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REGULATING CREDIT RATING AGENCIES: REDUCING THE CONFLICT OF INTEREST IN THE BOND MARKET

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Abstract

Legislative action during the financial crisis of 2008 aimed to reduce the conflict of interest problem in the credit rating industry. To test whether the informational content of ratings has improved, or investors lost their trust in credit rating agencies, I study the impact of credit rating events (CREs) on daily bond returns. Additionally, this paper compares the issuer pays model to the investor pays model using credit ratings from Standard & Poor's and Egan-Jones Rating. I find new evidence that daily bond returns are significantly impacted by CREs. Most of my results suggest that the impact is more pronounced in the post-crisis period, in line with the improved-information hypothesis. My results provide evidence that the significant difference between periods is mostly driven by the impact of CREs on bonds with financial issuers. Comparing EJR to S&P, my results suggest that the conflict of interest problem is still troubling in the post-crisis period. Namely, S&P provides on average 0.151 notch higher ratings compared to EJR and this difference is largely explained by the level of current debt. Additional analyses provide evidence that issuers exploit this rating inflation by increasing their debt at a lower cost of capital. Although rating inflation is still present in the post-crisis period, this research provides evidence for the usefulness of legislation to reduce the conflict of interest problem. Additional legislation is potentially effective in reducing the conflict of interest and its rating inflation.

Contents

1 Introduction

After John Moody sold its first credit rating to investors in the beginning of the 1900s, the credit rating industry has grown substantially. This expansion stopped at the outbreak of the financial crisis in 2007. In retrospective, inflated mortgage related securities caused financial markets to become illiquid and freeze in the summer of 2007. The underlying cause of the inflated ratings was potentially the conflict of interest problem, where the issuer pays for a credit rating (White, 2010). Fomented by public turmoil and to counter the financial meltdown and consequences of the issuer pays model, legislative action was taken by the U.S. government. This resulted in the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank act), enacted in July 2010. With a prime focus on reducing the conflict of interest, this is considered to be the biggest set of financial regulations since the Great Depression. This paper addresses the question whether this legislation improved the informational content of ratings, or that investors lost their trust in credit rating agencies (CRAs). Additionally, comparing issuer paid to investor paid CRAs, this paper will address whether rating inflation is a contemporary problem despite regulators' attempt to resolve the malfunctioning industry.

In the 1970s, the credit rating industry changed from investors pays to the business model called issuer pays. In this model, CRAs may be tempted to inflate ratings in favor of the issuer to keep future business, which is a potential conflict of interest. An inflated rating would be profitable to issuers since this would reduce the cost of capital for new debt issuances. For example, this conflict of interest was reflected in the Enron scandal in 2001.[1] As described, another manifestation of the conflict of interests is the financial crisis of 2008.

Based on contemporary literature, I hypothesize that downgrades (upgrades) by CRAs lead to a negative (positive) shock in daily bond returns. Given the substantial amount of new regulation, it is of paramount interest to examine whether the impact of CRAs on the bond market is more/less pronounced in the post-crisis period compared to the pre-crisis period. The implications of an increased/decreased impact of CRAs on daily bond returns can be assessed by understanding the function of CRAs. Bannier and Hirsch (2010) describe that their function is not just providing information certificates to the market, but that they additionally function as an active market monitoring device. If the impact has increased in the post-crisis period, CRAs provide more useful information to the market compared to the pre-crisis period. This may also suggest that CRAs are a better active monitoring device compared to the pre-crisis period. I will call this the improved-information hypothesis.

If the impact has decreased, the monitoring function and the provision of information by CRAs is sub-optimal. This is potentially problematic for financial sector stability. An explanation for this possible decrease could be a lower trust in CRAs after the crisis. As documented by White (2010) and Pagano and Volpin (2014), many ratings during the crisis were flawed. This is especially true for mortgage backed securities (MBS). In this case, the impact of credit rating events (CREs) is less pronounced in the post-crisis period compared to the pre-crisis period. I will call this the lost-trust hypothesis. Since the improved-information and lost-trust hypothesis are covering the same content, I will test these as one hypothesis: The impact of CREs on daily bond returns is greater/smaller in the post-crisis period than in the pre-crisis period.

In addition to testing differences between periods, I will compare the issuer pays model to the investor pays model using CREs from Egan-Jones Rating (EJR). EJR is known for its investor pays model and hence does not suffer from the conflict of interest problem. Since issuers with high current debt are more likely to issue new debt in the near future, current debt will function as a

[1] Millon (2003) described the Enron scandal and its relation to CRAs.

proxy for the severity of the conflict of interest. S&P might try to seduce issuers for requesting new ratings in the near future by inflating their ratings. I will examine the presence of the conflict of interest problem by testing my third hypothesis: Issuers with high current debt are more likely to receive a higher S&P rating compared to the EJR rating in the post-crisis period. If evidence for rating inflation is found, I will test whether the reduced cost of capital for these issuers is associated with higher debt growth. My last hypothesis is: Issuers that receive a higher rating from S&P compared to EJR and have high current debt levels are more likely to have higher debt growth. In essence, I will test the presence of the conflict of interest in the contemporary CRA industry.

I use conventional event study methodology to measure the impact of CREs on daily U.S. corporate bond returns. To provide reliable results, I will test the impact of CREs using multiple benchmarks that take into account credit risk, interest rate risk, and differences in maturity. This paper applies various univariate and multivariate regression models to analyze the effect of regulation during the financial crisis. The inclusion of EJR as an investor paid CRA allows to examine whether rating inflation is removed or that it is still a troubling issue despite regulators' attempts. The cardinal bond rating difference will be used to test rating inflation in the post-crisis period. Debt growth is used to test whether issuers exploit the inflated ratings by issuing significantly more debt at a lower cost of capital. Bond prices and rating information are assembled from the Mergent Fixed Income and Securities Database (FISD). Issuer specific information is assembled from COMPUSTAT, and EJR events are manually gathered from the Bloomberg database. The sample period is 2004-2006 for the pre-crisis period and 2014-2016 for the post-crisis period.

I find new evidence that daily bond returns are significantly impacted by CREs. Most of my results suggest that the impact is more pronounced in the post-crisis period, in line with the improved-information hypothesis. My results provide evidence that the significant difference between periods is mostly driven by the impact of CREs on bonds with financial issuers. Comparing the issuer pays model to the investors pays model, I find that the conflict of interest problem is still troubling in the post-crisis period. It seems that the S&P provides higher ratings compared to EJR, with a mean difference of approximately 0.151. This difference can be largely explained by the level of current debt. Further, my results suggest that rating inflation by S&P leads to significantly higher debt growth. These results indicate that rating inflation is still troubling in contemporary financial markets. Based on the comparison between periods, my evidence suggests that legislation is successful in improving the informational content of ratings. However, additional legislation is necessary and effective for reducing the conflict of interest and its rating inflation.

My results provide evidence for successful policy of regulators in improving the informational content of credit ratings. Additionally, my research contributes to the literature by providing evidence for rating inflation in the post-crisis period. These findings are of paramount interest for regulators and investors. For regulators, these results may be a spark for imposing additional legislation against CRAs to reduce the rating inflation, especially regarding transparency in the credit rating process. This would improve the rating quality and the informational content of CREs. Investors should take into account rating inflation in their investment policy. Under the assumption that investors base their investment strategy on credit ratings, risk is mispriced and capital is not optimally allocated. Improving transparency in rating procedures would be beneficial to investors and additionally it may lead to better allocation of capital.

The paper is structured as follows: In section 2, I will review the literature on CRAs and its impact on bonds/stocks/CDS. Further, it provides more context on the CRAs and on imposed regulation during the financial crisis. Section 3 reviews the data and provides descriptive statistics. Section 4 and 5 describe the methodology and results, respectively. Robustness tests are provided in section 6. Section 7 provides limitations and future research and section 8 presents the conclusions.

2 Theoretical framework

The literature on this topic can be divided in three main sections concerning the data. In conventional literature, three types of data are used: stocks, bonds, and CDS. I will discuss all of them in this section and compare potential differences. To provide more context, I will present a brief overview of the development of the CRA industry and criticism on this sector. In addition, I will describe recent financial legislation impacting CRAs and provide my hypothesis development.

2.1 Development of CRAs

When the CRAs originated in the 1900s, the investors paid for the rating. The first major change for the credit rating industry arises in the 1930s. Not surprisingly, just after the Great Depression the U.S. government issued legislation to prohibit market participants to invest in speculative financial products. Nowadays, these speculative financial products could be considered as junk bonds or non-investment grade bonds (White, 2010).[2] These opinions about bonds and other financial products should be, following this new legislation, based on so called 'recognized rating manuals'. Given this new regulation, investors needed a rating from rating agencies that published such manuals. The only agencies that published such manuals were the three rating agencies discussed above (White, 2010).

In the 1970s, the Securities and Exchange Commission (SEC) worried that the ratings did not reflect the riskiness of the financial products as a result of the vague subscriptions in the recognized rating manuals. For this reason, the SEC established the Nationally Recognized Statistical Rating Organization (NRSRO). Immediately after the establishment of the NRSRO, S&P, Moody's and Fitch were grandfathered, as described by White (2010). It can be observed that the discussed legislation and events in the 1930s and 1970s placed the three CRAs at the center of the financial market. The most important change in the credit rating industry, which emerged during the 1970s, is the shift from investor pays to issuer pays. This model could lead to a conflict of interests. Two reasons are provided by Smith and Walter (2002) why the issuer pays model did not cause any problems for such a long time. As Smith and Walter (2002) argue, the number of issuers is so immense that the threat of an issuer to go to another CRA is incredible. The rating agency would not mind about the loss of a few issuers. Second, the financial products that needed a rating were very simple in the 1970s. In case of malfunctioning, it would be easily observed and the reputational costs could be severe. In the 1970s, when financial products were relatively simple and the number of issuers were high, these arguments may have been accurate. However, the financial sector developed and financial products became more complex. In the run-up to the financial crisis of 2008, these arguments became unfounded. The number of issuers of MBS were issued by a small group of large investment banks. The threat of an issuer to go to another agency is credible now. For a CRA, losing one client would have much bigger consequences than in the 1970s. Furthermore, the bond issues were no longer plain vanilla bonds, but highly complex financial products.[3] For this reason, a mistake in the rating is no longer easy to observe. Since the probability of getting caught for providing inflated ratings to financial products is much lower, the reputational cost component described above diminishes (White, 2010).

It is still ambiguous why the industry changed from investor pays to issuer pays. However, White (2010) gives some potential explanation for this change. First, copy machines became popular in the 1970s. For this reason, a free-rider problem could become an issue. Second, White (2010) describes that the 1970s Penn-Central Railroad crash created pressure for issuers to show the investors that

[2] More detailed information on the interpretation of S&P ratings can be found on: www.standardandpoors.com.
[3] Crotty (2009) describes the complexity and mispricing of (higher power) collateralized debt obligation.

they are not risky and that they are willing to pay for a certificate to prove this. Third, the rating agencies knew that their approval was necessary to get the bonds in a financial portfolio, so the issuers were willing to pay for this.

Summarizing, the change from the investor pays model to issuer pays model is most relevant for this paper since this led to potential conflicts of interests. This brief description of the main changes in industry gives some insight in the development of the credit rating agency and its impact on the financial sector.[4]

2.2 Literature review

In essence, the literature on this topic starts with Fama (1970), who describes the Efficient Market Hypothesis (EMH).[5] Following the semi-strong form of EMH in national bond markets, where prices of bonds change if new information is provided to the market, CREs can influence bond prices. If the price change is permanent, this is in line with the information content hypothesis.

The first article testing the efficiency of the bond market is Katz (1974). Especially, Katz (1974) tests for a relation between CREs and bond yields. Katz (1974) finds no significant changes in prices after a CRE. Weinstein (1977) finds the same results. Grier and Katz (1976) finds price reduction for industrial bonds, but not for utility bonds. Both use data from S&P for the period 1966-1972. Hand, Holthausen and Leftwich (1992) use daily bond prices instead of monthly bond prices and include rating changes from S&P and Moody's. They find a price reduction after a downgrade, but less reliable effects after an upgrade. Furthermore, more recent evidence of Steiner and Heinke (2001) suggests that a downgrade by a CRA has a significant negative effect on bond yields on the announcement day. An upgrade, however, does not result in a significant positive effect on bonds on the announcement day. They provide two possible explanations for this discrepancy. First, "rating agencies face asymmetric loss functions" (Steiner and Heinke, 2001). Second, when a downgrade occurs, investors tend to sell. However, when an upgrade occurs, investors do not tend to buy (Steiner and Heinke, 2001). This is called asymmetric risk aversion. This implies that the loss in utility of investors when they lose a particular amount of assets is higher than the gain in utility when they gain the same particular amount of assets. Standard event study methodology is used in these studies. Mostly, abnormal returns are calculated using conventional benchmarks such as long-term treasury bills (T-bills). The Study of Steiner and Heinke (2001) has an international perspective. It does not focus on the U.S. alone, but includes international bond prices. To summarize, the research in using bond prices is relatively mixed. Some research provides evidence of significant abnormal returns after the rating event (e.g. Grier and Katz, (1976); Hand et al. (1992); and Steiner and Heinke, 2001), while others do not (e.g. Katz, 1974; Weinstein, 1977).

The second section in the literature uses stock prices to test for abnormal returns. The first article using stock data is Pinches and Singleton (1978). They find significant abnormal returns, but no abnormal returns after a CRE. Holthausen and Leftwich (1986), provide evidence of abnormal returns after a downgrade, but not after an upgrade. They use data from S&P and Moody's and the sample period 1977–1982. Other research, like Hand et al. (1992), find abnormal returns after a downgrade. For upgrades these abnormal returns are often lower or insignificant. Bannier and Hirsch (2010) include watchlisting in their data and provide evidence for an increased monitoring function after watchlistings are included. Factor models are often used for calculating abnormal returns, since the number of observations is much higher for stocks compared to bonds. It can be concluded that most of the literature using stock data, finds significant abnormal returns after

[4] A proper and extensive description of the development of CRAs can be found in White (2010).

[5] Based on following assumption: No transaction costs, information is costless, investors have homogeneous expectations and investors are rational (Fama, 1970).

a downgrade, but not after an upgrade. This is in accordance with the first main section in the literature.

Finnerty, Miller, and Chen (2013) use CDS spreads. As described by Finnerty et al. (2013), CDS spreads are a potential better proxy for default since the CDS spread is in essence the cost of protecting the firm from defaulting. The use of CDS spreads instead of daily/monthly bond price changes or bond yields has two advantages as described by Hull, Predescu and White (2004). First, the data used for bond price changes usually consists of information of dealers, where there is no commitment to trade. CDS spreads consists of bids and asks, where the dealer is committed to trade at the quote price. Second, to create credit spreads from bond yields, a doubtful assumption is necessary. Namely, the benchmark risk free rate. This benchmark can be approximated by various methods, but these methods are doubtful. By using CDS spreads they overcome this problem. Finnerty et al. (2013) conclude that upgrades and downgrades by CRAs have a significant impact on CDS spreads. Though significant, the impact of upgrades is smaller than the impact of downgrades. This is consistent with hull et al. (2004). Finnerty et al. (2013) also finds that the significance of the impact of the CREs increased as from 2003. Therefore, they conclude that the rating process of the agencies improved. CDS spreads are not much used since the derivatives market is relatively young and data is hard to gather (Norden and Weber, 2004).

Some articles describe that the CRAs do not provide new valuable information to the market. They show that the price change is before the CRE. However, watchlistings are potentially causing this. In general, some contradiction exists in the literature about the impact of a downgrade/upgrade in credit rating on bond prices/yields. However, most recent evidence suggests that a downgrade by a CRA has a significant negative impact on bond prices and yields, while an upgrade has less significant impact, or no significant impact at all. A full overview of the most important literature, regarding the impact on bonds, stocks and CDS spreads, can be found in Table 1, Table 2, and Table 3 respectively.

Author	**Sample period**	**Results**
Katz (1974)	1966 - 1972	No significant effects after a CRE.
Weinstein (1977)	1962 - 1974	No significant effects after a CRE.
Grier and Katz (1976)	1966 - 1972	Price reduction for industrial bonds after a CRE, but not for utility bonds.
Hand, Holthausen and Leftwich (1992)	1977 - 1982 and 1981 - 1983	Price reduction after a downgrade, but less reliable effects after an upgrade.
Steiner and Heinke (2001)	1985 - 1996	Downgrade by a CRA has significant negative effect on bond yields, an upgrade does not result in significant positive effects.

Table 1: Chronological overview of essential literature using bonds.

Author	Sample period	Results
Pinches and Singleton (1978)	1959 - 1972	Abnormal returns, but not after a CRE.
Holthausen and Leftwich (1986)	1962 - 1974 and 1977 - 1982	Abnormal returns after a downgrade, but not after an upgrade.
Hand, Holthausen and Leftwich (1992)	1977 - 1982 and 1981 - 1983	Price reduction after a downgrade, but less reliable effects after an upgrade.
Dichev and Piotroski (2001)	1970 - 1997	Abnormal returns after a downgrade, but not after and upgrade.
Bannier and Hirsch (2010)	1982 - 2004	Negative abnormal returns on the magnitude of 10 to 14 percent in the first year following downgrades, but not after and upgrade.

Table 2: Chronological overview of essential literature using stocks.

Author	Sample period	Results
Hull et al. (2004)	1998 - 2002	Significantly positive CDS spread changes before negative rating events.
Norden and Weber (2004)	2000 - 2002	Markets anticipate to downgrades and upgrades.
Finnert, Miller and Chen (2013)	2001 - 2009	Upgrades and downgrade by CRAs have a significant effect on CDS spreads.

Table 3: Chronological overview of essential literature using CDS spreads.

2.3 Criticism and legislation on CRAs

Since the financial crisis of 2008 and the resulting legislation is of great importance in this paper, I will briefly describe the criticism on the CRAs in this section. Pagano and Volpin (2014) provide an extensive article on the failures of credit rating agencies. The first issue during the financial crisis is called "rating inflation" by Pagano and Volpin (2014). Many high rated securities dropped in value when these ratings became untenable which triggered the financial crisis. Further, in the run-up to the financial crisis, securitization became very popular.[6] This securitization led to less informative ratings by the CRAs. When the crisis began, investors could not rely on the information by the CRAs. As a result, the markets froze and consequently became illiquid. The source of these problems is potentially the conflict of interest problem.

Besides the conflict of interest problem described above, another important issue is apparent. Namely, the CRAs are not transparent in their rating procedures. As reported by Securities and Exchange Commission (2008), the CRAs often do not provide the rationale for their deviation from their previous rating. Even before the financial crisis of 2008, there was a lot of criticism towards CRAs and the conflict of interest problem. To counter this issue, legislation was necessary. In the U.S. the legislation consists of the separate acts. First, the Credit Rating Agency Reform Act of 2006. This act aimed to increase competition in the CRA industry. Further, this act led to oversight of SEC to improve rating quality. The Dodd–Frank act of 2010 is the second Act impacting the CRA industry. This act led to more extensive oversight by the SEC. The complexity and importance of this act requires a separate explanation.

[6]More information about the increasing popularity of securitization in the run-up to the financial of 2008 can be found in Acharya and Richardson (2009): p.195-204.

2.4 Dodd-Frank Wall Street Reform and Consumer Protection Act

The Dodd-Frank act was a reaction on the financial crisis and was finalized in July 2010. This financial regulation can be seen as the biggest set of regulations since the establishment of the SEC in 1934. As discussed in Dimitrov, Palia and Tang (2015), two specific provisions in the Dodd-Frank act are most likely to impact CRAs.

First, if a rating by a CRA is found inaccurate, it is easier to plead against the rating agency for private actions. They do so by reducing the pleading standard. Secondly, due to the Dodd-Frank act it is much easier for the SEC to impose actions on CRAs. This is especially true for "material misstatements and fraud" (Dimitrov et al., 2015). In general, I will separate the impact of the Dodd-Frank act in two main sections: the liability provision and regulatory penalties.

Before the Dodd-Frank act, CRAs could argue and claim that the ratings they provide are just opinions that fall under the First Amendment. In this case, the plaintiffs should provide evidence that the CRA had knowledge of the inaccurate rating they provided. Now, plaintiffs should argue that the CRA did not conduct reasonable research. This potentially increases the number of lawsuits that come to trial. Besides this section, the Dodd-Frank act explicitly makes CRAs accountable for their ratings. The Dodd-Frank act also held the CRAs liable as experts. In reaction, CRAs did not give permission to add their ratings to registration statement for several securities. Proving the power of CRAs, this led to scratching the new rule.

Besides the liability provisions, the regulators also imposed regulatory penalties. First, the enforcement and penalties of federal securities law apply to statements made by CRAs to the same extend as these provisions apply to registered public accounting firms or securities analysts. This again facilitates the SEC to prove fraudulent acts. As described in the introduction, the transparency of CRAs is also improved. This is reflected in Dodd-Frank act, where CRAs are obliged to file annual reports and conducting internal audits. Further, they must disclose their rating methodologies and the success rate of their past ratings. An Office of Credit Ratings is established, where CRAs should monitor e.g. their compliance. The Credit Ratings Agency Reform Act of 2006 described that the NRSRO expand CRAs if they would not have enough resources to form reasonable opinions about a financial product. However, the Dodd-Frank act gives the SEC the authority to remove CRAs also if they think that the ratings are biased. This would lead to a reduced market share for the CRAs (Dimitrov et al., 2015).

2.5 Hypothesis development

Rating inflation plagued financial markets during the financial crisis, eventually leading to a financial meltdown and frozen markets. As a response, U.S. regulators imposed a huge set of legislation to counter the conflict of interest. This conflict of interest is essentially apprehended in the issuer pays model. Since regulators cannot reform the nature of their business model, legislation is concentrated on: Improving transparency in rating procedures, improve the quality and accountability, and reduce conflicts of interest by improving competition (White, 2010).

Based on contemporary literature, I hypothesize that downgrades (upgrades) by CRAs lead to a negative (positive) shock in daily bond returns. CRAs function as an active monitoring device and provide information to financial markets (Bannier and Hirsch, 2010). Given the Efficient Market Hypothesis (1970), it can be expected that new information is immediately priced. In particular, I hypothesize that CREs will result in significant abnormal returns in the period surrounding the CREs.

Based on this hypothesis, I proceed to the core of my paper. Especially, it can be argued that the informational content of ratings is more pronounced in the post-crisis period due to imposed financial legislation during the crisis. As described, this legislation was primarily focusing on reducing the conflict of interest and thereby inflated ratings. I will call this rationale the improved-information hypothesis. In this hypothesis, abnormal returns will be greater in the post-crisis period. On the other hand, potentially investors lost their trust in CRAs due to the rating inflation in the run up to the financial crisis. This incident may have had such a substantial impact on the trustworthiness of CRAs that the reliance on CRAs has diminished. The lost-trust hypothesis describes that despite the attempts of regulators to reduce the conflict of interest, investors no longer trust CRAs in providing credible information. Accordingly, this hypothesis will result in less pronounced abnormal returns in the post-crisis period. Combining these contradicting statements, my second hypothesis is: The impact of CREs on daily bond returns is greater/smaller in the post-crisis period than in the pre-crisis period.

In the previous analyses, I compare two periods to test the impact of financial regulation. In addition, this paper compares the contemporary issuer pays model to the investors pays model, which was abandoned in the 1970s. The investor pays model does not suffer from the conflict of interest problem. Usually, CRAs applying this model are being compensated on a subscription basis. EJR is one of the few CRAs that is compensated in this way and is certified by the NRSRO. Given the fundamental difference in business models, I compare these CRAs by testing differences in ARs. Secondly, despite the issued legislation the conflict of interest problem may still be present. In practice, issuer paid CRAs potentially try to preserve future business by inflating ratings of issuers. If this is true, then it is likely that the rating inflation is more severe if the issuer has a relatively high amount of current debt. Namely, high current debt is an indication of new debt issuance in the near future. Issuers that receive inflated ratings would benefit due to a lower cost of capital. To test whether the described rating inflation exist, I will test the following hypothesis: Issuers with high current debt are more likely to receive a higher S&P rating compared to the EJR rating in the post-crisis period. Conditional on the results of the previous hypothesis, I will test my fourth hypothesis: Issuers that receive a higher rating from S&P compared to EJR and have high current debt levels are more likely to have higher debt growth rates in the post-crisis period. A higher debt growth rate would provide evidence that rating inflation has real effects on issuers' financing strategy.

3 Data and descriptive statistics

To provide a clear difference between the pre-crisis and post-crisis period, I will create two samples. The first sample covers the period 2004-2006 (pre-crisis), while the second sample will cover the period 2014-2016 (post-crisis). I will exclude the run-up to the crisis (2007), the crisis (2008-2012), and the period just after the crisis (2013) to make sure the comparison is reliable.

The first dataset covers information about credit ratings from S&P. These data are gathered from the Mergent FISD for the pre-crisis and post-crisis period. Specifically, I used the Bond Ratings data within the Mergent FISD. This database consists of a huge sample of corporate debt securities, but also debt securities for U.S. treasury debt. To prevent the data to be contaminated with factors that are irrelevant for this study, for example a rating change due to mergers & acquisitions, I will drop these rating changes. To be concrete, I will only keep the CREs with Upgrade or Downgrade as reason code. Some articles use positive and negative outlooks or reviews for upgrades and downgrades. Including these in this study is inapplicable given the aim of this research. The same preparation of the data is conducted by Jorion, Lio and Shi (2005).

The rating scales of the three rating agencies can be found in Table 4. As one can observe, S&P has a rating scale from AAA to D. They use + & - as a modifier to specify the rating. Moody's also uses these kinds of modifiers but they do not provide a rating for total defaults. Further, the rating scales of Fitch are almost the same as those from S&P. It can be observed that the rating scales differ between rating agency. However, the interpretation (description) of the rating is approximately the same. The ratings are converted in cardinal variables to create notches. These notches describe the number of changes in rating. For example, an S&P rating change from AAA to AA+ will result in a downgrade (notch) of 1.

After dropping missing and incomplete observations, the data covers 858 downgrades and 885 upgrades in the pre-crisis period. In the post-crisis period, the sample contains 550 downgrades and 279 upgrades, as presented in Table 5. The ratio of downgrades to upgrades is >0 in the post-crisis period, which is common for bonds. Further, this potentially reflects CRAs to be more risk averse after the financial crisis.

The second dataset covers the bond trades from Mergent FISD. I gathered the bond trade data using the issue ID as an identifier to merge the data. In total, the data covers 1743 bonds in the 2004-2006 period and 829 bonds in the 2014-2016 sample period. The bonds are all U.S. bonds and include financial issuers, utility issuers, and industrial issuers. The last trade price will be kept if multiple trades occur on the same day. With these observations the returns are calculated. I dropped missing prices and I only kept institutional trades (trade size $>$ \$100.000), improving the reliability of the results (Bessembinder et al., 2009). The returns are winsorized at 2.5% to account for outliers. Descriptive statistics can be found in Table 6. The U.S. market is particularly interesting, since the regulations on the CRAs were most severe in the U.S.

My third dataset consists of EJR rating events. These data are manually gathered from Bloomberg and is crucial for the inclusion of the investor pays model. Using the CUSIP as an identifier, 278 bonds in my post-crisis sample received a rating from S&P and EJR. The distribution of CREs from EJR can be found in Table 7. Comparing the CREs from EJR to S&P, one can observe a significantly higher ratio of downgrades to upgrades. Potentially this is an indication of inflated credit ratings.

To control for issuer specific differences, I gathered additional data from COMPUSTAT using the CUSIP as an identifier. I gathered quarterly information on issuer specific sales, debt and equity differences, and multiple measures of firm size. This information will be used as control variables in my analyses.

	S&P	Moody's	Fitch	Description
Investment grade	AAA,	AAA,	AAA,	Prime
	AA+, AA, AA-,	Aa1, Aa2, Aa3,	AA+, AA, AA-,	High grade
	A+, A, A-,	A1, A2,	A+, A, A-,	Upper medium grade
Speculative grade	BBB+, BBB, BBB-,	Baa1, Baa2, Baa3,	BBB+, BBB, BBB-,	Lower medium
	BB+, BB, BB-,	Ba1, Ba2, Ba3,	BB+, BB, BB-,	Speculative
	B+, B, B-,	B1, B2, B3,	B+, B, B-,	Highly speculative
Non-investment grade	CCC+,	Caa1,	CCC,	Significant risk
	CCC,	Caa2,	-	Imminent default
	CCC-, CC, C,	Caa3, Ca, C,	-	Low recovery expectations
	D,	-	DDD, DD, D,	Total default

Table 4: This table represents the credit rating scales of S&P, Moody's and Fitch.

	Pre-crisis			Post-crisis		
Notches	Downgrade	Upgrade	Down/up	Downgrade	Upgrade	Down/up
1	410	768		372	231	
2	406	88		144	39	
3	16	8		15	9	
4	-	-		12	-	
5	21	14		2	-	
6	2	-		2	-	
7	3	-		1	-	
8	-	3		-	-	
9	-	1		2	-	
10	-	2		-	-	
Total	858	885	0.8	550	279	1.9

Table 5: This table represents the distribution of rating changes from S&P for the pre-crisis (post-crisis) period. Notches represent the cardinal change in credit rating. Down/up represents the ratio of Downgrades to Upgrades.

	Pre-crisis		Post-crisis		Total
	Downgrades	Upgrades	Downgrades	Upgrades	
Mean return in %	-0.004	0.001	-0.001	0.002	0.001
# bonds	858	885	550	279	2572
Financial issuer	478 (55%)	599 (68%)	497 (90%)	244 (87%)	1818 (70%)
Industrial issuer	351 (41%)	249 (28%)	42 (8%)	17 (6%)	659 (27%)
Utility issuer	29 (4%)	37 (4%)	11 (2%)	18 (7%)	95 (3%)
% non-investment grade	32		34		33
Mean rating (cardinal)	9.7		11		10.1

Table 6: This table provides descriptive statistics on return, issuers and credit rating.

Notches	Downgrade	Upgrade	Down/up
1	145	58	
2	43	3	
3	25	1	
4	3	-	
Total	216	62	3.5

Table 7: This table presents the distribution of rating changes from EJR in the post-crisis period. Notches represent the cardinal change in credit rating. Down/up represents the ratio of Downgrades to Upgrades.

4 Methodology

4.1 Event study methodology

As described, in this paper I will test the impact of CREs on ARs. To test this, a proper model is required to measure the benchmark. Multiple models can be used for calculating abnormal bond returns. In general, these models can be separated in mean-adjusted models, matching portfolio models, and factor models. In the mean-adjusted model, introduced by Handjinicolaou (1984), a matching T-Bill is deducted from the historical returns. As described by Handjinicolaou (1984), this model assumes a constant risk premium and is widely used in event study methodology concerning bond returns. Matching portfolio models use a portfolio of returns with a matching maturity to calculate abnormal returns. In these models, default risk and maturity differences are mostly addressed. Factor models, like Fama and French (1993), can also be used for calculating abnormal returns, however this method requires enough observations to obtain reliable results. This requirement is often an obstruction for using factor models in event studies using bonds.

I will use daily bond returns as used in Steiner and Heinke (2001). Using daily returns instead of monthly returns result in more reliable results, as described by Bessembinder et al. (2009). The same methodology is used in Hand et al. (1992) and Norden and Weber (2004). The first step is to calculate the daily return of the bond. The daily return of the bond is calculated by:

$$R_{it} = (\frac{P_{it}}{P_{it-1}}) - 1 \tag{1}$$

Where R_{it} is the daily return of bond i on day t. P_{it} and P_{it-1} are the bond prices of bond i on day t and $t-1$, respectively. I will use the clean bond price, hence excluding accrued interest. Including the accrued interest would not change the S.D. or the reliability of the results, as described by Bessembinder et al. (2009).

The next step in this procedure is to calculate the daily abnormal returns. To do so, a benchmark is necessary. I will use the mean-adjusted model for my main model, but I will not use the regular T-Bill benchmark. The benchmark is the average daily return of the bond corresponding to the same credit rating, instead of a regular T-bill. To be clear, using a bond with credit rating AAA, the average daily return of all bonds with the rating AAA in the sample will be deducted to create AR_{it}. In most studies using this model, the benchmark bond is a 10-year fixed term index U.S. T-Bill. This U.S. T-Bill would capture shifts in interest rates due to changes in expected inflation or changes in the real interest rate. However, it does not take into account the quality of the bond (credit rating), which presumably impacts daily returns. Further, the T-Bill does not capture default premiums since long-term U.S. T-Bills are riskless (Hand et al., 1992). Daily abnormal returns can be calculated using the following equation:

$$AR_{it} = R_{it} - R_{Bt} \tag{2}$$

Where AR_{it} is the Abnormal Return for bond i on day t and R_{Bt} is the average return of the bond with corresponding credit rating.

In the last step, the cumulative abnormal return (CAR_t), the mean abnormal return (AAR_t), and the cumulative average abnormal return ($CAAR_{km}$) will be calculated. These will be calculated by:

$$CAR_t = \sum_{i=1}^{N} AR_{it} \tag{3}$$

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{4}$$

$$CAAR_{km} = \sum_{t=k}^{m} \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{5}$$

Where CAR_t is the cumulative abnormal return on day t, AAR_t is the Average Abnormal Return at day t, $CAAR_{km}$ is the Cumulative Average Abnormal Return between day $t = k$ and day $t = m$ and N is the number of observations (Steiner and Heinke, 2001).

This methodology will be applied to the sub-samples as described in the data section. Using parametric tests, I will measure whether an impact of CREs exists and whether this impact changes significantly between the pre-crisis period and the post-crisis period. Steiner and Heinke (2001) show that the CAARs manifest up until 90 days after the CRE. Therefore, I will calculate the abnormal returns as from -90 to +90 days before and after the announcement day, respectively (Steiner and Heinke, 2001).

The AARs will be calculated over each day in the event window [-10,10]. This metric aggregates all the abnormal returns in the data for the event window and is useful for individual analysis. The advantage of aggregating the abnormal returns for all the days in the event window, is that it eliminates the idiosyncratic differences in the bonds. The CARs and CAAR are more useful for statistical testing, since all the days in the testing period are summed up.

To ensure reliable results, I will use different benchmarks for robustness. Beside my baseline model, I will use a regular 10Y U.S. T-bill as a benchmark to calculate the abnormal returns. In addition, I will test for robustness with a benchmark that includes both rating differences and maturity differences. I will elaborate on these benchmarks in the robustness section.

4.2 Univariate methodology

In this univariate analysis, I will test whether the results hold under different sub-samples. The aim is to find the main drivers of price fluctuations and potential abnormal returns. Doing so, I will create three dummy variables, based on previous literature on this topic, and compare differences between the dummy variables. In addition, I will test whether the impact is more pronounced the post-crisis period.

The first dummy variable ONE will capture the number of rating changes (notches). This variable will be one if the CRE captures only one notch and it will be zero if the number of notches is more than one. I expect the impact on the CAR to be smaller if the notch is one, since the informational content is potentially smaller.

Second, in conventional literature oftentimes the issuer hypothesis is tested. Since the financial industry is highly regulated, this hypothesis predicts that the impact of a rating change may be less pronounced. My data consists of the following industry groups: Industrial (1), Financial (2), Utility (3). FIN will be a dummy variable taking the value one for issuers in the industry group Financial (2) and zero for the other industry groups. This variable is especially interesting given the role of the financial industry in the crisis of 2008.

The dummy variable IG will capture the bonds that have an investment grade rating. IG will take the value one in case of investment grade and zero if the bond has a rating corresponding to a non-investment grade rating. I expect the impact of a CRE to be more pronounced for non-investment grade bonds, since some investors are not allowed to invest in such bonds and most investors are presumably risk averse. This is possibly reducing demand and thereby prices and returns. An overview of the definitions of the dummy variables can be found in Table 8.

I will test the downgrades and upgrades separately. Further, I will provide mean comparison tests of the CARs in the 3-day event window [-1,1] and compare the differences between the dummy variables. In addition, I will compare the CARs between the pre-crisis and post-crisis period using the same event window and dummy variables. As an additional analysis, I will compare potential differences between industries. Since most of my data consists of financial and industrial issuers, as described in Table 6, I will only present potential differences in CARs between financial and industrial issuers.

Variable	Definition
ONE	Dummy with value 1 (0), if the rating change is 1 notch (more than 1 notch).
FIN	Dummy with value 1 (0), if the issuer is financial (non-financial).
IG	Dummy with value 1 (0), if rating level is investment grade (non-investment grade).
POST	Dummy with value 1 (0), if rating event is in the post-crisis (pre-crisis) period.
IND	Dummy with value 1 (0), if the issuer is industrial (non-industrial).
UTI	Dummy with value 1 (0), if the issuer is utility (non-utility).
EJR	Dummy with value 1 (0), if the rating change is from EJR (S&P).
INF	Dummy with value 1 (0) for issuers when DIFF>0 and Ln(CD) is above average.
S&P	The daily return in % of the S&P500.
IS	Index for investor sentiment created by Baker and Wurgler (2006).
Liquidity	A proxy for liquidity measuring the number of non-trading days.
Ln(sales)	The logarithm of the quarterly sales of the bond issuer.
Leverage	Leverage defined as the total debt divided by total equity.
DIFF	Cardinal rating differences between EJR and S&P.
Ln(CD)	The logarithm of the issuer's current debt.
DEBT	The quarterly percentage change in total debt

Table 8: This table provides the definitions of the variables used in the univariate and multivariate analyses.

4.3 Multivariate methodology

This multivariate analysis aims to test the persistence of my univariate results. In addition, this analysis addresses the question whether potential differences exist between industries and whether these differences vary among periods. Furthermore, differences between industries will be tested.

In my univariate analysis, I am testing the drivers of potential abnormal returns by comparing CARs of sub-samples using the dummy variables ONE, FIN, IG. To test whether these results are unchanged in a multivariate analysis, I will include these variables in a multivariate model. In addition, I will include the dummy variable POST which will take the value one if the CRE is in the post-crisis period, and zero otherwise. This variable will capture potential differences of impact between periods. In my univariate analysis, I test whether the impact on CARs under the dummy ONE, FIN, and IG change between periods. To exam this in a multivariate model, I will create three interaction terms named ONE*POST, FIN*POST, and IG*POST. The same kind of model is tested in Bannier and Hirsch (2010). As an example, if the interaction terms displays a significant negative effect for downgrades, I can conclude that the effect is more pronounced in the post-crisis period for the specific dummy variable (ONE, FIN, IG). In order to obtain valid results, I will separately run the model for downgrades and upgrades. The following model will be tested:

$$CAR_{[t1,t2]} = b_0 + \beta_1\text{ONE} + \beta_2\text{FIN} + \beta_3\text{IG} + \beta_4\text{POST} + \beta 5\text{ONE*POST} + \\ \beta 6\text{FIN*POST} + \beta 7\text{IG*POST} + \beta_n\text{control variables} + \epsilon_i \quad (6)$$

Where $CAR_{[t1,t2]}$ are the Cumulative Abnormal Returns over the event window t_1 and t_2. In addition, β_1 - β_7 are the coefficients of the variables in the above model. β_n presents the control variables: S&P return, investor sentiment, liquidity, Ln(sales) and leverage. The definitions of the dummy variables in the above model can be found in Table 8.

I will run the regression with and without the interaction effects. The model without the interaction effect aims to measure general differences between the dummy variables ONE, FIN, and IG over both periods. Further, in the model without interactions, the POST variable is important to test whether differences in CARs exists between periods. To be concrete, this variable is essential for testing the improved-information or the lost-trust hypothesis. I will use the event window [-1,1] to measure and compare the short term impact on the CAR. For the downgrade analysis, a negative sign for POST would support the improved-information hypothesis. A positive sign for POST would provide evidence for the lost-trust hypothesis. Coherently, this rationale is reversed in the regression for upgrades. As explained, the model with the interaction terms addresses the question whether the impact of the dummy variables is more pronounced in the post-crisis period.

To extend my analysis, I will compare differences between industries. Since the Dodd-Frank act is primarily focusing on the financial sector, one could expect the impact of CREs to increase especially for financial issuers compared to industrial and utility issuers. On the other hand, the impact could also be reduced for financial issuers since potentially investors lost their trust especially for issuers in this sector. These two rationales evidently coincide with respectively the improved-information and the lost-trust hypothesis. To measure potential differences between industries, I will run a separate model with the variables FIN and IND. The dummy variable FIN will take the value one if the bond has a financial issuer and zero otherwise. The dummy variable IND will be one when the bond has an industrial issuer and will be zero otherwise. To test whether differences exist between periods, the interaction terms FIN*POST and IND*POST will be included in the model. These variables capture whether the impact of the dummy variable FIN and IND is more pronounced in the post-crisis period. For downgrades, a negative coefficient for FIN*POST would indicate that especially for financial issuers the CARs are impacted, in line with the improved-information hypothesis. A positive coefficient would provide evidence for the lost-trust hypothesis. The model that will be tested is:

$$CAR_{[t1,t2]} = b_0 + \beta_1\text{FIN} + \beta_2\text{IND} + \beta_3\text{POST}+ \\ \beta 4\text{FIN*POST} + \beta 5\text{IND*POST} + \beta_n\text{control variables} + \epsilon_i \quad (7)$$

Where $CAR_{[t1,t2]}$ are the Cumulative Abnormal Returns over the event window t_1 and t_2. In addition, β_1 - β_5 are the coefficients of the variables in the above model. β_n presents the control variables: S&P return, investor sentiment, liquidity, Ln(sales) and leverage.

In my multivariate analyses, I will control for several variables that could potentially drive the differences between the pre-crisis and post-crisis period. I will control for differences in macro-economic changes, investor sentiment and liquidity. First, I will use the returns from the S&P500 as a macro-variables, since these are closely linked to the macro-economy but also to shorter term geopolitical tensions impacting financial markets such as trade conflicts. This variable may help to explain differences between periods. Since the market may be impacted by high/low investor sentiment, described by Baker and Wurgler (2006), I will include this as a control variable. This index captures mispricing in assets due to non-rational, sentiment-based reasons. Since I am testing abnormal returns, mispricing may have an impact on my results. Further, I control for differences in liquidity. Several measures can be used as a proxy for bond market liquidity. In this multivariate model, I am using the number of non-trading days. Additionally, the logarithm of sales and leverage will be included to control for differences between issuers.

4.4 Egan-Jones Rating methodology

As previously described, for several decades only a few players were active in the CRA industry. In 2007 EJR got the NRSRO classification. EJR is an important exception in the CRA industry since its business model is different. EJR is an investor paid CRA and therefore it does not suffer from the conflict of interest problem. To specify, the business model of EJR is based on a subscription basis by investors. It provides independent ratings using the same rating scale as S&P, as described in Table 4. EJR became known by being the first CRA to make a correct projection on the Enron scandal and the failure of Lehman Brothers. The CREs from EJR can be found in Table 7.

To compare the impact of S&P and EJR, I will provide a univariate model and a multivariate model. In the univariate model, I will test whether significant ARs are found for CREs from EJR. In my multivariate model, I will use a dummy variable equal to one if the CRE is from EJR and zero if the rating change is from S&P. This regression model will be separated from downgrades and upgrades to provide reliable results. Out of the 829 bonds that have a CRE from S&P in the post-period, 278 also have a rating from EJR. To control for issuers characteristics, financial information is included in the model. The model that will be tested is:

$$\text{CAR}_{[t1,t2]} = b_0 + \beta_1\text{EJR} + \beta_n\text{control variables} + \epsilon_i(8)$$

Where $CAR_{[t1,t2]}$ are the Cumulative Abnormal Returns over the event window t_1 and t_2. EJR is a dummy equal to one (zero) if the CRE is from EJR (S&P). β_n presents the control variables: S&P return, investor sentiment, liquidity, Ln(sales) and leverage.

To test whether rating inflation is still present in the post-crisis period, I will compare the impact of S&P rating events to the impact of EJR rating events. I will not be able to specify between the pre-crisis and post-crisis period, since EJR was only approved to the NRSRO in 2007. I would not be able to know whether potential differences are due to the change in certification (NRSRO), or due to legislation during the financial crisis. For this reason, I will only test differences between S&P and EJR in the post-crisis period. The prime aim for adding EJR rating events to my sample, is to test whether the conflict of interest problem is still pronounced in the CRA industry. To test this, I will compare bonds that have a rating from EJR and S&P. In this analysis, I will deduct the cardinal S&P rating from the cardinal EJR rating. For example if a bond of a specific issuer has rating BBB (9) from EJR and rating BBB+ (8) from S&P, the cardinal difference equals 1. In this case, S&P assigned a more favorable rating. This variable will be the dependent variable in the model and will be tested against the logarithm of the issuer's current debt. Short term debt serves as a proxy for the conflict of interest problem, where higher current debt is positively associated with the severity of the conflict of interest problem. Since new debt issuance/financing is likely in the near future when current debts are high, CRAs potentially inflate ratings in order to preserve future business. If the conflict of interest problem exists, then a significant positive relation between the cardinal difference of ratings and current debt is likely to exist.

The model that will be tested is:

$$\text{DIFF} = b_0 + \beta_1\text{Ln(CD)} + \beta_n\text{control variables} + \epsilon_i \tag{9}$$

Where $DIFF$ is the cardinal rating difference between EJR and S&P. Ln(CD) is the logarithm of the issuer's current debt. β_n presents the control variables: S&P return, investor sentiment, liquidity, Ln(sales) and leverage.

To provide evidence on hypothesis four, I will use the issuers with a positive cardinal rating difference and an above mean current debt. I will use this sample to test whether these issuers have higher debt growth. Rationally, a positive cardinal rating difference results in a lower cost of capital. Combining this with a high current debt, rating inflation potentially has real effects on debt growth when companies exploit the low cost of capital. I will use the following model:

$$\text{DEBT}_{[t1,t2]} = b_0 + \beta_1 \text{INF} + \beta_n \text{control variables} + \epsilon_i (10)$$

Where DEBT is defined as the quarterly percentage change in total debt in the first quarter the positive rating difference originates. INF is a dummy variable for issuers with a positive cardinal rating difference and an above average current debt. In other words, INF equal one for issuers that are likely to have inflated credit ratings, and zero otherwise. β_n presents the control variables: S&P return, investor sentiment, liquidity, Ln(sales) and leverage. Table 8 provides the definitions of the variables used in this regression model.

5 Results

5.1 Event study results

Table 9 shows the CAARs for the event windows [-10,1], [-1,1], [-1,10] for downgrades and upgrades. Further, I make a distinction between the pre-crisis and post-crisis period to compare potential differences in CAAR. For downgrades (upgrades), I observe negative (positive) coefficients for all event windows in both periods. These findings are consistent with my first hypothesis and with most of the conclusions in conventional literature. Before the upgrade or downgrade is definite, many bonds are set on a watchlisting which is a potential indication of either an upgrade or a downgrade, depending on the type of watchlisting. Hence, based on the variable CAAR[-10,1], it seems that the market incorporates this information before the rating is definite.

Besides observing whether the CAARs are positive/negative, Table 9 shows that the impact of downgrades is bigger than the impact of upgrades for the event windows [-10,1] and [-1,1]. This is consistent with Kahneman and Tversky (1979). In the last event window [-1,10], upgrades seem to have a larger impact than downgrades.

Further, to test for differences in CAAR between the sample periods, mean difference tests in CAARs are presented in Table 9. For downgrades, the impact is significantly increased in the event window [-10,1], while the impact is significantly decreased for the event window [-1,10]. For upgrades, the impact has increased significantly in the event window [-10,1] and [-1,1]. Three of the six variables shown are in line with the improved-information hypothesis, while one test supports the lost-trust hypothesis. To test where these changes originate, I will present individual AARs in Table 10.

	Downgrades			Upgrades		
	Pre-crisis	Post-crisis	t-Statistics	Pre-crisis	Post-crisis	t-Statistic
CAAR [-10,1]	-1.275	-2.059***	3.187	0.195	0.661***	-8.367
CAAR [-1,1]	-1.005	-1.217	0.556	0.099	0.340***	-2.641
CAAR [-1,10]	-0.556	-0.142***	-2.86	0.775	0.632	1.349

Table 9: This table presents the Cumulative Average Abnormal Returns in % (CAAR) for downgrades and upgrades over the event widows [-10,1], [-1,1], [-1,10] and compares the impact in the pre-crisis and post-crisis period. The t-Statistics are presented, including the asterisks *, **, and *** which denote the 10%, 5% and 1% level of significance, respectively.

In Table 10, the daily AARs are presented for downgrades and upgrades, comparing the two sample periods. For downgrades in the pre-crisis period, I find highly negative AARs on $t = 0$ and $t = 1$ with a t-Statistics of respectively -4,107 and -4,828. Comparing this to the post-crisis period, I find highly significant negative AARs on $t = -4$, $t = -2$ and $t = -1$. This table shows that the impact of a downgrade on the AARs is significant for both periods, but the impact seems to have extended to the at least a few days before the CRE. This is in line with the previous shown CAAR[-10,1] in Table 9.

When observing and comparing the AARs of the upgrades, I find t-Statistics that are in general less significant. This is in line with the reasoning of Kahneman and Tversky (1979). To be more specific, in the pre-crisis period I find significant positive AARs on day $t = -1$, $t = 0$, $t = 1$ and $t = 3$. Surprisingly, on day $t = -1$, I find significant negative returns of -0,176%. Since there is no clear rationale or theory for this result, it is thinkable that other factors or events had an impact on this result. In the post-crisis period, it is clear that the market also anticipates to the rating event on day $t = 0$, since the AAR is positive and significant at the 5% significance level.

In order to grasp whether the market implemented new information earlier, I will plot the CAARs over the event window [-90, 90] in Figure 1 and Figure 2. In both figures, the CAARs are presented in % against the trading days, where $t = 0$ is the announcement day.

The CAARs for downgrades presented in Figure 1, show a strong negative trend until approximately $t = 0$. After the CRE on $t = 0$, a positive trend occurs that reaches approximately -2% CAAR on $t = 90$. Comparing this to the post-crisis period, it is clear that the results are approximately the same. The CAAR is negative over the whole period [-90, 0]. After $t = 0$, one can observe an increasing trend. Starting from $t = 50$, this trend seems to be less steep in the post-crisis period, which may suggest that the information provided is not just a temporarily shock but is permanent for this event window. Providing weak evidence for the improved-information hypothesis, the market seems to incorporate more information since the CAARs remain more negative in the post-crisis period. The difference between the pre-crisis and post-crisis period on day $t = 90$ is approximately 2%. The market seems to overreact to downgrades, since the negative returns are reversed just after the announcement date.

In Figure 2, the CAARs for upgrades are plotted for both periods. One can observe a clear positive trend. The CAARs are higher in the post-crisis period starting from approximately day $t = -25$. This result is consistent with the improved-information hypothesis. Further, the post-crisis CAAR remains higher than the pre-crisis CAAR until at least day $t = 90$.

A clear difference between the CAARs of downgrades and upgrades is the changing trend that occurs on day $t = 0$ with downgrades. This may suggest that the market overreacts to the forthcoming downgrade. This reversing trend does not arise for upgrades.

	Downgrades				**Upgrades**			
	Pre-crisis		Post-crisis		Pre-crisis		Post-crsis	
Day	AAR	t-Statistic	AAR	t-Statistic	AAR	t-Statistic	AAR	t-Statistic
-10	-0.096	-0.566	-0.088	-0.434	0.027	0.228	0.025	0.222
-9	-0.038	-0.280	-0.216	-1.207	0.059	0.732	0.169	1.586
-8	0.254**	2.038	0.143	0.940	-0.089	-0.910	-0.015	-0.193
-7	-0.149	-1.303	0.200	1.450	0.045	0.619	0.080	0.957
-6	0.219*	1.664	0.081	0.568	-0.045	-0.586	0.079	0.674
-5	-0.096	-0.607	0.062	0.368	-0.030	-0.288	0.080	0.585
-4	-0.011	-0.069	-0.466***	-2.626	-0.065	-0.777	0.083	0.584
-3	-0.290*	-1.790	0.151	0.929	0.093	0.773	-0.073	-0.493
-2	-0.062	-0.390	-0.708***	-3.203	0.101	0.985	-0.106	-1.205
-1	0.144	1.220	-0.630***	-4.015	-0.176**	-2.145	0.059	0.637
0	-0.454***	-4.107	-0.081	-0.589	0.119*	1.863	0.178**	2.094
1	-0.696***	-4.828	-0.506***	-3.512***	0.156**	2.148	0.103	1.141
2	0.229	1.323	-0.207	-1.241	0.021	0.251	-0.109	-0.967
3	-0.112	-0.691	0.042	0.231	0.270***	2.944	0.037	0.420
4	-0.119	-0.678	0.213	1.022	0.067	0.823	0.209	1.581
5	0.317**	2.040	0.388**	2.262	0.044	0.637	0.061	0.660
6	0.179	1.532	-0.136	-0.894	0.128	1.515	0.015	0.122
7	-0.101	-0.985	0.115	1.017	-0.019	-0.260	-0.054	-0.540
8	0.051	0.373	0.060	0.410	0.090	1.201	0.084	0.946
9	-0.098	-0.460	0.354**	1.913	-0.020	-0.216	-0.043	-0.576
10	0.105	0.584	0.247	1.320	0.094	1.059	0.093	1.059

Table 10: This table presents the Average Abnormal Returns (AAR) and t-Statistics in the event window [-10,10]. Upgrades and downgrades are separated as well as the pre-crisis and post-crisis period. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

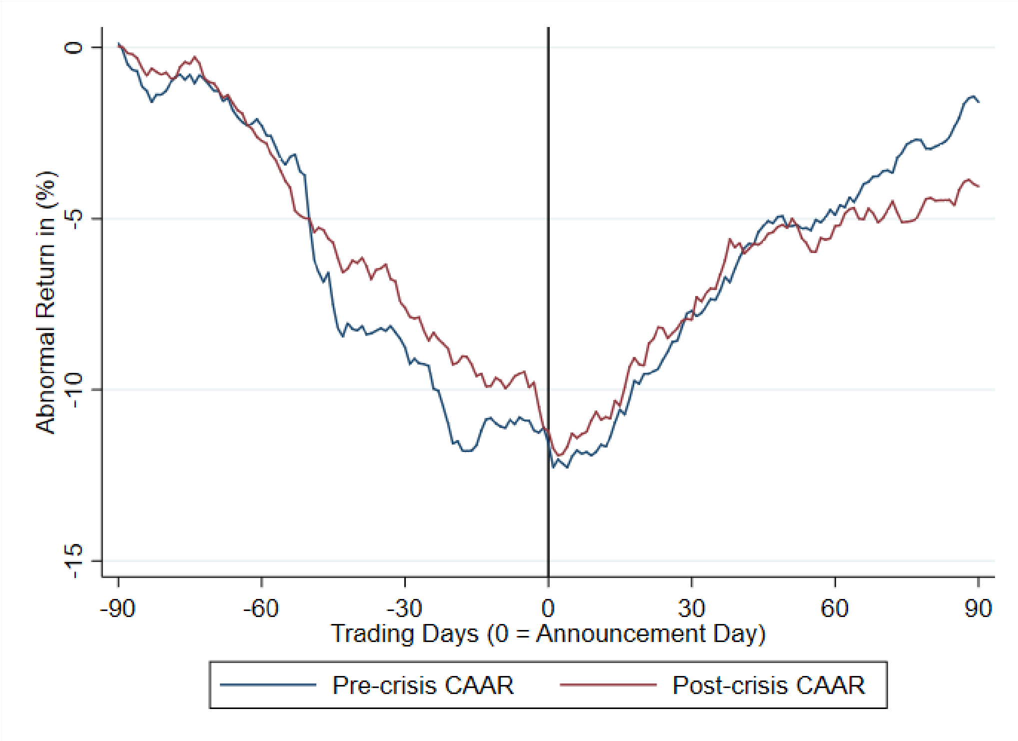

Figure 1: This graph represents the Cumulative Average Abnormal Returns in % (CAAR) over the 180 days event window [-90, 90] for Downgrades in the pre-crisis and post-crisis period. On the Y-axis the CAARs are presented in (%). On the X-axis, the Trading Days are presented where day $t = 0$ is the announcement day.

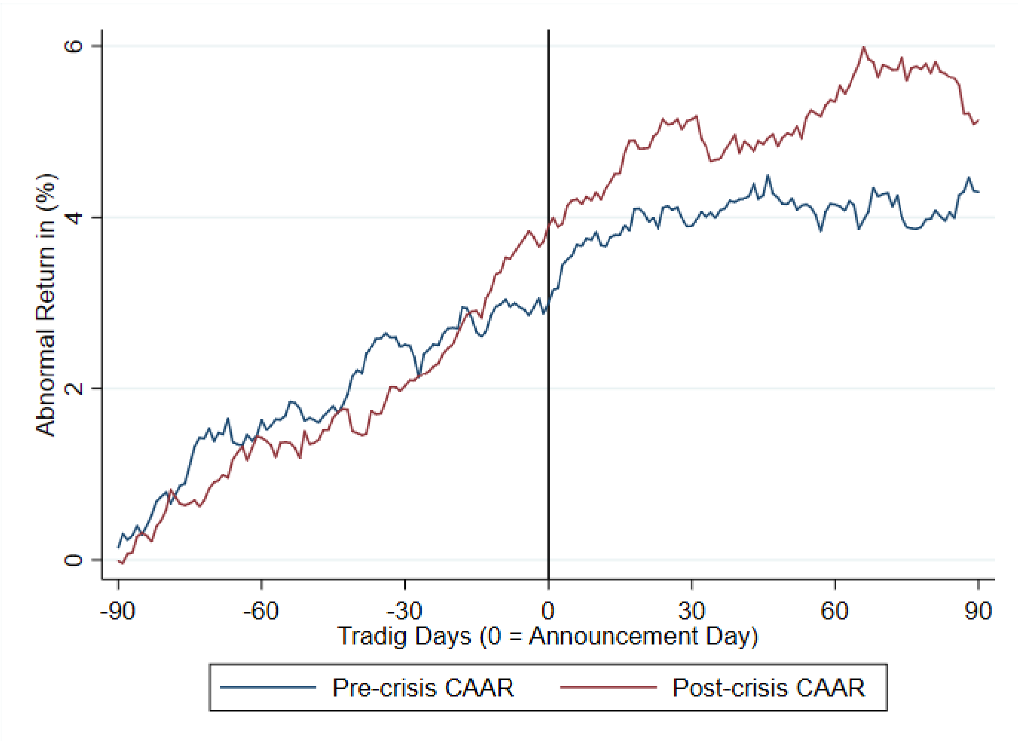

Figure 2: This graph represents the Cumulative Average Abnormal Returns over the 180 days event window [-90, 90] for Upgrades in the pre-crisis and post-crisis period. On the Y-axis the CAARs are presented in %. On the X-axis, the Trading Days are presented where day $t = 0$ is the announcement day.

5.2 Univariate results

As described in the univariate methodology, I will use three dummy variables to measure whether differences between periods exist using several dummy variables. In addition, I will test whether differences between the dummy variables exist.

In Table 11, I compare the difference in means of the dummy variables over the event window [-1,1]. For downgrades, I find a positive and significant difference for ONE. When the rating change is one notch (ONE=1), the CAR equals on average -0.501% for downgrades. If the rating change is more than 1 (ONE=0), the CAR is approximately -1,346%. Comparing the difference in means, shows a t-Statistic of 5.79 which is significant at the 1% level. I find the same pattern for upgrades and this is in line with my expectation. If the bond has a financial issuer ($FIN = 1$), these results provide a larger CAR compared to non-financial issuers ($FIN = 0$). This result is captured in FIN and is not in line with expectations since financial firms are monitored more heavily. In line with my expectation, this table provides a mean CAR of -0.289% if the bond has an investment grade rating ($IG = 1$), while a non-investment grade bond ($IG = 0$) show an average CAR of -1.062% which is significantly lower. For upgrades, all the differences between dummy variables are in line with expectations. For downgrades, the only exception is the dummy variable FIN. This table presents evidence for significant differences between dummy variables.

Since the results suggest that differences exist between the dummy variables, I will test whether differences exist between periods using these dummy variables. If the impact of CREs is significantly more pronounced in the post-crisis period, this would provide evidence for the improved-information hypothesis. Conversely, if the impact is significantly smaller in the post-crisis period, this would provide evidence for the lost-trust hypothesis. Table 12 presents a comparison of the impact between the pre-crisis and post-crisis period to test my second hypothesis. To be specific, this table presents the CARs over the event window [-1,1] when the dummy variables equal one and zero and shows t-statistics for differences between the means. For downgrades, the impact for ONE is increased when the number of notches is one ($ONE = 1$), in line with the improved information hypothesis. When the notches are more than one ($ONE = 0$), the impact seems to reduce in the post-crisis period, providing evidence for the lost-trust hypothesis. For financial issuers (FIN), I find significant changes between periods, in line with the improved-information hypothesis. For upgrades a significant change can be found when $IG = 1$ and $ONE = 0$, supporting the improved-information hypothesis. Meaning, the impact of a CRE on the CARs is more pronounced in the post-crisis period for the above-mentioned variables. For example, the differences between the pre-crisis period and post-crisis period for IG equal -0.493%, which is significant at the 1% level (t-Statistic = -4.36).

Table 13 compares the CARs for downgrades and upgrades using the dummy variables FIN and IND. These results suggest that the impact of downgrades on CARs is significantly more pronounced for FIN compared to IND in all the presented event windows. In the event window [-1,1], CARs for financial issuers are on average -1,313%, while the CAR for industrial issuers is on average -0.691%. For upgrades, it seems that the opposite is true, the impact of a CRE is less for FIN compared to IND. In absolute values, bonds that have a financial issuer show on average lower CARs. Potentially this can be explained by the financial regulation during the financial crisis. In other words, especially for financial issuers the impact of financial legislation may have resulted in an improved rating quality. Therefore, in my multivariate analysis, I will test whether the impact of downgrades and upgrades is significantly more pronounced for financial issuers in the post-crisis period. This could provide evidence for the success of the Dodd-Frank act, which is evidently focusing on financial sector reforms. In addition to comparing the differences between issuer types, I will present the CARs for several large markets in my sample. This is presented in Table 14.

Downgrades				
Dummy	1	0	Δ	t-Statistic
ONE	-0.501	-1.346	0.844***	5.79
FIN	-1.313	-0.662	-0.650***	-4.26
IG	-0.289	-1.062	0.773***	4.39
Upgrades				
ONE	0.110	0.448	-0.338***	-2.82
FIN	0.047	0.253	-0.205***	-2.48
IG	0.077	0.249	-0.172***	-2.08

Table 11: This table describes the mean comparison t-Statistics of the [-1,1] CARs (in %) for the dummy variables created for the whole sample. Δ Provides the difference in CAR when the dummy variable is either one or zero. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

Downgrades					
Variable	Dummy	Pre-crisis	Post-crisis	Δ	t-Statistic
ONE	1	-0.063	-0.928	0.864***	4.69
	0	-1.56	-0.835	-0.731***	-2.93
FIN	1	-1.250	-2.013**	0.763*	1.76
	0	-0.448	-0.810	0.362*	1.93
IG	1	-0.337	-0.251	-0.085	-0.68
	0	-0.996	-1.17	0.179	0.94
Upgrades					
ONE	1	0.092	0.160	0.110	-0.68
	0	0.277	0.775	0.448**	-2.17
FIN	1	0.044	0.157	-0.113	-0.37
	0	0.235	0.272	-0.036	-0.30
IG	1	-0.030	0.463	-0.493***	-4.36
	0	0.317	0.124	0.193	1.30

Table 12: This table describes the mean sample Cumulative abnormal Returns (CAR) in % over the event window [-1,1] and t-Statistics of the means of the pre-crisis and post-crisis period. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

Downgrades	FIN	IND	Δ	t-Statisic
CAR[-1,10]	-1.279	-0.824	-0.971***	-3.29
CAR[1,1]	-1.313	-0.691	-0.621***	-4.23
CAR[-1,10]	-1.279	-0.824	-0.455***	-3.29
Upgrades				
CAR[-1,10]	0.133	0.360	-0.226***	-3.32
CAR[1,1]	0.047	0.285	-0.237***	-2.78
CAR[-1,10]	0.308	0.456	-0.148***	-2.64

Table 13: This table presents the CARs (in %) for downgrades in the event windows [-10,1], [-1,1], [-1,10] for bonds with a financial (FIN) and industrial (IND) issuer. Δ Presents the difference between FIN and IND. T-statistic presents the mean difference test.

Downgrades				
Industry	Market	CAR[-10,1]	CAR[-1,1]	CAR[-1,10]
Financial	Credit/Financing	-1.069	-1.291	-1.078
	Financial Services	-0.195	-0.260	-0.037
	Insurance	-3.481	1.284	1.127
Industrial	Manufacturing	-0.593	-0.625	0.461
	Media & Communication	-0.195	-0.260	-0.036
	Oil & Gas	-2.001	-1.521	-1.386
Utility	Electric	-1.116	-1.431	-1.897
Upgrades				
Financial	Credit/Financing	-0.261	-0.126	0.546
	Financial Services	-0.003	-0.014	0.349
	Insurance	0.729	0.126	0.139
Industrial	Manufacturing	0.631	0.329	0.437
	Media & Communication	-0.003	-0.014	0.349
	Oil & Gas	-0.709	-0.362	-0.208
Utility	Electric	0.176	0.086	0.512

Table 14: This table presents the Cumulative Abnormal Returns (CARs) for specific markets in my data. It separates Financial, Industrial & Utility industries. CAR[-10,1], CAR[-1,1] and CAR[-1,10] show the CARs for the specific event windows.

5.3 Multivariate results

In this multivariate analysis, I will compare differences between the dummy variables and test whether these are more pronounced in the post-crisis period. In addition, I will provide a multivariate analysis to test potential differences between industries.

In Table 8, the definition of the variables used in the regression are provided. As described in the methodology, the interaction terms are also included to test whether the dummy variables are more pronounced in the post-crisis period. Taking multicollinearity into account, I will calculate Spearman's correlation coefficient and calculate the VIFs. The correlations are greater than -0.5 and smaller than 0.5, indicating that the variables can be used in a multivariate regression model. In addition, the VIF scores for these dummy variables are acceptable. However, when the interaction terms are included, I find high correlations between the variables ONE*POST and POST (77%) and high VIF scores. To provide reliable coefficients, I will drop ONE*POST from my model. In this way, I cannot test whether ONE is more pronounced in the post-crisis period, but I can test it for the other dummy variables.

Table 15 shows the multivariate results for the event window [-1,1]. Five models are shown for upgrades and downgrades. Observing the dummy variables for downgrades (upgrades), a positive sign indicates a smaller (bigger) impact on the CARs, while a negative sign indicates a larger (smaller) impact on the CARs. This model aims to measure the general differences between the dummy variables in my data. The POST variable measures potential differences of impact between the two periods. The interaction effects between POST and the two dummy variables, will test whether the impact of the dummies is more pronounced in the post-crisis period. I will compare the interaction effects with my univariate results to regard potential differences

Table 15 shows the multivariate regression model for downgrades in the event window [-1,1]. In model 1, one can observe a highly significant negative intercept (-0.942%). Further the coefficients for the three dummy variables are significant. The results are approximately in line with the event study and univariate results in 11. The dummy variables ONE and IG are on average resulting in a lower CARs, while FIN is positively significant. The variable POST is highly significant (1% level) in model 1, in line with the improved-information hypothesis. The variable POST provides evidence of higher CARs in the post-crisis period, compared to the pre-crisis period. The interaction terms, included in model 2-5, will test whether the two dummy variables are more pronounced in the post-crisis period. This table shows no significant results for the interaction effects. This means that the significant impact of FIN and IG is not dependent on the POST variable. In other words, FIN and IG in the post-crisis period are not resulting in a significantly higher impact on CARs in this multivariate model. Comparing this to the univariate results in Table 12, it seems that the significant difference found in the univariate model can be attributed to general differences that are potentially captured in POST instead of the interaction effects.

For upgrades in model 1, the three dummy variables partially show the same pattern as in the univariate results. Namely, ONE and IG are significantly negative in line with expectations, but FIN is no longer significant. Further, The POST variable does not show significant results. When including the interaction terms in model 2-5, except from IG*POST, no variables show significance. Investment grade bonds show 0.595 % higher CARs in the post-crisis period, in line with the univariate results in Table 12 and in line with the improved-information hypothesis.

In general, the results are mostly in line with my univariate results. Except from some changes in significance for the dummy variables, I observe significant CARs for upgrades and downgrades, in line with my first hypothesis. In addition, for downgrades I find evidence the improved-information hypothesis. The results suggest that the POST variable remains significant after including the interaction terms. The interaction effects do not show significant results except from IG*POST for upgrades.

In Table 16, I compare differences between financial issuers and industrial issuers. The results suggest that financial issuers have a highly significant negative impact on returns after a downgrade compared to non-financial issuers. This is captured in the variable FIN and is consistent with Table 13. In addition, in model 1 it seems that the impact is more pronounced in the post-crisis period since POST has a coefficient of -0.397% with a t-Statistic of 2.31. To test whether this difference can be explained by one or more industries, I include the interaction terms in model 2-5. Now, the POST variable becomes insignificant, but FIN*POST is significant at the 10% level. It seems that the interaction term FIN*POST is significantly driving the general differences in CARs between the pre-crisis and post-crisis period. In addition, I do not find significant results for industrial issuers. The regulation that has been focusing on the financial sector, seems to have more pronounced impact for financial issuers. These results are in line with the improved-information hypothesis. The same regression model for upgrades can be found in Table tab:industrydowngrade11, but the results are insignificant for all important variables tested.

The above tables provide evidence for significant CARs, in line with my first hypothesis. In addition, these results suggest that the financial legislation, in this case especially the Dodd-Frank act, has impacted the CRA industry for downgrades. It seems that regulation is successful in reducing the conflict of interest problem that existed in the CRA industry. The results provide evidence that investors rely and respond heavier on CREs in the post-crisis period compared to the pre-crisis period. A significant driver of this result are bonds with financial issuers. The control variables reduce the significance for some coefficients but cannot explain the significant abnormal returns nor the difference between the pre-crisis and post-crisis period.

Downgrades		CAR[-1,1]				
	Predicted	1	2	3	4	5
ONE	+	0.651***	0.678***	0.708***	0.719***	0.658***
		(4.11)	(4.25)	(4.42)	(4.48)	(4.14)
FIN	+	-0.572***	-0.459**	-0.470**	-0.462**	-0.424**
		(-3.13)	(-2.27)	(-2.30)	(-2.27)	(-2.10)
IG	+	0.457***	0.377*	0.409**	0.422**	0.396*
		(2.45)	(1.85)	(2.00)	(2.07)	(1.95)
POST	+/-	-0.483***	-0.422**	-0.338*	-0.321*	-0.139
		(-2.84)	(-2.23)	(-1.76)	(-1.67)	(-0.72)
FIN*POST	+/-		-0.742	-0.678	-0.659	-0.871*
			(-1.53)	(-1.40)	(-1.36)	(-1.81)
IG*POST	+/-		0.435	0.493	0.569	0.489
			(1.14)	(1.29)	(1.48)	(1.28)
S&P return				0.391***	0.391***	0.395***
				(4.05)	(4.05)	(4.13)
Investor sentiment				2.434	2.423	2.826*
				(1.43)	(1.42)	(1.67)
Liquidity				-0.004	-0.004	-0.004
				(-0.43)	(-0.44)	(-0.40)
Ln(sales)					-0.358	-0.269
					(-1.35)	(-1.02)
Leverage	-					-0.979***
						(-7.41)
β_0		-0.942***	-1.003***	-1.060***	-1.071***	-0.599***
		(-5.63)	(-5.62)	(-5.89)	(-5.95)	(-3.16)
N		3132	3132	3132	3132	3132
adj. R^2		1.60	1.60	2.10	2.20	3.80
Upgrades						
ONE	-	-0.341***	-0.353***	-0.367***	-0.362***	-0.352***
		(-2.83)	(-2.93)	(-3.04)	(-3.00)	(-2.93)
FIN	-	-0.131	-0.103	-0.119	-0.117	-0.0675
		(-1.31)	(-0.99)	(-1.11)	(-1.09)	(-0.63)
IG	-	-0.148*	-0.247***	-0.273***	-0.279***	-0.369***
		(-1.70)	(-2.66)	(-2.87)	(-2.92)	(-3.81)
POST	+/-	0.0359	-0.109	-0.0965	-0.0767	-0.0765
		(0.33)	(-0.89)	(-0.79)	(-0.62)	(-0.62)
FIN*POST	+/-		0.119	0.135	0.115	0.260
			(0.33)	(0.38)	(0.32)	(0.73)
IG*POST	+/-		0.605***	0.598***	0.582***	0.673***
			(3.02)	(2.99)	(2.91)	(3.36)
S&P Return				0.055	0.057	0.074
				(1.00)	(1.04)	(1.35)
Investor sentiment				0.490	0.494	0.501
				(0.66)	(0.67)	(0.68)
Liquidity				0.008***	0.008***	0.009***
				(2.43)	(2.43)	(2.46)
Ln(sales)					-0.144	-0.110
					(-1.35)	(-1.03)
Leverage	-					-1.663***
						(-4.64)
β_0		0.581***	0.632***	0.625***	0.622***	1.476***
		(4.27)	(4.59)	(4.51)	(4.49)	(6.42)
N		2209	2209	2209	2209	2209
adj. R^2		0.60	0.90	1.10	1.10	2.00

Table 15: This table presents regressions on the independent variable Cumulative Abnormal Returns (CAR) for downgrades (upper table) and upgrades (lower table) in the event window [-1,1]. The dependent variables are, One, FIN, IG and POST in Model 1. In model 2, the interaction terms FIN*POST and IG*POST are included. In model 3, I control for S&P Return, investor sentiment, and liquidity. In model 4 and 5, I control for respectively Sales and Leverage. The predicted sign of the coefficients is captured in the column Pred. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

Downgrades		CAR[-1,1]				
	Predicted	1	2	3	4	5
FIN	-	-1.335***	-0.897*	-0.933*	-0.933*	-0.923*
		(-3.02)	(-1.73)	(-1.81)	(-1.81)	(-1.80)
IND		-0.506	-0.104	-0.106	-0.106	-0.172
		(-1.16)	(-0.20)	(-0.20)	(-0.20)	(-0.33)
POST		-0.397**	1.004	1.104	1.104	1.130
		(-2.31)	(1.08)	(1.19)	(1.19)	(1.23)
FIN*POST	-		-1.768*	-1.714*	-1.702*	-1.794*
			(-1.71)	(-1.66)	(-1.65)	(-1.76)
IND*POST			-1.392	-1.411	-1.405	-1.240
			(-1.47)	(-1.49)	(-1.48)	(-1.32)
S&P return				0.358***	0.358***	0.365***
				(3.70)	(3.70)	(3.80)
Investor Sentiment				1.939	1.933	2.396
				(1.14)	(1.13)	(1.42)
Liquidity				-0.008	-0.008	-0.007
				(-0.08)	(-0.09)	(-0.07)
Ln(sales)					-0.088	-0.020
					(-0.33)	(-0.08)
Leverage						-1.030***
						(-7.78)
β_0		0.054	-0.353	-0.382	-0.382	0.126
		(0.13)	(-0.70)	(-0.76)	(-0.76)	(0.25)
N		3132	3132	3132	3132	3132
adj. R^2		0.70	0.80	1.10	1.11	3.00
Upgrades						
FIN	+	0.142	-0.036	-0.064	-0.064	-0.050
		(0.69)	(-0.15)	(-0.25)	(-0.25)	(-0.20)
IND		0.366	0.175	0.176	0.176	0.173
		(1.80)	(0.68)	(0.69)	(0.69)	(0.68)
POST		0.0283	-0.463	-0.460	-0.367	-0.372
		(0.26)	(-1.15)	(-1.14)	(-0.89)	(-0.90)
FIN*POST	+		0.576	0.613	0.520	0.671
			(1.09)	(1.16)	(0.97)	(1.25)
IND*POST			0.523	0.528	0.442	0.462
			(1.24)	(1.26)	(1.03)	(1.08)
S&P*return				0.0267	0.0269	0.0333
				(0.50)	(0.50)	(0.63)
IS				0.418	0.417	0.395
				(0.57)	(0.56)	(0.54)
Liquidity				0.083***	0.083***	0.083***
				(2.38)	(2.38)	(2.39)
Ln(Sales)					-0.109	-0.076
					(-0.99)	(-0.69)
Leverage						-1.410***
						(-4.00)
β_0		-0.095	0.080	0.051	0.051	0.756***
		(-0.48)	(0.33)	(0.21)	(0.21)	(2.54)
N		2209	2209	2209	2209	2209
adj. R^2		0.30	0.30	0.40	0.40	1.11

Table 16: This table presents regressions on the independent variable Cumulative Abnormal Returns (CAR) for downgrades (upper table) and upgrades (lower table) in the event window [-1,1]. The dependent variables are, FIN, IND and POST in Model 1. In Model 2, I include the interaction effects FIN*POST and IND*POST. In model 3, I control for respectively macro-economy, investor sentiment, and liquidity. In model 4 and 5, I control for respectively Sales and Leverage. The expected sign of the coefficients is captured in the column Predicted. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

5.4 Egan-Jones Rating results

The previous results from S&P suggest that the conflict of interest problem is countered by the legislation during the financial crisis. This part of the results is related to my third and fourth hypothesis. Although the conflict of interest problem is reduced, it is not fundamentally solved. For this reason, I will provide an additional analysis focusing on the difference between ratings from S&P and EJR. Table 17 presents the CAARs and t-Statistics for multiple event windows. This table provides evidence that the CAARs are significant for some event windows, in line with expectations. It seems however that the CREs from EJR have less impact on the daily bond returns than CREs from S&P. To elaborate on this, I will test this in a multivariate model using the dummy variable EJR.

In the multivariate models, presented in Table 18, one can observe results that are in line with the univariate results. In model 1 and 2 for downgrades, the intercept is significantly negative. Interestingly for downgrades, the dummy variable EJR is positive. This indicates that the impact of downgrades is reduced by 0.520% when the CRE is from EJR. For upgrades, the intercept is significantly positive but the dummy variable EJR is insignificant. This indicates that no significant differences are observed between EJR and S&P for upgrades.

	Downgrades	t-Statistic	Upgrades	t-Statistic
CAAR[-10,1]	-0.441***	-2.807	0.094	1.093
CAAR[-1,1]	-0.201	-1.476	0.168*	1.921
CAAR[-1,10]	-0.025	-0.171	-0.065	-0.926

Table 17: This table presents the Cumulative Average Abnormal Returns in % (CAAR) for downgrades and upgrades over the event widows [-10,1], [-1,1], [-1,10] for Egan-Jones Rating (EJR). The t-Statistics are presented, including the asterisks *, **, and *** which denote the 10%, 5% and 1% level of significance, respectively.

	Downgrades			**Upgrades**		
Dep. variable	Predicted	1	2	Predicted	4	5
EJR	+/-	0.668***	0.520***	+/-	-0.051	0.055
		(3.37)	(2.54)		(-0.27)	(0.29)
S&P Return			0.434***			0.173*
			(3.79)			(1.94)
IS			2.050			-4.544
			(0.96)			(-1.04)
Liquidity			-0.063*			0.006
			(-1.90)			(0.71)
Ln(sales)			0.168			0.401
			(0.50)			(0.56)
Leverage			-0.187			-1.387***
			(-1.16)			(-5.48)
β_0	-	-0.870***	-0.657***	+	0.267***	0.438***
		(-8.14)	(-4.96)		(3.48)	(5.13)
N		1810	1810		727	727
adj. R^2		0.60	1.40		0.10	4.00

Table 18: This table presents regressions on the independent variable Cumulative Abnormal Returns (CAR) for downgrades (model 1 and 2) and upgrades (model 3 and 4) in the event window [-1,1]. In model 2 and 4, I include several control variables. The predicted sign of the coefficients is captured in the column Predicted. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

Besides comparing the impact of EJR and S&P in the post-crisis period, I will test the presence of the conflict of interest problem in the post-crisis period. To do so, I will test whether the differences in rating between EJR and S&P are correlated with the logarithm of the current debt of the bond issuer. From all the bonds with a rating from S&P in the post-crisis sample, 278 also have a rating from EJR. To test the difference in rating, the cardinal rating difference is calculated by deducting the cardinal S&P rating from the cardinal EJR rating. In Table 19, one can observe a mean difference of 0.151 notch over 278 rating differences. This indicates that on average S&P issues ratings that are 0.151 notch higher.

To test the presence of rating inflation, I wil test whether the rating difference is positively associated with current debt. In model 3 of Table 20, I find that the variable Ln(CD) is significant at the 1% level with a coefficient equal to 0.130. In essence, this means that a one standard deviation increase in Ln(CD) increases the rating of S&P compared to EJR by approximately 0.130 notch. Besides the statistical significance, economically this is highly significant. Although some of the control variables are significant, they do not reduce the significance of Ln(CD). This evidence suggests that increasing current debt levels is triggering S&P to issue higher ratings. This is a strong indicator of the existence of the conflict of interest problem in the post-crisis period.

#Obs.	Mean	St. Dev.	25% Percentile	75% Percentile
278	0.151	1.573	-1	1

Table 19: Descriptive statistics of the cardinal difference between Egan-Jones Rating (EJR) and Standard & Poor's (S&P).

Dep. Variable		DIFF		
	Predicted	1	2	3
Ln(CD)	+	0.209***	0.180***	0.130***
		(4.96)	(4.43)	(3.19)
S&P Return			0.400***	0.421***
			(5.15)	(5.57)
Liquidity			-0.094**	-0.090**
			(-2.01)	(-1.98)
Ln(sales)				-0.688
				(-1.44)
Leverage				-0.673***
				(-4.40)
β_0		-0.029	0.103	0.335***
		(-0.35)	(1.05)	(3.14)
N		278	278	278
adj. R^2		6.90	14.80	20.10

Table 20: This table presents regressions on the independent variable Cardinal rating difference. Ln(CD) presents the logarithm of the current debt. In model 2 and 3, I include several control variables. The predicted sign of the coefficients is captured in the column Predicted. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

To delve further into the implications of rating inflation, I will use specific bond issuers with a positive cardinal rating difference (DIFF>0) and an above average current debt. Out of the 278 issuers, 99 issuers pass these requirements. Table 21 presents the regression model using the % quarterly debt growth as the dependent variable and INF and the control variables as independent variables. This table provides evidence that the % quarterly debt growth is significantly greater for issuers with a positive rating difference and a relatively high current debt. To be concrete, after including several control variables in model 3, if INF=1 the quarterly debt growth is approximately 0.781%, which is significant at the 10% level. This result is in line with expectation and supports the hypothesis that INF is positively associated with debt growth rates.

Dep. Variable		DEBT		
	Predicted	1	2	3
INF	+	0.792**	0.825**	0.781*
		(2.09)	(2.11)	(1.93)
S&P return			-0.028	-0.020
			(-0.14)	(-0.10)
IS			1.040	1.152
			(0.08)	(0.08)
Liquidity			0.081	0.084
			(0.65)	(0.67)
Ln(sales)				-0.001
				(-0.08)
Leverage				-0.167
				(-0.40)
β_0		0.015	-0.093	-0.033
		(0.07)	(-0.33)	(-0.11)
N		278	278	278
adj. R^2		1.00	0.20	0.30

Table 21: This table presents regressions on the independent variable % quarterly debt growth (DEBT). INF presents the issuers when DIFF>0 and Ln(CD) is above average. In model 2 and 3, I include several control variables. The predicted sign of the coefficients is captured in the column Predicted. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

6 Robustness

To test whether my multivariate results are robust to changes in the event window, I replicated the multivariate results for the event window [-10,1]. Besides minor changes in significance, the main results seem robust to changes in the event window. This also holds for the comparison between industries provided in Table 16.

Considering the importance of the benchmark to calculate the abnormal returns, I will calculate the CARs using different benchmarks to improve the reliability of my results. First, I will use a 10Y U.S. T-Bill to calculate the CARs. This benchmark is used a lot in the literature. In addition, some research suggests that accounting for maturity is an important factor in the benchmark. To address this issue, I will modify the benchmark used in my baseline model. Instead of subtracting the average return for every corresponding rating class, I will create three rating categories and specify between two maturity groups. To be concrete, the three cardinal rating classes are 1-7, 8-16, and 17-22. The groups for time to maturity are more than five years and shorter than five years. As described, accounting for time to maturity possibly improves the quality of the benchmark. However, a bias in the benchmark is a potential risk, since the classes may become relatively small when specifying for credit risk and maturity. In my sample, I do not observe small benchmark groups. In my whole sample, 1209 bonds have a time to maturity shorter than five years. The results, using these benchmarks, are in line with my previous analyses and can be found in Table 22. As one can observe, these robustness tests provide the same results as in my baseline model. Comparing industries in a separate model, Table 23 is provided for downgrades and upgrades. The results are predominantly unchanged compared to my baseline models, indicating that the results are robust to changes in benchmark. The only change is the interaction term FIN*POST in model 3 and 4. FIN*POST is negative for downgrades, but it is not statistically significant.

As described by Strobl and Xia (2011), potentially a reverse causality issue exists. If an issuers gets assigned a high rating from S&P issuers may want to refinance thereby inflating their current debt. Taking into account this potential reverse causality, I will use long term debt that is due in one year as an additional proxy for the severity of the conflict of interest. This variable is additionally gathered from COMPUSTAT and is defined as a logarithm. The repayment schedules for long-term debt are mostly determined years in the past (Strobl and Xia, 2011). I find no significant differences compared to Table 20.

Downgrades		CAR[-1,1]			
	Predicted	T-bill (1)	T-bill (2)	Maturity (3)	Maturity (4)
ONE	+	0.360**	0.343**	0.666***	0.602***
		(2.23)	(2.14)	(4.24)	(3.88)
FIN	+	-0.344*	-0.304	-0.555***	-0.499***
		(-1.69)	(-1.50)	(-2.77)	(-2.53)
IG	+	0.355*	0.378*	0.322	0.303
		(1.72)	(1.86)	(1.61)	(1.53)
POST	+/-	-0.550***	-0.225	-0.372**	-0.126
		(-2.88)	(-1.16)	(-1.98)	(-0.67)
FIN*POST	+/-	-1.217***	-1.359***	-0.745	-0.990**
		(-2.48)	(-2.81)	(-1.57)	(-2.11)
IG*POST	+/-	0.342	0.409	0.411	0.391
		(0.89)	(1.06)	(1.10)	(1.05)
β_0	-	-0.734***	-0.284	-0.888***	-0.309*
		(-4.07)	(-1.49)	(-5.03)	(-1.67)
N		3132	3132	3132	3132
adj. R^2		1.10	4.00	2.10	4.80
Upgrades					
ONE	-	-0.453***	-0.465***	-0.341***	-0.339***
		(-3.68)	(-3.78)	(-2.88)	(-2.86)
FIN	-	-0.197*	-0.134	-0.218**	-0.154
		(-1.84)	(-1.22)	(-2.11)	(-1.46)
IG	-	-0.191**	-0.338***	-0.162*	-0.280***
		(-2.01)	(-3.41)	(-1.76)	(-2.93)
POST	+/-	-0.134	-0.097	-0.118	-0.091
		(-1.07)	(-0.78)	(-0.98)	(-0.75)
FIN*POST	+/-	0.394	0.501	0.224	0.327
		(1.08)	(1.37)	(0.64)	(0.93)
IG*POST	+/-	0.288	0.358*	0.521***	0.598***
		(1.41)	(1.75)	(2.65)	(3.03)
β_0	+	0.668***	1.538***	0.548***	1.389***
		(4.74)	(6.54)	(4.04)	(6.13)
N		2209	2209	2209	2209
adj. R^2		0.90	2.10	0.90	1.80

Table 22: This table presents regressions on the independent variable Cumulative Abnormal Returns (CAR) for downgrades in the event window [-1,1]. Two benchmarks are used in this model: 10Y U.S. T-Bill (model 1 & 2) and a benchmark including differences in maturity (model 3 & 4). The dependent variables are ONE, FIN, IG and POST. In model 2 and 4, I control for S&P return, investor sentiment, liquidity, Ln(sales), and leverage. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

Downgrades		CAR[-1,1]			
	Predicted	T-bill (1)	T-bill (2)	Maturity (3)	Maturity (4)
FIN	-	-0.793	-0.822	-0.867*	-0.888*
		(-1.52)	(-1.60)	(-1.71)	(-1.78)
IND		-0.251	-0.327	-0.014	-0.098
		(-0.48)	(-0.63)	(-0.03)	(-0.20)
POST		0.256	0.417	0.557	0.676
		(0.27)	(0.45)	(0.61)	(0.75)
FIN*POST	-	-1.771*	-1.788*	-1.423	-1.486
		(-1.71)	(-1.75)	(-1.41)	(-1.49)
IND*POST		-0.761	-0.596	-0.965	-0.776
		(-0.80)	(-0.63)	(-1.04)	(-0.85)
β_0		-0.164	0.368	-0.333	0.282
		(-0.32)	(0.73)	(-0.68)	(0.58)
N		3132	3132	3132	3132
adj. R^2		0.70	3.60	0.90	4.10
Upgrades					
FIN	+	-0.259	-0.256	-0.144	-0.130
		(-1.02)	(-1.01)	(-0.59)	(-0.53)
IND		0.0132	0.00871	0.151	0.145
		(0.05)	(0.03)	(0.60)	(0.58)
POST		-0.431	-0.341	-0.453	-0.382
		(-1.04)	(-0.81)	(-1.14)	(-0.94)
FIN*POST	+	0.755	0.833	0.638	0.715
		(1.40)	(1.52)	(1.23)	(1.36)
IND*POST		0.396	0.343	0.486	0.446
		(0.92)	(0.78)	(1.17)	(1.06)
β_0		0.196	0.907***	0.0598	0.773***
		(0.79)	(2.97)	(0.25)	(2.63)
N		2209	2209	2209	2209
adj. R^2		0.20	1.10	0.50	1.10

Table 23: This table presents regressions on the independent variable Cumulative Abnormal Returns (CAR) for downgrades in the event window [-1,1]. Two benchmarks are used in this model to compare industries: 10Y U.S. T-Bill (model 1 & 2) and a benchmark including differences in maturity (model 3 & 4). The dependent variables are FIN, IND and POST. In model 2 and 4, I control for S&P return, investor sentiment, liquidity, Ln(sales), and leverage. Asterisks *, **, and *** denote the 10%, 5% and 1% level of significance, respectively.

7 Limitations and future research

My study knows some limitations. First, I am using U.S. data. Although a lot of legislative action was taken during the crisis in the U.S., other regions such as the EU may be interesting to examine. More research may shed light on the effectiveness on specific regulation. In addition, I am using abnormal bond returns to measure the informational content of CREs. Although results are not expected to be significantly different, research can be expanded to stock returns and CDS spreads. Although it is not likely that the informativeness of ratings differs between CRAs, I am only using S&P data to test for abnormal returns. The main limitation in this study is the sample size in comparing EJR to S&P. Using a more substantial sample could improve the reliability of the results.

I would suggest future research to use different samples from different countries, since legislation is also incorporated in multiple regions. An interesting region to investigate would be the EU given the comparable regulation. Further, it may be interesting to use different kinds of data such as stocks and CDS spreads and use this methodology on a larger sample. Especially using CDS spreads would be interesting in future research since the data on CDS spreads are expanding. In this paper I used S&P CREs, this could be extended with Moody's and Fitch to control for my findings.

8 Conclusion

In this paper, I research the impact of CREs on daily abnormal bond returns and test the improved-information hypothesis and lost-trust hypothesis. Additionally, I test whether the conflict of interest problem is still troubling the credit rating industry by comparing EJR ratings to S&P rating. Employing multiple models for calculating abnormal returns, I find that the impact of CREs leads to significant CARs. My evidence suggests that the impact is more pronounced in the post-crisis period, in line with the improved-information hypothesis. Additionally, this paper suggests that the impact of CREs from S&P is greater than the impact of EJR credit rating. Using current debt as a proxy for the severity of the conflict of interest, I find evidence for the conflict of interest problem in the post-crisis period. Linking the inflated ratings to debt growth, I find that issuers exploit a lower cost of capital by increasing their debt in case of rating inflation.

In general, the legislation during the financial crisis reduced the conflict of interest problem and improved the informational content of S&P's credit ratings. However, the conflict of interest problem is not fundamentally solved and is still present in the current CRA industry. Additional legislation to counter the conflict of interest problem would potentially reduce the problem, as has been done during the financial crisis.

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