit risk. Review of Accounting Studies, 1-41.

Kliger, D., & Sarig, O., (2000). The information value of bond ratings. Journal of Finance, 55(6), 2879-2902.

Knapp, M. L. (1972). Nonverbal communication in human interaction.

Kraft, P. (2015). Do rating agencies cater? Evidence from rating-based contracts. *Journal of Accounting and Economics*, *59*(2), 264-283.

Kraft, P. (2014). Rating agency adjustments to GAAP financial statements and their effect on ratings and credit spreads. *The Accounting Review*, *90*(2), 641-674.

Liu, P., Seyyed, F. J., & Smith, S. D. (1999). The independent impact of credit rating changes? the case of moody's rating refinement on yield premiums. Journal of Business Finance & Accounting, 26(3-4), 337-363.

Livingston, M., Wei, J., & Zhou, L. (2010). Moody's and S&P ratings: Are they equivalent? conservative ratings and split rated bond yields. Journal of Money, Credit & Banking, 42(7), 1267-1293.

Loury, G. C., (1993). Self-censorship in public discourse: A theory of “Political correctness” and related phenomena. Rationality and Society, 6(4), 428-461.

Mehrabian, Albert. (1972). Nonverbal Communication. Chicago: Aldine-Atherton.

Moody's. (2002). Understanding moody's corporate bond ratings and rating process.

Moody’s Investors Service. (2002). Moody’s US Municipal Bond Rating Scale.

Moody’s Investors Service. (2006). Analyzing the tradeoff between ratings accuracy and stability.

Moody’s. (2006). Moody’s approach to global standard adjustments in the analysis of financial statements for non-financial corporations - part I.

Moody’s. (2007). Financial reporting and credit ratings, CARE conference, Napa California.

Moody’s Investors Service. (2008). Moody’s rating symbols & definitions,

Moody's Investor Service. (2010). Recalibration of Moody’s U.S. municipal ratings to its global rating scale.

Moody's Investor Service. (2010). U.S. municipal bond defaults and recoveries, 1970-2009: special comment.

Moody's Investor Service. (2010). Special comment: U.S. municipal bond defaults and recoveries, 1970-2009.

Morris, S., (2001). Political correctness. Journal of Political Economy, 109(2), 231-265.

Opp, C. C., Opp, M. M., & Harris, M., (2013). Rating agencies in the face of regulation. Journal of Financial Economics, 108(1), 46-61.

Peltzman, S., (1975). The effects of automobile safety regulation. Journal of Political Economy, 83(4), 677-725.

Petersen, M. A. (2004). Information: Hard and Soft. Unpublished working paper. Northwestern University.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies, 22(1), 435-480.

Petersen, M. A., & Rajan, R. G. (2002). Does distance still matter? the information revolution in small business lending. The Journal of Finance, 57(6), 2533-2570.

Schaeffer, P. V., & Millerick, C. A., (1991). The impact of historic district designation on property values: An empirical study. Economic Development Quarterly, 5(4), 301-312.

Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patented inventions. The American Economic Review, 55(5), 1097-1125.

SEC (U.S. Securities and Exchange Commission). (2003). Report on the role and function of credit rating agencies in the operation of the securities markets as required by Section 702(b) of the Sarbanes-Oxley Act of 2002. Washington, D.C.

Skreta, V., & Veldkamp, L., (2009). Ratings shopping and asset complexity: A theory of ratings inflation. Journal of Monetary Economics, 56(5), 678-695.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? Accounting Review, 71(3), 289-315.

Standard and Poor's. (2008). Corporate ratings criteria.

Standard & Poors. (2010). Guide to credit ratings: Why criteria are important and how they are applied.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. The Journal of Finance, 57(5), 1891-1921.

Stiglitz, J., (2008), quoted in "Bringing down Wall Street as ratings let loose subprime scourge," Bloomberg, September 24, 2008.

Strobl, G., & Xia, H., (2012). The issuer-pays rating model and ratings inflation: Evidence from corporate credit ratings. Unpublished working paper. Frankfurt School of Finance and Management and University of Texas at Dallas.

Stotz, O. (2011). The influence of geography on the success of private equity: Investments in listed equity. Applied Financial Economics, 21(21), 1605-1615.

Strausz, R. (2005). Honest certification and the threat of capture. International Journal of Industrial Organization, 23(1–2), 45-62.

Tang, T. T. (2009). Information asymmetry and firms' credit market access: Evidence from moody's credit rating format refinement. Journal of Financial Economics, 93(2), 325-351.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. Journal of Financial Economics, 99(1), 1-10.

United States Government Accountability Office. (2012). Municipal securities: Overview of market structure, pricing, and regulation.

Uysal, V. B., Kedia, S., & Panchapagesan, V. (2008). Geography and acquirer returns. Journal of Financial Intermediation, 17(2), 256-275.

Vergoossen, R. G. A. (1997). Changes in accounting policies and investment analysts' fixation on accounting figures. Accounting, Organizations and Society, 22(6), 589-607.

White, L. J. (2002). The credit rating industry: An industrial organization analysis Springer.

APPENDIX A:

TABLES AND FIGURES

Table 1: Variable measurement

Variable name	Variable measurement
Rating announcement bond returns	Bond returns are calculated based on the volume-weighted trade price for the closest trade date within a five-day period prior to a rating announcement date, and the volume-weighted trade price for the closest trade date within a five-day period following the rating announcement date.
Rating announcement stock returns	Stock returns are calculated as the buy-and-hold returns over the three-day period centered at the rating announcement date minus the corresponding return on the CRSP value-weighted index.
Rating level	Numerical credit rating. See Appendix B for numerical rating conversion.
Rating type II error	Dichotomous variable which equals one for a bond issue rated as speculative grade that does not default within one year, and zero otherwise.
Years to maturity	The number of years to maturity of a bond issue relative to the rating announcement date.
ROA	Return on assets, calculated as net income divided by total assets, for the fiscal quarter ending prior to the rating announcement date.
Market value	Share price times number of common shares outstanding for the fiscal quarter ending prior to the rating announcement date
Interest coverage	Income before extraordinary items divided by interest expense for the fiscal quarter ending prior to the rating announcement date.
Book-to-market	Book value of equity divided by market value of equity for the fiscal quarter ending prior to the rating announcement date.
LT debt-to-equity	Total long-term debt divided by book value of equity for the fiscal quarter ending prior to the rating announcement date.
Operating margin	Operating income before depreciation divided by total sales for the fiscal quarter ending prior to the rating announcement date

Table 1 Continues: Variable measurement

Variable name	Variable measurement
LT debt leverage	Total long-term debt divided by total assets for the fiscal quarter ending prior to the rating announcement date.
Total debt leverage	Total debt divided by total assets for the fiscal quarter ending prior to the rating announcement date.
Bond index return	CRSP 30-year treasury bond index return over the year ending the month prior to the rating announcement date.
Stock beta	CAPM beta estimated using the CRSP value-weighted index as the market index and daily stock returns over the fiscal quarter ending prior to the rating announcement date.
Total stock return volatility	Standard deviation of daily stock returns measured over the fiscal quarter ending prior to the rating announcement date.
Idiosyncratic stock return volatility	Standard deviation of residual stock returns relative to the CAPM model, estimated using the CRSP value-weighted index as the market index and daily stock returns over the fiscal quarter ending prior to the rating announcement date.

Table 2: Summary statistics

	Before Dodd-Frank				After Dodd-Frank			
Variable	#Obs	Mean	Min	Max	#Obs	Mean	Min	Max
Rating announcement bond returns	7,120	-0.002	-0.159	0.094	3,715	-0.001	-0.159	0.094
Rating announcement stock return	17,687	-0.005	-0.355	0.262	7,648	0.000	-0.355	0.262
Rating level	18,606	10.850	1.000	21.000	8,019	10.125	1.000	21.000
Rating type II error	18,606	0.448	0.000	1.000	8,019	0.392	0.000	1.000
Years to maturity	18,600	10.439	0.000	98.564	8,019	9.824	0.000	100.080
ROA	18,601	0.004	-0.126	0.050	8,019	0.010	-0.126	0.050
Log Market value	18,606	8.693	0.033	12.944	8,019	9.052	1.858	12.391
Interest coverage	18,238	2.499	-15.309	26.599	7,933	4.304	-15.309	26.599
Book-to-market	17,218	0.641	0.010	4.275	7,486	0.561	0.011	4.275
LT debt-to-equity	17,266	1.657	0.000	19.449	7,502	1.508	0.000	19.449
Operating margin	18,189	0.171	-0.539	0.880	7,962	0.217	-0.539	0.827
LT debt leverage	18,599	0.316	0.014	0.968	8,009	0.304	0.014	0.968
Total debt leverage	17,711	0.352	0.027	1.031	7,834	0.337	0.027	1.031
Bond index return	18,606	0.053	-0.260	0.417	8,019	0.135	-0.044	0.392
Stock beta	17,903	1.159	-1.768	5.294	7,701	1.112	-0.772	3.147
Total stock return volatility	17,658	0.029	0.007	0.121	7,642	0.021	0.007	0.121
Idiosyncratic stock return volatility	17,903	0.023	0.001	0.374	7,701	0.015	0.001	0.179

This table reports descriptive statistics for key variables. The sample consists of all rating announcements for U.S. corporate bonds between January 2006 and May 2012, excluding the financial industry as defined according the Fama-French 12 industry classification. The Before Dodd-Frank period incorporates rating actions between January 2006 and July 21, 2010 while the After Dodd-Frank period incorporates rating actions after July 21, 2010. Variable definitions are provided in Table 1.

Table 3: Rating levels before and after Dodd-Frank

	Model 1 Main Model			Model 2 Fitch Market Share Interaction		
Variable	Pred. Sign	Coefficient	z-stat.	Pred. Sign	Coefficient	z-stat.
After Dodd-Frank	+	0.171**	2.14	+/-	-0.090	-0.91
Fitch market share	/			+/-	-0.426**	-2.39
After Dodd-Frank x Fitch market share	/			+	0.908***	3.39
Moody	+/-	0.096*	1.77	+/-	0.103*	1.94
Fitch	+/-	-0.325***	-3.68	+/-		
Operating margin	+/-	1.009**	2.15	+/-	0.635	1.47
LT debt leverage	+	2.383	0.86	+	1.682	0.78
Total debt leverage	+	1.195	0.36	+	1.467	0.55
Log of market value	-	-1.004***	-6.73	-	-1.004***	-7.67
Stock beta	+	0.652***	5.10	+	0.540***	4.89
Idiosyncratic stock return volatility	+	17.869***	3.44	+	16.067***	3.81
Interest coverage	-	-0.061***	-5.50	-	-0.047***	-4.78
# Observations		23,687			12,895	
Pseudo R^2		20.26%			19.58%	

This table shows ordered logistic regression results for numerical rating codes for all credit rating announcements between January 2006 and May 2012. The sample excludes financial industry firms. The dependent variable is the numerical rating for a bond, ranging from 1-21 (AAA-C). After Dodd-Frank is a dummy variable which is one for ratings assigned after July 21, 2010 and zero for ratings assigned between January 2006 and July 21, 2010. Fitch market share is a dummy variable equal to one for ratings in industries with Fitch market share below the 25^{th} percentile. Industries are defined according to the Fama-French 12 industry classification and Fitch market share percentiles are calculated by year and industry. Moody and Fitch are dummy variables showing which agency rated the bond. The remaining variables are defined in Table 1. Standard errors are clustered by firm. ***,**,* represent significance beyond the 1^{st}, 5^{th}, and 10^{th} percentile levels, respectively.

Table 4: False warnings before and after Dodd-Frank

	Model 1 Main Model			Model 2 Fitch Market Share Interaction		
Variable	Pred. Sign	Coefficient	z-stat.	Pred. Sign	Coefficient	z-stat.
After Dodd-Frank	+	0.607***	4.77	+/-	0.299*	1.86
Fitch market share	/			+/-	-0.217	-0.89
After Dodd-Frank x Fitch market share	/			+	1.810***	4.21
Bond index return	-	-3.379***	-6.52	-	-4.944***	-7.83
Moody	+/-	-0.096	-1.02	+/-	-0.077	-0.82
Fitch	+/-	-0.704***	-5.15	+/-		
Years to maturity	+/-	-0.009*	-1.71	+/-	-0.009	-1.52
ROA	+	2.582	0.50	+	-1.245	-0.26
Log of market value	-	-1.126***	-8.66	-	-1.193***	-11.80
Interest coverage	-	-0.074***	-3.33	-	-0.050**	-2.53
Total stock return volatility	+	31.024***	3.93	+	23.953***	3.15
Book-to-market	-	-0.491**	-2.06	-	-0.476*	-1.90
LT debt-to-equity	+	0.416***	3.76	+	0.327***	3.10
Intercept	/	9.104***	7.45	/	10.017***	10.66
# Observations		23,105			12,462	
Pseudo R^2		44.17%			43.15%	

This table shows logistic regression results for type II errors (false warnings) for all credit rating announcements between January 2006 and May 2012. The sample excludes financial industry firms. The dependent variable is a dichotomous error measure representing a value of one for a BB+ or lower rated issue that does not default within one year, and zero otherwise. After Dodd-Frank is a dummy variable which is one for ratings assigned after July 21, 2010 and zero for ratings assigned between January 2006 and July 21, 2010. Fitch market share is a dummy variable equal to one for ratings in industries with Fitch market share below the 25^{th} percentile. Industries are defined according to the Fama-French 12 industry classification and Fitch market share percentiles are calculated by year and industry. Moody and Fitch are dummy variables showing which agency rated the bond. The remaining variables are defined in Table 1. Standard errors are clustered by firm. ***,**,* represent significance beyond the 1^{st}, 5^{th}, and 10^{th} percentile levels, respectively.

Table 5: Bond price response to rating downgrades and upgrades before and after Dodd-Frank

Panel A: Sample of rating changes

	Credit Rating Downgrades		Credit Rating Upgrades	
Year	# Observations	Magnitude of Rating Change	# Observations	Magnitude of Rating Change
2006	510	1.46	394	1.15
2007	468	1.42	261	1.18
2008	542	1.36	176	1.29
2009	510	1.46	161	1.73
2010	252	1.15	433	1.53
2011	398	1.21	464	1.20
2012	161	1.11	162	1.04
Before Dodd-Frank	2,170	1.41	1,216	1.33
After Dodd-Frank	671	1.17	835	1.24
Total	2,841	1.35	2,051	1.30

Panel B: Rating announcement bond returns

Panel B.1.: Full sample

	Credit Rating Downgrades			Credit Rating Upgrades		
	# Obs.	Mean Return %	Median Return %	# Obs.	Mean Return %	Median Return %
Before Dodd-Frank	2,170	-1.023***	-0.251***	1,216	0.300***	0.197***
After Dodd-Frank	671	-0.654***	-0.246***	835	0.344***	0.165***
Difference (After-Before)		0.369**	-0.005		0.044	-0.032
T-statistic		2.11	0.36		0.52	0.12

Panel B.2.: Bottom quartile of Fitch market share

	Credit Rating Downgrades			Credit Rating Upgrades		
	# Obs.	Mean Return %	Median Return %	# Obs.	Mean Return %	Median Return %
Before Dodd-Frank	411	-1.485***	-0.563***	151	0.425*	0.050
After Dodd-Frank	148	-0.402***	-0.234**	225	0.201	0.077
Difference (After-Before)		1.083**	0.329		-0.224	0.027
T-statistic		2.47	1.39		1.25	1.17

Panel B.3.: Top three quartiles of Fitch market share

	Credit Rating Downgrades			Credit Rating Upgrades		
	# Obs.	Mean Return %	Median Return %	# Obs.	Mean Return %	Median Return %
Before Dodd-Frank	1,237	-0.869***	-0.233***	858	0.341***	0.254***
After Dodd-Frank	330	-0.904***	-0.404***	414	0.391***	0.145***
Difference (After-Before)		0.035	-0.171**		0.050	-0.109
T-statistic		0.15	2.14		0.45	1.20

This table shows bond returns surrounding credit rating downgrade and upgrade announcements before and after the Dodd–Frank Wall Street Reform and Consumer Protection Act. The sample excludes financial industry firms. After Dodd-Frank is a dummy variable which is one for ratings assigned after July 21, 2010 and zero for ratings assigned between January 2006 and July 21, 2010. Industries are defined according to the Fama-French 12 industry classification and Fitch market share percentiles are calculated by year and industry. Panel A shows the sample of credit rating downgrades and upgrades by year. Panel B shows bond returns surrounding the rating announcement date. Panel B.1 shows bond returns for the entire sample. Panel B.2 is restricted to downgrades/upgrades in industries with Fitch market share below the 25th percentile. Panel B.3 is restricted to downgrades/upgrades in industries with Fitch market share above the 25th percentile. Mean and median returns are shown as percentages. Mean and median differences are tested using the T and Wilcoxon two-sample tests, respectively. Variables are defined in Table 1. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

Table 6: Stock price response to rating downgrades and upgrades before and after Dodd-Frank

Panel A: Sample of rating changes

	Credit Rating Downgrades		Credit Rating Upgrades	
Year	# Observations	Magnitude of Rating Change	# Observations	Magnitude of Rating Change
2006	300	1.36	286	1.12
2007	269	1.35	216	1.25
2008	307	1.35	221	1.27
2009	319	1.47	113	1.58
2010	124	1.21	269	1.24
2011	181	1.20	237	1.16
2012	65	1.19	112	1.06
Before Dodd-	1,273	1.38	983	1.26
After Dodd-	292	1.20	471	1.15
Total	1,565		1,454	

Panel B: Rating announcement stock returns

Panel B.1.: Full sample

	Credit Rating Downgrades			Credit Rating Upgrades		
	# Obs.	Mean Return %	Median Return %	# Obs.	Mean Return %	Median Return %
Before Dodd-Frank	1,273	-2.461***	-0.982***	983	0.062	0.095
After Dodd-Frank	292	-1.248**	-0.384	471	0.369**	0.235*
Difference (After-Before)		1.212*	0.598***		0.308	0.140
T-statistic		1.81	2.63		1.14	1.26

Panel B.2.: Bottom quartile of Fitch market share

	Credit Rating Downgrades			Credit Rating Upgrades		
	# Obs.	Mean Return %	Median Return %	# Obs.	Mean Return %	Median Return %
Before Dodd-Frank	255	-3.890***	-2.394***	121	-0.060	-0.259
After Dodd-Frank	79	-0.914	-0.832	108	-0.237	-0.274
Difference (After-Before)		2.976**	1.562**		-0.177	-0.015
T-statistic		2.05	2.52		0.29	0.12

Panel B.3.: Top three quartiles of Fitch market share

	Credit Rating Downgrades			Credit Rating Upgrades		
	# Obs.	Mean Return %	Median Return %	# Obs.	Mean Return %	Median Return %
Before Dodd-Frank	812	-2.138***	-0.736***	743	0.227	0.142
After Dodd-Frank	160	-1.472*	-0.287	299	0.607***	0.377**
Difference (After-Before)		0.666	0.449*		0.380	0.235
T-statistic		0.73	1.65		1.20	1.42

This table shows stock returns surrounding credit rating downgrade and upgrade announcements before and after the Dodd–Frank Wall Street Reform and Consumer Protection Act. The sample excludes financial industry firms. After Dodd-Frank is a dummy variable which is one for ratings assigned after July 21, 2010 and zero for ratings assigned between January 2006 and July 21, 2010. Industries are defined according to the Fama-French 12 industry classification and median percentiles are calculated by year and industry. Panel A shows the sample of credit rating downgrades and upgrades by year. Panel B shows stock returns surrounding the rating announcement date. Panel B.1 shows stock returns for the entire sample. Panel B.2 is restricted to downgrades/upgrades in industries with Fitch market share below the 25th percentile. Panel B.3 is restricted to downgrades/upgrades in industries with Fitch market share above the 25th percentile. Mean and median returns are shown as percentages. Mean and median differences are tested using the T and Wilcoxon two-sample tests, respectively. Variables are defined in Table 1. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

Table 7: Rating levels and false warnings for alternative start dates of the post-Dodd-Frank period

Panel A: Rating levels

Coefficients	Start of the Post-Dodd-Frank Period July 2009	December 2009	July 2010	May 2011
After Dodd-Frank (Corresponds to Model 1 of Table 3)	0.018	0.150*	0.171**	0.130
After Dodd-Frank x Fitch market share (Corresponds to Model 2 of Table 3)	0.342	0.754***	0.908***	0.826***

Panel B: False warnings

Coefficients	Start of the Post-Dodd-Frank Period July 2009	December 2009	July 2010	May 2011
After Dodd-Frank (Corresponds to Model 1 of Table 4)	0.135	0.354***	0.607***	0.784***
After Dodd-Frank x Fitch market share (Corresponds to Model 2 of Table 4)	1.473***	1.809***	1.810***	1.781***

This table shows ordered logistic regression results for numerical rating codes (Panel A) and logistic regression results for type II errors (false warnings) (Panel B) for all credit rating announcements between January 2006 and May 2012, conditional on the starting date of the post-Dodd-Frank period. Panel A & Panel B correspond to the regression specifications in Table 3 & Table 4, respectively, with the coefficients on the control variables omitted for brevity. The sample excludes financial industry firms. In Panel A, the dependent variable is the numerical rating for a bond, ranging from 1-21 (AAA-C). In Panel B, the dependent variable is a dichotomous error measure representing a value of one for a BB+ or lower rated issue that does not default within one year, and zero otherwise. After Dodd-Frank is a dummy variable which is one for ratings assigned after the corresponding date in the table and zero otherwise. Fitch market share is a dummy variable equal to one for ratings in industries with Fitch market share below the 25th percentile. Industries are defined according to the Fama-French 12 industry classification and Fitch market share percentiles are calculated by year and industry. Variables are defined in Table 1. Standard errors are clustered by firm. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

Table 1
Variable Measurement

Variable name	Description
Distance to New York	The distance is measured in kilometers between a firm's headquarters and New York City. This distance is calculated using the Haversine formula based on longitudes and latitudes of U.S. cities listed on the 2010 census.
Non Direct	Dichotomous variable which equals one for cities without direct flights to NYC and are at least 100 kilometers away from NYC, and zero otherwise.
Rating Code	Numerical credit rating. See Appendix A for details.
Type 1 error rate	Dichotomous variable which equals one for a bond issue rated as investment grade that does default within two years, and zero otherwise.
Type 2 error rate	Dichotomous variable which equals one for a bond issue rated as speculative grade that does not default within two years, and zero otherwise.
Dahead	The number of days between a downgrade date and default date. The event window for downgrades is two years prior to a default date.
Analyst following	The number of equity analysts covering a particular firm in the fiscal quarter ending prior to the rating announcement date.
Complexity	The number of product segments for a firm in the fiscal quarter ending prior to the rating announcement date.
Years to maturity	The number of years to maturity of a bond issue relative to the rating announcement date.
ROA	Return on assets, calculated as net income divided by total assets, for the fiscal quarter ending prior to the rating announcement date.
Market value	Share price times number of common shares outstanding for the fiscal quarter ending prior to the rating announcement date
Interest coverage	Income before extraordinary items divided by interest expense for the fiscal quarter ending prior to the rating announcement date.
Book-to-market	Book value of equity divided by market value of equity for the fiscal quarter ending prior to the rating announcement date.
Debt to equity ratio	Total long-term debt divided by book value of equity for the fiscal quarter ending prior to the rating announcement date.

Table 8 Continues
Variable Measurement

Variable name	Description
Operating margin	Operating income before depreciation divided by total sales for the fiscal quarter ending prior to the rating announcement date
Return volatility	Standard deviation of daily returns measured over the fiscal quarter ending prior to the rating announcement date.
LT debt to assets	Total long-term debt divided by total assets for the fiscal quarter ending prior to the rating announcement date.
Total debt to assets	Total debt divided by total assets for the fiscal quarter ending prior to the rating announcement date.
Stock beta	CAPM beta estimated using the CRSP value-weighted index as the market index and daily returns over the fiscal quarter ending prior to the rating announcement date.
Idiosyncratic stock return volatility (RMSE)	Standard deviation of residual returns relative to the CAPM model, estimated using the CRSP value-weighted index as the market index and daily returns over the fiscal quarter ending prior to the rating announcement date.
2001 recession	A dummy variable representing 1 during the 2001 recession between March 2001 and November 2001 and 0 otherwise.
Financial crisis	A dummy variable representing 1 during the financial crisis between December 2007 and May 2009 and 0 otherwise.

TABLE 2

Descriptive Statistics

Distributional Characteristics of Variables

Variable	Full Sample N	Mean	Min	Max
Continuous Variables				
Distance to New York	96271	1322.301	0.000	7978.103
Rating Code	96271	9.418	1.000	21.000
Dahead	2126	199.230	0.000	730
Analyst following	96271	13.603	0.000	47.000
Complexity	74543	3.482	1.000	9.000
Years to maturity	96261	10.139	-8.419	100.143
ROA	95898	0.003	-0.122	0.048
Market value	96271	8.689	0.033	12.579
Interest coverage	86283	4.423	-8.903	38.500
Book-to-market	90410	0.675	0.010	4.202
Debt to equity ratio	90586	2.034	0.000	19.155
Operating margin	78301	0.208	-0.582	0.882
Return volatility	93418	0.029	0.007	0.121
LT debt to assets	95776	0.300	0.018	0.954
Total debt to assets	88467	0.384	0.036	1.009
Stock beta	94976	1.111	-9.654	8.485
Idiosyncratic stock return volatility (RMSE)	94976	0.026	0.001	0.374
Dichotomous Variables				
Non Direct	76253	0.593	0.000	1.000
Type 1 error rate	96271	0.008	0.000	1.000
Type 2 error rate	96271	0.296	0.000	1.000
Financial crisis	96271	0.122	0.000	1.000
2001 recession	96271	0.062	0.000	1.000

This table reports descriptive statistics for key variables. See table 1 for variable definitions. N is the number of observations. Mean is the average value, min is the minimum and max is the maximum value. All variables excluding distance, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value, debt to equity and book to market ratios are restricted to positive values.

TABLE 3

Logistic Regression Results on the Association Between Geographic Distance and Type 1 Error Rate

	Predicted Sign	Model 1 Main Model		Model 2 With Industry Effects		Model 3 With Industry and Year Effects	
		Coefficient	Z Statistic	Coefficient	Z Statistic	Coefficient	Z Statistic
Distance to NYC	**+**	**0.00048**	**3.15*** **	**0.00041**	**2.25** **	**0.00040**	**2.24** **
Moody Rating	+/-	-0.41336	-3.09***	-0.47969	-3.51***	-0.46981	-3.38***
Fitch Rating	+/-	-0.54536	-2.22**	-0.56449	-2.22**	-0.43021	-1.75*
Maturity	-	-0.01730	-1.53	-0.01235	-1.54	-0.00794	-0.87
NYC dummy	+/-	0.89196	0.83	1.34736	1.74*	1.41077	1.79*
Financial Crisis	+	0.27563	0.29	0.44563	0.57	/	/
2001 Recession	+	1.79737	5.59***	1.80622	5.30***	/	/
Return on Assets	+/-	17.26238	6.41***	23.28273	2.07**	35.49909	2.20**
Log Market Value	+	0.50686	1.43	0.50422	1.62	0.42809	1.77*
Interest Coverage	-	-0.13983	-1.58	-0.21303	-1.58	-0.20575	-1.67*
Return Volatility	+	25.09430	3.55***	26.61171	3.02***	31.70765	2.74***
Book to Market Ratio	+/-	0.34843	1.38	0.28021	0.82	0.30073	0.95
Debt Equity Ratio	+	0.12959	2.14**	0.18356	3.04***	0.19639	2.96***
Intercept	/	-11.36777	-4.36***	-12.88344	-3.75***	-27.44416	-5.42***
N		78,753		78,753		78,753	
Pseudo Rsquared		20.09%		30.34%		36.52%	

This table shows the logistic regression results for models 1-3. Model 1 is the main model, model 2 includes industry fixed effects, and model 3 includes industry and year fixed effects. All logistic regressions are clustered by both firm (GVKEY) and time (fiscal year quarter). See table 1 for variable descriptions. N is the sample size of the regression. Pseudo Rsquared represents is a goodness of fit measure. All variables excluding distance, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value, debt to equity and book to market ratios are restricted to positive values. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

TABLE 4

Logistic Regression Results on the Association Between Geographic Distance and Type 2 Error Rate

		Model 1		Model 2		Model 3	
		Main Model		With Industry Effects		With Industry and Year Effects	
	Predicted Sign	Coefficient	Z Statistic	Coefficient	Z Statistic	Coefficient	Z Statistic
Distance to NYC	**+**	**0.00021**	**2.90*** **	**0.00015**	**1.97** **	**0.00013**	**1.75***
Moody Rating	+/-	0.17635	1.71*	0.22297	2.08**	0.25273	2.60***
Fitch Rating	+/-	-0.03201	-0.23	0.10040	0.67	-0.11367	-0.86
Maturity	-	-0.01604	-2.91***	-0.01686	-3.10***	-0.01460	-2.74***
NYC dummy	+/-	-0.72889	-1.63	0.17978	0.48	0.09235	0.27
Financial Crisis	-	-0.10649	-0.49	0.07513	0.37	/	/
2001 Recession	-	-0.51321	-3.52***	-0.57455	-3.78***	/	/
Return on Assets	+/-	-1.01182	-0.38	1.80346	0.78	4.14801	1.85*
Log Market Value	-	-0.86174	-14.48***	-0.90835	-14.55***	-0.97861	-16.04***
Interest Coverage	-	-0.05086	-4.19***	-0.06245	-4.68***	-0.07611	-5.80***
Return Volatility	+	20.01785	4.02***	15.89094	3.65***	31.20233	6.31***
Book to Market Ratio	-	-0.69034	-5.15***	-0.51167	-3.51***	-0.66108	-3.93***
Debt Equity Ratio	+	0.08325	2.56**	0.10989	2.95***	0.08343	2.13**
Intercept	/	6.10324	11.10***	6.83307	11.25***	7.05107	12.03***
N		78,753		78,753		78,753	
Pseudo Rsquared		31.27%		35.43%		40.13%	

This table shows the logistic regression results for models 1-3. Model 1 is the main model, model 2 includes industry fixed effects, and model 3 includes industry and year fixed effects. All logistic regressions are clustered by both firm (GVKEY) and time (fiscal year quarter). See table 1 for variable descriptions. N is the sample size of the regression. Pseudo Rsquared represents is a goodness of fit measure. All variables excluding distance, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value, debt to equity and book to market ratios are restricted to positive values. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

TABLE 5

OLS Regression Results on the Association Between Geographic Distance and Timeliness of Downgrades

		Model 1		Model2		Model3	
		Main Model		With Industry Effects		With Industry and Year Effects	
	Predicted Sign	Coefficient	t- Statistic	Coefficient	t- Statistic	Coefficient	t- Statistic
Distance to NYC	**+**	**-0.03359**	**-2.00****	**-0.03255**	**-2.02****	**-0.02755**	**-1.84***
Moody Rating	+/-	11.22813	0.97	14.66021	1.37	12.68066	0.99
Fitch Rating	+/-	13.25125	0.73	8.79871	0.46	15.76189	1.08
Maturity	+/-	0.67870	0.58	0.52979	0.50	0.33804	0.41
NYC dummy	+/-	63.41001	0.84	122.68120	1.40	55.88903	0.58
Financial Crisis	+	140.77210	1.83*	125.62530	1.79*	/	/
2001 Recession	+	-44.90498	-1.23	-73.16247	-1.95**	/	/
Return on Assets	+/-	408.85620	1.25	849.00190	2.50***	813.43370	2.02**
Log Market Value	+	-45.53945	-3.34***	-41.58492	-3.73***	-15.05017	-1.23
Interest Coverage	-	-6.25615	-0.95	-7.34811	-1.25	-4.16149	-0.89
Return Volatility	+	-2230.60800	-4.57***	-1952.39300	-6.57***	-651.14640	-1.11
Book to Market Ratio	-	-25.52979	-1.77*	-40.36245	-2.51***	-19.96891	-1.48
Debt Equity Ratio	+	-1.89540	-0.39	-3.82194	-0.82	0.31653	0.07
Intercept	/	713.72740	6.86***	774.39760	7.69***	257.35180	2.08**
N		1,669		1,669		1,669	
Rsquared		23.43%		31.52%		42.96%	

This table shows the regression results for models 1-3. Model 1 is the main model, model 2 includes industry fixed effects, and model 3 includes industry and year fixed effects. All logistic regressions are clustered by both firm (GVKEY) and time (fiscal year quarter). See table 1 for variable descriptions. N is the sample size of the regression. Rsquared represents is a goodness of fit measure. All variables excluding distance, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value, debt to equity and book to market ratios are restricted to positive values. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

TABLE 6

Logistic Regression Results for the Interaction Effect between Complexity and Distance to NYC

	Model 1 Logistic Regression Results on Type 1 Error Rate			Model 2 Logistic Regression Results on Type 2 Error Rate			Model 3 OLS Regression Results on the Timeliness of Downgrades		
	Predicted Sign	Coefficient	Z Statistic	Predicted Sign	Coefficient	Z Statistic	Predicted Sign	Coefficient	t-Statistic
Distance to NYC	/	-0.00228	-1.61	/	-0.00047	-1.48	/	-0.05909	-1.22
Distance x Complexity	**+**	**0.00079**	**2.13****	**+**	**0.00002**	**0.13**	**-**	**-0.11382**	**-2.76*****
Complexity	/	-1.12339	-1.25	/	-0.17722	-0.69	/	251.60910	3.35***
Size Interaction	+/-	0.00028	1.70*	+/-	0.00007	1.72*	+/-	0.00822	1.02
Moody Rating	+/-	-0.38655	-2.59***	+/-	0.23398	2.69***	+/-	13.58924	1.16
Fitch Rating	+/-	-0.46124	-1.99**	+/-	-0.17526	-1.48	+/-	21.91642	1.60
Maturity	-	-0.00666	-0.83	-	-0.01419	-2.69***	+/-	-0.03189	-0.04
NYC dummy	+/-	1.73316	2.21**	+/-	0.08965	0.26	+/-	18.13804	0.17
Return on Assets	+	36.01492	2.21**	+/-	4.05928	1.85*	+/-	719.64840	2.42**
Log Market Value	+	0.28086	1.22	-	-1.08857	-12.22***	+	-30.58028	-1.54
Interest Coverage	-	-0.23894	-2.21**	-	-0.07632	-6.09***	-	-6.98262	-1.41
Return Volatility	+	36.89362	3.35***	+	30.84754	6.32***	+	-322.58220	-0.61
Book to Market Ratio	-	0.32408	0.87	-	-0.67740	-4.13***	-	-41.35823	-2.84***

Debt Equity Ratio	+	0.20522	3.46***	+	0.08312	2.07**	+	-5.77755	-1.11
Intercept	/	-12.32208	-4.92***	/	8.49040	10.81***	/	423.07540	2.38**
N		78,753			78,753			1,669	
Pseudo Rsquared		36.84%			40.69%			49.81%	

This table shows the regression results for interaction effect between complexity and distance to NYC for type 1 errors (model 1), type 2 errors (model 2), and rating timeliness (model 3). All regressions are clustered by both firm (GVKEY) and time (fiscal year quarter) and include industry and year fixed effects. See table 1 for variable descriptions. All variables excluding distance, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value, debt to equity and book to market ratios are restricted to positive values. N is the sample size of the regression. Pseudo Rsquared represents is a goodness of fit measure. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

TABLE 7

Logistic Regression Results for the Interaction Effect between Analyst Following and Distance to NYC

	Model 1 Logistic Regression Results on Type 1 Error Rate			Model 2 Logistic Regression Results on Type 2 Error Rate			Model 3 OLS Regression Results on Downgrades		
	Predicted Sign	Coefficient	Z Statistic	Predicted Sign	Coefficient	Z Statistic	Predicted Sign	Coefficient	t-Statistic
Distance to NYC	/	-0.00213	-1.59	/	-0.00027	-0.79	/	-0.00505	-0.05
Distance x Analyst Following	**-**	**-0.00004**	**-1.83***	-	**0.00001**	**0.74**	+	**0.00374**	**1.88***
Analyst Following	/	0.09386	1.56	/	-0.00650	-0.23	/	-15.10807	-2.39**
Size Interaction	+/-	0.00036	2.12**	+/-	0.00004	0.71	+/-	-0.00826	-0.43
Moody Rating	+/-	-0.39066	-2.49**	**+/-**	0.22663	2.52**	+/-	12.93290	0.97
Fitch Rating	+/-	-0.40859	-1.77*	+/-	-0.17502	-1.44	+/-	17.18197	1.00
Maturity	-	-0.00667	-0.86	-	-0.01416	-2.62***	+/-	0.52067	0.53
NYC dummy	+/-	1.51840	1.77*	+/-	0.04080	0.11	+/-	57.77056	0.66
Return on Assets	+	30.67103	1.93*	+/-	4.04931	1.82	+/-	374.54970	0.79
Log Market Value	+	-0.00873	-0.04	-	-1.08176	-8.89***	+	25.28573	0.66
Interest Coverage	-	-0.22845	-2.22**	-	-0.07635	-5.89***	-	-4.48976	-0.99
Return Volatility	+	37.26740	3.06***	+	32.53361	6.18***	+	-1334.70400	-2.69***
Book to Market Ratio	-	0.06486	0.12	-	-0.70018	-4.06***	-	-17.37091	-0.98
Debt Equity Ratio	+	0.18698	3.44***	+	0.08757	2.10**	+	-1.91193	-0.35
Intercept	/	-11.10877	-5.37***	/	8.47406	9.83***	/	461.76360	2.42**

N	76,791	76,791	1,669
Pseudo Rsquared	36.13%	41.26%	46.56%

This table shows the regression results for interaction effect between analyst following and distance to NYC for type 1 errors (model 1), type 2 errors (model 2), and rating timeliness (model 3). All regressions are clustered by both firm (GVKEY) and time (fiscal year quarter) and include industry and year fixed effects. See table 1 for variable descriptions. All variables excluding distance, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value, debt to equity and book to market ratios are restricted to positive values. N is the sample size of the regression. Pseudo Rsquared represents is a goodness of fit measure. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

TABLE 8
Logistic Regression Results on the Association Between Rating Levels and Geographic Distance

		Model 1		Model 2	
		Main Model		With Industry and Year Effects	
	Predicted Sign	Coefficient	Z Statistic	Coefficient	Z Statistic
Distance to NYC	**/**	**0.0002**	**3.21*** **	**0.0001**	**2.11** **
Moody Rating	+/-	0.0386	0.73	0.0614	0.98
Fitch Rating	+/-	-0.1146	-1.32	-0.3689	-5.30***
Operating Margin	-	-1.0568	-2.72***	-1.1888	-2.92***
LT Debt to Assets	+/-	6.8821	8.53***	4.3807	5.07***
Debt to Assets	+/-	-3.4840	-4.97***	-1.3409	-1.83*
Log of Market Value	-	-0.8912	-12.94***	-1.0287	-13.59***
Beta	+	0.5076	6.57***	0.1808	2.62***
RMSE	+	9.2142	2.58**	20.8671	4.85***
Interest Coverage	-	-0.0386	-4.58***	-0.0545	-5.74***
N		70,721		70,721	
Pseudo Rsquared		19.24%		23.15%	

This table shows the ordered logistic regression results for numerical rating codes. All regressions are clustered by firm (GVKEY). See table 1 for variable descriptions. N is the sample size of the regression. Pseudo R-squared represents is a goodness of fit measure. All variables excluding rating code, log values, and dummy variables are winsorized at the 1st and 99th percentiles. Market value is also restricted to positive values. ***, **,* represent significance beyond the 1st, 5th, and 10th percentile levels respectively.

Table 1: Moody's Rating Recalibration for U.S. States and territories

State	Old Rating	Old Outlook	New Rating	New Outlook	Difference
Alabama	Aa2	Stable	Aa1	Stable	1
Alaska	Aa2	Stable	Aa1	Stable	1
Arizona	A1	Negative	Aa2	Negative	2
Arkansas	Aa2	Stable	Aa1	Stable	1
California	Baa1	Stable	A1	Stable	3
Colorado	Aa2	Stable	Aa1	Stable	1
Connecticut	Aa3	Negative	Aa2	Stable	1
Delaware	Aaa	Stable	Aaa	Stable	0
District of Columbia	A1	Stable	Aa2	Stable	2
Florida	Aa1	Negative	Aa1	Stable	0
Georgia	Aaa	Stable	Aaa	Stable	0
Hawaii	Aa2	Negative	Aa1	Negative	1
Idaho	Aa2	Stable	Aa1	Stable	1
Illinois	A2	Negative	Aa3	Negative	2
Indiana	Aa1	Stable	Aaa	Stable	1
Iowa	Aa1	Stable	Aaa	Stable	1
Kansas	Aa1	Negative	Aa1	Stable	0
Kentucky	Aa2	Negative	Aa1	Negative	1
Louisiana	A1	Positive	Aa2	Stable	1
Maine	Aa3	Stable	Aa2	Stable	1
Maryland	Aaa	Stable	Aaa	Stable	0
Massachusetts	Aa2	Stable	Aa1	Stable	1
Michigan	Aa3	Negative	Aa2	Stable	1
Minnesota	Aa1	Negative	Aa1	Stable	0
Mississippi	Aa3	Stable	Aa2	Stable	1
Missouri	Aaa	Stable	Aaa	Stable	0
Montana	Aa2	Stable	Aa1	Stable	1
Nevada	Aa2	Stable	Aa1	Stable	1
New Hampshire	Aa2	Stable	Aa1	Stable	1
New Jersey	Aa3	Negative	Aa2	Stable	1
New Mexico	Aa1	Stable	Aaa	Stable	1
New York (State and	Aa3	Stable	Aa2	Stable	1
North Carolina	Aaa	Stable	Aaa	Stable	0
North Dakota	Aa2	Stable	Aa1	Stable	1
Ohio	Aa2	Negative	Aa1	Negative	1
Oklahoma	Aa3	Stable	Aa2	Stable	1
Oregon	Aa2	Stable	Aa1	Stable	1
Pennsylvania	Aa2	Negative	Aa1	Negative	1
Puerto Rico	Baa3	Stable	A3	Stable	3
Rhode Island	Aa3	Negative	Aa2	Stable	1
South Carolina	Aaa	Stable	Aaa	Stable	0
Tennessee	Aa1	Stable	Aaa	Stable	1
Texas	Aa1	Stable	Aaa	Stable	1
Utah	Aaa	Stable	Aaa	Stable	0
Vermont	Aaa	Stable	Aaa	Stable	0
Virginia	Aaa	Stable	Aaa	Stable	0
Washington	Aa1	Negative	Aa1	Stable	0
West Virginia	Aa3	Positive	Aa2	Positive	1
Wisconsin	Aa3	Negative	Aa2	Stable	1

This table shows the pre and post recalibrated ratings for Moody's. Moody's recalibration of municipal bond ratings was announced on March 16th, 2010 and implemented on April 19th, 2010. Old ratings represent the ratings of general obligation bonds for each state prior to recalibration. New ratings represent the ratings of general obligation bonds for each state after recalibration. The difference column measures the rating change, measured as the difference between the new rating and the old rating as a result of recalibration. New York City and New York State are included together because they have the same rating pre and post recalibration. Moody's does not maintain general obligation bond ratings for Nebraska, South Dakota, and Wyoming.

Table 2

Bond Price Response to Moody's Implementation

Panel A: Entire Sample	All States	3 notches	2 notches	1 notch	0 notch (Original Aaa)
Observations	876	333	40	503	185
Average Maturity	12.86	15.13	11.46	11.48	12.29
Mean Return	0.527	0.814	0.327	0.353	0.116
	(10.464)***	(8.700)***	(1.423)	(6.080)***	(0.550)
Median Return	0.228	0.545	0.105	0.190	0.148
	(9.850)***	(8.263)***	(1.251)	(5.768)***	(2.535)**

Panel B: Retail Sample	All States	3 notches	2 notches	1 notch	0 notch (Original Aaa)
Observations	460	149	14	297	104
Average Maturity	12.57	14.98	7.84	11.58	12.16
Mean Return	0.605	1.095	0.557	0.362	0.027
	(7.970)***	(6.733)***	(1.122)	(4.633)***	(0.074)
Median Return	0.383	0.760	0.253	0.157	0.186
	(7.499)***	(6.300)***	(1.319)	(4.286)***	(2.187)**

This table shows the bond price response to the implementation of recalibration by Moody's on April 19, 2010 for the entire sample (Panel A) and bonds held by retail investors (Panel B). Retail held bonds are restricted to bonds that only trade in denominations of less than 250,000 during the period surrounding recalibration. All States includes only states with rating improvements (rating level) during the recalibration process and excludes states originally rated triple A-stable or originally rated Aa1. The results are separated based on the difference in ratings after implementation. Rating differences are defined as the difference between a new recalibrated rating and the old rating and are categorized as notches of three, two, one and zero. Rating differences of zero are restricted to states which were originally rated triple A-stable and remained triple A-stable after recalibration. Returns are calculated as the percentage change in price between the closest weighted average trade price within a 5 day window prior to announcement and the closest weighted average trade price within a 5 day window after announcement. Average maturity measures the number of years to maturity for the bonds included in the sample. Mean returns are tested using a one sample mean comparison test with null return of zero. Median returns are tested using the Wilcoxon signed rank test. T statistics (mean) and Z statistics (median) are provided in parenthesis. ***,**,* represent significance at the 1st, 5th, and 10th percentile levels for two tailed tests, respectively.

Table 3

Bond Price Response to Moody's Announcement

Panel A: Entire Sample	All States	3 notches	2 notches	1 notch	0 notch (Original Aaa)
Observations	798	320	31	447	162
Average Maturity	13.673	15.00	10.13	12.98	12.31
Mean Return	0.025	0.013	-0.422	0.065	-0.113
	(0.541)	(0.190)	(1.829)*	(0.990)	(0.732)
Median Return	0.000	-0.008	-0.218	0.000	-0.048
	(0.956)	(0.426)	(1.809)*	(0.388)	(1.266)

Panel B: Retail Sample	All States	3 notches	2 notches	1 notch	0 notch (Original Aaa)
Observations	398	129	13	256	78
Average Maturity	13.518	14.71	10.36	13.079	12.93
Mean Return	0.019	-0.113	-0.257	0.100	-0.113
	(0.257)	(1.015)	(1.035)	(0.998)	(0.638)
Median Return	-0.017	-0.065	-0.210	0.000	-0.0137
	(0.815)	(1.275)	(0.911)	(0.081)	(1.081)

This table shows the bond price response to the announcement of recalibration by Moody's on March 16, 2010 for the entire sample (Panel A) and bonds held by retail investors (Panel B). Retail held bonds are restricted to bonds that only trade in denominations of less than 250,000 during the period surrounding recalibration. All States includes only states with rating improvements (rating level) during the recalibration process and excludes states originally rated triple A-stable or originally rated Aa1. The results are separated based on the difference in ratings indicated during announcement. Rating differences are defined as the difference between a new recalibrated rating and the old rating and are categorized as notches of three, two, one and zero. Rating differences of zero are restricted to states which were originally rated triple A-stable and remained triple A-stable after recalibration. Returns are calculated as the percentage change in price between the closest weighted average trade price within a 5 day window prior to announcement and the closest weighted average trade price within a 5 day window after announcement. Average maturity measures the number of years to maturity for the bonds included in the sample. Mean returns are tested using a one sample mean comparison test with null return of zero. Median returns are tested using the Wilcoxon signed rank test. T statistics (mean) and Z statistics (median) are provided in parenthesis. ***,**,* represent significance at the 1st, 5th, and 10th percentile levels for two tailed tests, respectively.

Table 4

Regression Analysis for Investor Reactions Surrounding the Announcement and Implementation of Recalibration

Announcement Date Returns

	Entire Sample			Retail Sample		
Variable	Predicted Sign	Coefficient	T Statistic	Predicted Sign	Coefficient	T Statistic
Rating Diff	**+/-**	**0.009**	**0.21**	**+/-**	**0.007**	**0.10**
YTM	+	0.008	1.37	+	0.020*	1.94
Amount	+	-0.000	0.25	+	-0.000*	1.94
Constant	/	-0.119	1.10	/	-0.132	0.80
N			947			466
Rsquared		0.210%			1.14%	

Implementation Date Returns

	Entire Sample			Retail Sample		
Variable	Predicted Sign	Coefficient	T Statistic	Predicted Sign	Coefficient	T Statistic
Rating Diff	**+**	**0.223*** **	**4.26**	**+**	**0.324*** **	**3.62**
YTM	+	0.010	1.38	+	0.013	0.99
Amount	+	-0.000	1.07	+	0.000	0.29
Constant	/	0.025	0.20	/	-0.121	0.61
N			1043			551
Rsquared		2.04%			3.13%	

This table shows regression results for bond market returns surrounding the announcement and implementation dates of recalibration. Returns are calculated as the percentage change in price between the closest weighted average trade price within a 5 day window prior to announcement and the closest weighted average trade price within a 5 day window after announcement. The results include all states with rating improvements (rating level) during the recalibration process and excludes states originally rated triple A-stable or originally rated Aa1. Retail held bonds are restricted to bonds that only trade in denominations of less than 250,000 during the period surrounding recalibration. Rating Diff is defined as the difference between a new recalibrated rating and the old rating and is categorized as notches of three, two and one. For ease of exposition, Rating Diff is divided by 100. ***,**,* represent significance beyond the 1st, 5th, and 10th percentile levels, respectively.

Table 5

Bond Price Response to Uncertainty surrounding Moody's Recalibration

	Entire Sample		Retail Sample	
	Positive Outcome	No Uncertainty	Positive Outcome	No Uncertainty
	3 notches	3 notches	3 notches	3 notches
Observations	92	241	51	98
Mean Return	0.661	0.873	0.748	1.276
	(3.357)***	(8.292)***	(2.463)**	(6.757)***
	1 notch	1 notch	1 notch	1 notch
Observations	57	503	32	297
Mean Return	-0.068	0.353	-0.025	0.362
	(0.407)	(6.080)***	(0.112)	(4.633)***

This table shows the bond price response to the implementation of recalibration by Moody's on April 19, 2010 for bonds which received a positive outcome on the implementation date and bonds for which there was no uncertainty. Bonds with a positive outcome are Aa1 and Baa3 rated bonds which shifted upwards of one or three notches on the implementation date rather than zero or two notches. Bonds with no uncertainty are bonds which shifted upwards of one or three notches as indicated on the announcement date. Retail held bonds are restricted to bonds that only trade in denominations of less than 250,000 during the period surrounding recalibration. Returns are calculated as the percentage change in price between the closest weighted average trade price within a 5 day window prior to announcement and the closest weighted average trade price within a 5 day window after announcement. Mean returns are tested using a one sample mean comparison test with null return of zero. T statistics are provided in parenthesis. ***,**,* represent significance at the 1st, 5th, and 10th percentile levels for two tailed tests, respectively.

Appendix A: Summary of subtitle C of Dodd-Frank

Section	Title	Main Provisions	Implementation
931	Findings	(1) The activities of CRAs are matters of national public interest; (2) CRAs' role is similar to that of analysts and auditors and justifies a similar level of public oversight and accountability; (3) CRAs' activities are fundamentally commercial in character and should be subject to the same standards of liability and oversight as those that apply to auditors, securities analysts, and investment bankers; (4) CRAs face conflicts of interest that should be regulated under the authority of the SEC; (5) Inaccuracies in the ratings of structured finance products contributed to the recent financial crisis and necessitate increased accountability by CRAs.	Immediate.
932	Enhanced regulation, accountability, and transparency of NRSROs	(1) NRSROs shall "file" rather than "furnish" statements with the SEC; (2) NRSROs shall establish internal controls over the ratings process; (3) The SEC shall prescribe appropriate internal control factors to NRSROs; (4) The SEC shall have the power to suspend or revoke NRSRO's registration with respect to a particular class of securities if ratings are inaccurate; (5) The SEC shall perform annual reviews of NRSROs; (6) Mandates rules for the separation of ratings from sales and marketing activities; (7) NRSROs shall perform look-back reviews when rating analysts join the issuer within a year of issuing a rating; (8) The SEC shall establish the Office of Credit Ratings; (9) Mandates additional disclosure of NRSROs' ratings and rating methodologies; (10) The SEC shall prescribe rules with respect to the procedures and methodologies used by NRSRO to determine credit ratings; (11) Prescribes requirements for NRSROs' board of directors.	Immediate for (1), (2), (4), (5), & (11). SEC proposed rules in May 2011 regarding (3), (6), (7), (9), & (10). No final rules issued as of November 2013. Office of Credit Ratings (8) formed in June 2012.
933	State of mind in private actions	(1) Statements made by CRAs are subject to the same provisions under the securities law as those made by a registered public accounting firm or a securities analyst; (2) CRAs' statements are no longer deemed "forward-looking" for the purposes of securities law; (3) When pleading any required state of mind, plaintiff must show that CRAs "knowingly or recklessly failed to conduct a reasonable investigation of the rated security" or "to obtain reasonable verification" of factual elements from third parties.	Immediate.

934	Referring tips to law enforcement or regulatory authorities	NRSROs have duty to report information alleging a violation of law that has not been adjudicated by a Federal or State court.	Immediate.
935	Consideration of information from sources other than the issuer in rating decisions	NRSROs shall consider credible information about an issuer from third parties.	Immediate.
936	Qualification standards for credit rating analysts	The SEC shall issue rules for the minimum qualification of credit rating analysts including standards of training, experience, competence, and testing.	SEC proposed rules in May 2011.
937	Timing of regulation	Unless otherwise specified, the SEC shall issue final regulation no later than one year after the date of enactment of the Act.	Immediate.
938	Universal rating symbols	The SEC shall require each NRSROs to establish, maintain, and enforce written policies and procedures with regards to determining default probabilities, the meaning and definition of rating symbols, and the consistent application of these rating symbols.	SEC proposed rules in May 2011.
939	Removal of statutory references to credit ratings	Requires the removal of statutory references to credit ratings from the Federal Deposit Insurance Act, the Federal Housing Enterprises Financial Safety and Soundness Act of 1992, the Investment Company Act of 1940, the Revised Statues of the United States, the Securities and Exchange Act of 1934, and the World Bank Discussion.	Effective dates vary across acts and statutes; most changes completed as of 7/21/2012.
939A	Review of reliance on ratings	Each federal agency shall remove reference to or requirement of reliance on credit ratings and make appropriate substitutions using alternative measures of credit-worthiness.	Effective dates vary by federal agency; SEC rules effective as of 9/2/2011; OCC rules effective as of 1/1/2013.

939B	Elimination of exemption from Fair Disclosure rule	The SEC shall revise Regulation FD to remove the exemption of CRAs.	Effective as of 10/4/2010.
939C 939D 939E	Mandated studies by the SEC and the GAO	(1) The SEC shall conduct a study of the independence of NRSROs and the effect of such independence on credit ratings; (2) GAO shall study alternative means of compensating NRSROs for credit ratings; (3) GAO shall study "the feasibility and merits of creating an independent professional organization for rating analysts".	(1) & (3) not completed as of November 2013; (2) completed in January 2012.
939F	Study and rulemaking on assigned credit ratings	"The SEC shall carry out a study of the credit rating process for structured finance products and the conflict of interest associated with the issuer-pay and the subscriber-pay models" and "the feasibility of establishing a system in which a public or private utility or a self-regulatory organization assigns NRSROs to determine the credit rating of structured finance products". After issuing the report, the SEC shall "establish a system for the assignment of NRSROs to determine the initial credit ratings of structure finance produces" that prevents the issuers from selecting the NRSROs.	Study completed in December 2012; as of November 2013, no alternative system has been established.
939G	Effect of rule 436(g)	Rule 436(g) under the Securities Act of 1933 shall have no force or effect; Rule 436 (g) originally states that in the case of new securities issues, credit ratings are not considered part of a registration statement or certified by an "expert".	Immediate.
939H	Sense of Congress	The SEC shall exercise its authority under the Securities Exchange Act of 1934 to prevent conflict of interests arising from NRSROs providing consulting, advisory, or other services to issuers.	Immediate.

Appendix B: Numerical transformation of alphanumerical rating codes

Credit Rating	Moody's	Standard & Poor's	Fitch	Numerical Code
Highest grade	Aaa	AAA	AAA	1
	Aa1	AA+	AA+	2
High grade	Aa2	AA	AA	3
	Aa3	AA-	AA-	4
	A1	A+	A+	5
Upper medium grade	A2	A	A	6
	A3	A-	A-	7
	Baa1	BBB+	BBB+	8
	Baa2	BBB	BBB	9
	Baa3	BBB-	BBB-	10
Non-investment grade	Ba1	BB+	BB+	11
	Ba2	BB	BB	12
	Ba3	BB-	BB-	13
	B1	B+	B+	14
Low grade	B2	B	B	15
	B3	B-	B-	16
	Caa1	CCC+	CCC+	17
	Caa2	CCC	CCC	18
	Caa3	CCC-	CCC-	19
	Ca	CC	CC	20
	C	C	C	21
Default	N/A	D	DDD/DD/D	22

This table presents the numerical codes associated with the alphanumerical ratings assigned by Moody's, S&P, and Fitch. Ratings coded 1 through 21 are assigned ex-ante and represent predictions of default probability while ratings coded as 22 are assigned ex-post indicating an actual default. Moody's does not issue a rating for an actual default.

Appendix C
Data Selection

	Number of Observations
Panel A: Sample Selection Procedure	
U.S. Corporate Bond Issues On Mergent FISD 1992-2010	161,315
Less:	
Bonds without complete rating information or not rated by Moodys S&P or Fitch	19,027
Bonds without identifying information on Compustat or CRSP	38,464
Bonds rated in cities not listed on the US census	6,717
Defaulted bonds	836
Final Sample	96,271
Panel B: Error Sample	
Bond Issues with Type 1 Errors	732
Bond Issues with Type 2 Errors	28,454

This table reports data selection procedure for the sample. Panel A describes the sample selection procedures leading to the final dataset. Ratings information for bond issues are obtained from Mergent FISD and merged with Compustat quarterly financial data and CRSP daily data. Distance information is collected from the U.S. census and only includes U.S. cities. Final models may have differing sample sizes then the final sample depending on the availability financial inputs needed under each specific model. Panel B describes the error sample for type 1 and type 2 errors. Type 1 rating errors are defined as investment grade bonds which default within 2 years. Type 2 errors are defined as speculative grade bonds which do not default within 2 years.

Figure 1: Moody's 2010 Default Study (Distribution of all Municipal and Corporate rated bonds on January 2010)

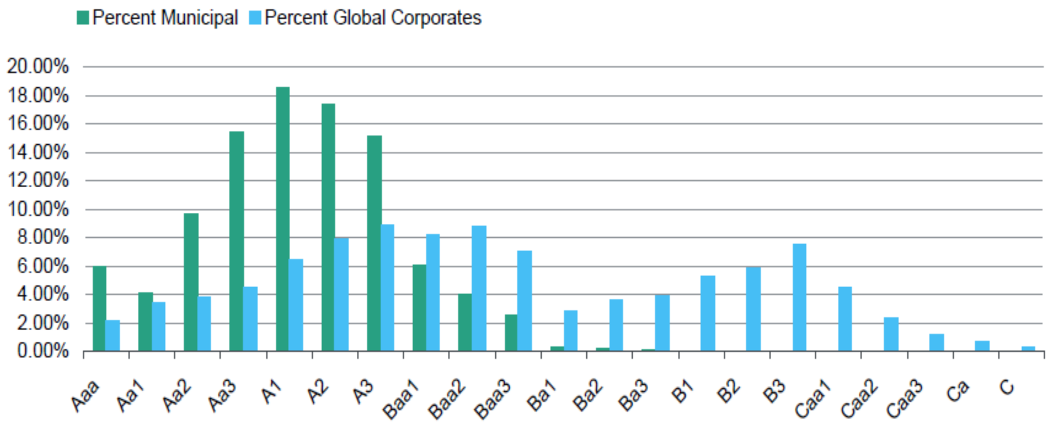

Figure 2: Bond Yields May 17th, 2010 (National and Florida bond yields by maturity and rating)

AA RATED

ISSUE	Maturity Range	Today	Last Week	Year Ago
National	10 Year	3.40	3.55	3.60
National	20 Year	4.70	4.80	4.60
National	30 Year	5.10	5.15	4.90
Florida	30 Year	5.05	5.10	4.85

A RATED

ISSUE	Maturity Range	Today	Last Week	Year Ago
National	10 Year	4.40	4.45	4.10
National	20 Year	5.30	5.45	5.00
National	30 Year	6.05	6.10	5.50
Florida	30 Year	6.00	6.05	5.45

Figure 3: Indicated recalibrations on the announcement date

Primary Algorithms by Sector

Upward Shift in Ratings (# of notches)

MUNICIPAL SCALE RATING	GENERAL OBLIGATION; WATER & SEWER; DISTRIBUTION-ONLY UTILITIES; MUNICIPAL UTILITY DISTRICTS (MUDS)	SPECIAL TAX (NON-GO); MASS TRANSIT; NON-UTILITY ENTERPRISES; TAX INCREMENT FINANCING DISTRICTS (TIFS); GRANT ANTICIPATION REVENUE BONDS (GARVEES)	PUBLIC UNIVERSITIES AND PUBLIC UNIVERSITY FOUNDATIONS	HEALTH CARE; HOUSING; PRIVATE K-12 & CHARTER SCHOOLS; PRIVATE UNIVERSITIES & OTHER NOT-FOR-PROFITS; TRANSPORTATION & OTHER INFRASTRUCTURE ENTERPRISES; POWER GENERATING UTILITIES; STATE REVOLVING FUNDS; BOND BANKS; FEDERAL LEASES
Aaa	0	0	0	0
Aa1	0-1	1	0-1	0
Aa2	1	1	1	0
Aa3	1	1	1	0
A1	2	1	1	0
A2	2	1	1	0
A3	2	1	1	0
Baa1	3	1	1	0
Baa2	3	0	1	0
Baa3	2-3	0	1	0
Ba1	0	0	0	0
Ba2	0	0	0	0
Ba3	0	0	0	0
B1	0	0	0	0
B2	0	0	0	0
B3	0	0	0	0
Caa1	0	0	0	0
Caa2	0	0	0	0
Caa3	0	0	0	0