Essays on Credit Ratings

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ABSTRACT

Credit ratings play an important role as a gatekeeper of capital markets. Firms with higher credit ratings are likely to access the capital markets at a lower cost. Hence, understanding credit rating properties is essential, and this topic is of great importance for academics, regulators, and practitioners. This thesis includes three essays on credit ratings.

Traditional issuer-paid credit rating agencies (CRAs hereafter) such as Standard & Poor's (S&P hereafter), Moody's and Fitch Ratings (Fitch hereafter) have faced criticisms about the lack of timeliness and accuracy in negative signals due to the conflict of interest in their business model. However, this is not the case for the positive signals. In contrast, investor-paid CRAs, without conflict of interest in their business model, issue more timely and accurate negative signal. The first essay investigates how institutional investors who have advanced trading skills and knowledge respond to credit rating changes issued by two types of CRAs: issuer- and investor-paid CRAs. I find that investors react asymmetrically: they abnormally sell stocks surrounding rating downgrades by investor-paid CRAs, while abnormally buying stocks around rating upgrades by issuer-paid CRAs. In contrast, they have no significant reaction to positive signals from the investor-paid CRA and negative signals from the issuer-paid CRAs. The first essay suggests that, through their trades, institutional investors do capitalize on value-relevant rating information: negative and positive signals provided by investor- and issuer-paid CRAs respectively. More importantly, I further find that a dynamic trading strategy specifically based on rating downgrades by investor-paid CRA and rating upgrades by issuer-paid CRAs generates significant abnormal returns.

The second essay focuses on the relationship between politics and credit ratings. Specifically, I investigate whether political similarities between CRAs and bond issuers impact credit

ratings. I find that a higher degree of similarity of political affiliation leads to a decrease in timeliness and accuracy of rating downgrades prior to default events. The findings support the notion that CRAs tend to maintain/assign relative rating advantages to politically similar firms via favourable rating activities. I further show that these politically similar firms tend to increase the proportion of political donations to their favoured party following favourable credit ratings. Interestingly, this result is confined to Republican-leaning firms. The results indicate that CRAs successfully use biased credit ratings as an indirect channel of political party support. The second essay thus contributes to the body of knowledge on the importance of political connections in corporate finance as well as CRAs' rating behaviours.

The third essay examines the effect of natural disasters on credit ratings. Natural disasters are exogenous shocks to CRAs' rating behaviours. I find that firms located in the disaster states (i.e., affected firms) are downgraded by CRAs. I also find the same patterns in changes in stock returns of affected firms. The findings support hypothesis that credit rating changes are driven by firm's fundamental changes caused by natural disasters. By using instrumental variable (IV) analysis to extract affected firms' rating changes caused by natural disasters, I further investigate the spill-over effects of natural disasters on rating changes of non-affected firms (i.e., firms are not located in the disaster states). I find that the affected firms' rating changes positively spill-over to connected firms' rating changes which are not directly impacted by natural disasters. Connected firms are selected from the same industry, the adjoining states, or supplier-customer relationships with the affected firms. I also find the negative spill-over effects from the affected firms' rating changes to their competitors' rating changes. Finally, I replicate the spill-over channels for stock returns, a proxy for market reactions to natural disasters, and find delays in the stock return spill-over. This is significant evidence on CRAs' sensitivity to natural extreme events.

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TABLE OF CONTENTS

ABSTRACT i
ACKNOWLEGMENTS iii
TABLE OF CONTENTS v
LIST OF TABLES vii
CHAPTER ONE 1
1.1. Introduction 2
1.2. Essay One 3
1.3. Essay Two 4
1.4. Essay Three 5
1.5. Research Output of the Thesis 6
1.6. Structure of the Thesis 7
CHAPTER TWO 8
2.1. Introduction 9
2.2. Sample Selection, Variable Measurements, and Summary Statistics 13
2.2.1. Sample selection 13
2.2.2. Variable definitions 15
2.2.3.*Control variables* 17
2.2.4. Summary statistics 17
2.3. Main Results 23
2.3.1. Institutional responses to issuer- and investor-paid rating adjustments 23
2.3.2. Do CRAs behave the way I assume they do? 33
2.3.3. Profitability of asymmetric trading strategies 36
2.3.4. The case of Fitch ratings 41
2.4. Robustness Tests 43
2.4.1. Alternative event windows *43*
2.4.2. Raw institutional trading 44
2.4.3. 'Big issuer-paid CRA' 44
2.5. Conclusion 45
APPENDIX A 47
CHAPTER THREE 67
3.1. Introduction 73
3.2. Data Selection, Variable Definitions and Descriptive Statistics 77
3.2.1. Sample selection 77

3.2.2. Variable definition 78
3.3. Methodology and Empirical Results 85
3.3.1. Political similarity and credit rating properties 85
3.3.2. Non-defaulting bonds: A further investigation 91
3.3.3. Favourable credit ratings and political contributions 97
3.4. Robustness Tests 101
3.4.1. Controlling for personal characteristics 101
3.4.2. Impact of Dodd-Frank Act (2010) 101
3.4.3. Political similarity dummy 102
3.4.4. Rating levels at different times prior to default events 102
3.4.5. Alternative cut-off points for Category II error computation 102
3.4.6. Alternative time periods for measuring Category I and II errors 103
3.4.7. Excluding non-contributing firms from the analysis 103
3.4.8. Evidence of political similarity based on Chairpersons' political contributions 103
3.4.9. CEO Turnover……………………………………………………………………… 104
3.5. Conclusion 104
APPENDIX B 106
CHAPTER FOUR 132
4.1. Introduction 133
4.2. Sample Selection, Variable Measurements, and Summary Statistics 137
4.3. Methodology and Empirical Results 142
4.3.1. Baseline results 142
4.3.2. Spillover effects 149
4.4. Conclusion 163
APPENDIX C 165
CHAPTER FIVE 175
REFERENCE 178

LIST OF TABLES

Table 2.1: Institutional trading sample statistics 18
Table 2.2: Credit rating sample statistics 20
Table 2.3: Control variables statistics 22
Table 2.4: Institutional investors' abnormal responses to credit rating adjustments in the [0, 5] day window 25
Table 2.5: Mutual fund (12F) and institutional investor (13F)' abnormal responses to credit rating adjustments 31
2.6: The relative role of issuer- and investor-paid CRAs in negative and positive signals 35
Table 2.7: Notional trading strategy profitability 38
Table 2.8: Institutional trading strategy profitability 40
Table 3.1: Summary Statistics 82
Table 3.2: Rating Timeliness and Accuracy Measures 84
Table 3.3: Rating Timeliness and Political Similarity 87
Table 3.4: Rating Accuracy and Political Similarity 90
Table 3.5: Rating Properties and Political Similarity - PSM Approach 94
Table 3.6: Political Donations and Credit Rating Favouritism 99
Table 4.1: Statistics on Natural Disaster at State Level 139
Table 4.2: Statistics on Credit Rating Score Changes (Monthly Basis) 140
Table 4.3: Statistics on Firm Characteristics (Control Variables) 141
Table 4.4: Natural Disasters and Credit Rating Changes (Direct Effects) 144
Table 4.5: Natural Disasters and Stock Return (Direct Effects) 147
Table 4.6: Natural Disasters and Credit Rating Changes (Spillover Effects) 153
Table 4.7: Spillover Impact of Natural Disasters on Stock Returns (Spillover Effects) 159

CHAPTER ONE

INTRODUCTION

The chapter provides an overview of this thesis. Section 1.1 illustrates gaps in the literature that this thesis aims to address. There are three main essays, including "Asymmetric Trading Responses to Credit Rating Announcements from Issuer- versus Investor-Paid Rating Agencies", "Politically Motivated Credit Ratings" and "Natural Disasters and Credit Ratings". The overview and motivations of the three essays are outlined in Sections 1.2, 1.3 and 1.4 respectively. Section 1.5 reports the current outputs. The chapter ends with Section 1.6, which outlines the structure of the remainder of this thesis.

1.1. Introduction

Corporate credit ratings are an important indicator in financial markets. Hence, it is essential to understand the properties of corporate credit rating. Even though, in recent times, the topic of corporate credit ratings has attracted the attention, it is still under-examined. This thesis aims to extend the literature of corporate credit ratings.

Consisting of three essays, this thesis is motivated by two current popular themes in credit rating literature. The first theme relates to the importance of investor-paid CRAs, new players operating alongside long-established CRAs such as S&P, Moody's and Fitch which follow the 'issuer-pays' principle. The latest studies (Xia, 2014; Ramsay, 2011; Cornaggia and Cornaggia, 2013) examine the impact of the entry of investor-paid CRAs on the credit rating industry. In general, they find that the appearance of investor-paid CRAs, such as Egan-Jones Ratings (EJR) and Rapid Ratings, motivated major issuer-paid CRAs to improve the quality of their credit ratings to protect their reputation. The theme of the first essay of this thesis is to extend the knowledge on the importance of investor-paid CRAs. I investigate how financial market participants dynamically respond to credit ratings following the appearance of investor-paid CRAs, besides traditional issuer-paid CRAs. The second theme focuses on understanding which non-fundamental factors can potentially affect credit ratings. Beyond firm fundamental characteristics, recent studies find that credit ratings are distorted by non-fundamental factors. These factors include the ability of the CRAs to access information (Jaggi and Tang, 2017; Bonsall, Green, and Muller, 2018; Khatami, Marchica, and Mura, 2016), competition amongst the credit rating industry (Güttler and Wahrenburg, 2007; Kisgen and Strahan, 2010; Becker and Milbourn, 2011; Bolton, Freixas, and Shapiro, 2012; Bongaerts, Cremers, and Goetzman, 2012; Kedia, Rajgopal, and Zhou, 2014; Goel and Thakor, 2015), conflict of interest from their business model (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Jiang, Stanford, and

Xie, 2012; Cornaggia and Cornaggia, 2013; Baghai and Becker, 2018), conflict of interest from their ownership structure (Kedia, Rajgopal, and Zhou, 2017), and conflicts of interest at the analyst level (Isaac and Shapiro, 2011; Cornaggia, Cornaggia, and Xia, 2016). The balance of the thesis aims to contribute to the second theme. The second essay examines whether political similarity between CRAs and rated firms has an impact on credit ratings. The third essay investigates whether credit ratings are driven by exogenous shocks such as natural disasters; and more importantly, I further examine spill-over effects of natural disasters on credit ratings.

The remainder of this chapter is organized as follows. Sections 1.2, 1.3, and 1.4 provide an overview and the motivations for first, second and third essay respectively. Section 1.5 presents the current outputs, and section 1.6 provides the structure for the remainder of the thesis.

1.2. Essay One

The credit rating sector has long been dominated by three major issuer-paid CRAs: S&P, Moody's and Fitch. However, these issuer-paid CRAs have been criticised for a lack of timeliness in providing negative rating adjustments in cases of high-profile bankruptcies, such as Enron (2001), WorldCom (2002), and Lehman Brothers (2008). Issuer-paid CRAs tend to delay the release of negative ratings to their rated firms due to conflict-of-interest problems. This is especially true in the business model where they extract fees directly from rated firms, or "clients" (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Cornaggia and Cornaggia, 2013). In contrast, investor-paid CRAs such as EJR and Rapid Ratings are free from these conflict-of-interest problems because they are paid by the end users of their ratings, such as institutional investors. As a result, they provide more timely downgrades than issuer-paid CRAs (Cornaggia and Cornaggia, 2013; Xia, 2014). There is, interestingly, no evidence to indicate delays in positive signals from issuer-paid CRAs compared to investor-paid CRAs. It therefore remains unclear whether institutional investors who have advanced trading skills and knowledge (Puckett and Yan, 2011) show different trading patterns when responding to negative and positive credit rating adjustments from issuer- and investor-paid CRAs. Understanding these issues is important to enable a better understanding of the relevance and viability of different types of CRAs from the institutional investor perspective.

The first essay of this thesis examines how institutional investors, skilled players in the financial markets, dynamically respond to credit rating changes issued by issuer- and investor-paid CRAs. This essay asserts that investors react asymmetrically: they abnormally sell equity stakes around rating downgrades by investor-paid CRAs, while abnormally buying around rating upgrades by issuer-paid CRAs. However, they do not react to negative or positive signals from issuer- and investor-paid CRAs respectively. The first essay suggests that, through their trades, institutional investors capitalize on value-relevant information provided by both types of CRAs. More importantly, I even find that a dynamic trading strategy based on taking advantage of this information generates significant abnormal returns. This essay contributes to the knowledge about the importance of investor-paid CRAs in the financial markets, acting alongside traditional issuer-paid CRAs.

1.3. Essay Two

Credit ratings is not only driven by fundamental factors. The literature on credit ratings is expanding to investigate which non-fundamental factors impact credit ratings. Recent studies find that several factors could distort credit ratings, beyond their fundamental characteristics. These are the CRAs' ability to access to information (Jaggi and Tang, 2017; Bonsall, Green, and Muller, 2018), competition amongst the credit rating industry (Bongaerts, Cremers, and Goetzman, 2012; Kedia, Rajgopal, and Zhou, 2014; Goel and Thakor, 2015), and different sources of conflict of interest (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Jiang, Stanford, and Xie, 2012; Kedia, Rajgopal, and Zhou, 2017; Cornaggia, Cornaggia, and Xia, 2016).

The second essay contributes to the literature by investigating whether the non-fundamental factor of political similarities between rating agencies and rated firms impacts credit ratings. I find that a higher degree of similarity in political affiliation leads to a decrease in timeliness and accuracy of downgrades prior to default events. The findings support the notion that CRAs tend to maintain or assign relative rating advantages to politically similar firms through favourable rating activities. The empirical results further show that these politically similar firms tend to increase the proportion of political donations to their favoured party following favourable credit ratings. Interestingly, this result is confined to Republican-leaning firms. The findings imply that CRAs successfully use biased credit ratings as an indirect channel to support a political party.

1.4. Essay Three

Natural disasters are more frequent and unpredictable. These extreme events result in not only property damages to homes, businesses, and automobiles, but also psychological damage (e.g., Barth, Sun and Zhang, 2019). Therefore, natural disasters are exogenous and negative shocks to communities. The recent literature finds that natural disasters significantly drive market participant behaviours, including investors (De Bondt and Thaler, 1985; Alok, Kumar and Wermers, 2020; Huynh and Xia, 2021), banks (Chavaz, 2016; Noth and Schuwer, 2018; Brown, Gustafson and Ivanov, 2021), and insurance firms (Massa and Zhang, 2021).

CRAs are an important contributor of information in the financial markets. The third essay investigates whether CRAs adjust their credit ratings of affected firms following natural disasters and more importantly, the essay is extended to analyse the spill-over effect of natural disasters on credit ratings of connected firms that are not directly affected by the extreme events.

I find that CRAs tend to downgrade the firms located in states affected by natural disasters. By using instrumental variable (IV) analysis to extract the credit rating changes of firms affected by natural disasters, I investigate whether the natural disasters cause a spill-over effect in credit rating changes from affected firms to non-affected firms . I find that the affected firms' credit rating changes positively spill-over to credit rating changes in connected firms which are not directly impacted by natural disasters. Connected firms are selected from the same industry, adjoining states, or those with supplier-customer relationships with the affected firms. Conversely, changes in the credit rating of the affected firms negatively spill-over to their competitors' credit rating changes. Interestingly, both spill-over channels continue in the month following natural disasters. These results are highly robust and use different identifications of natural disaster.

1.5. Research Output of the Thesis

Essay One

The first essay has been invited to be revised and resubmitted (R&R, second round) at the Journal of Business Finance and Accounting (ABS3 and ABDC: A*).

The first essay was also presented at the New Zealand Finance Colloquium 2020, Auckland University of Technology, New Zealand.

Nguyen, Q.M.P., Do, H.X., Molchanov, A., Nguyen, L., & Nguyen, N.H. (2021). Asymmetric Trading Responses to Credit Rating Announcements from Issuer- versus Investor-Paid Rating Agencies.

Essay Two

The second essay was presented at the 6th Vietnam Symposium in Banking and Finance (VSBF2021).

Nguyen, Q.M.P., Do, H.X., Molchanov, A., Nguyen, L., & Nguyen, N.H. (2021). Politically Motivated Credit Ratings.

Essay Three

The third essay has been completed and will be submitted to a suitable journal soon.

1.6. Structure of the Thesis

The remainder of this thesis is structured as follows. The first essay is presented in Chapter 2. Chapter 3 presents second essay. Chapter 4 presents the third essay. Chapter 5 outlines the main findings and their implications for future research. Supplementary information is shown in the Appendix.

CHAPTER TWO

Asymmetric Trading Responses to Credit Rating Announcements from Issuer- versus Investor-Paid Rating Agencies

ESSAY ONE

This chapter presents the first essay of this thesis. As an overview, the first essay addresses a question in the literature of credit ratings that how institutional investors react to credit rating changes from issuer- and investor-paid CRAs. The chapter is organized as follows. Section 2.1 provides the background, motivation, and contributions of the first essay. Section 2.2 summarizes data collection, variable measurements, and summary statistics. Section 2.3 presents the methodology and empirical results. Robustness checks are presented in section 2.4. Section 2.5 concludes. The essay's Appendix and References are shown at the end of this chapter and in the references section, respectively.

2.1. Introduction

The credit rating sector has long been dominated by three major CRAs: S&P, Moody's and Fitch. These issuer-paid CRAs extract fees directly from bond issuers, which might lead to potential conflicts of interest when they provide rating services to those issuers. Issuer-paid CRAs tend to delay the release of negative ratings (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Cornaggia and Cornaggia, 2013) while giving favourable ratings to stocks in their owners' portfolios (Kedia, Rajgopal, and Zhou, 2017). Baghai and Becker (2018) find evidence that issuer-paid CRAs assign higher ratings even to those issuers who pay them for non-rating services. The lack of timeliness in negative rating adjustments in high-profile bankruptcies, such as Enron (2001), WorldCom (2002), and Lehman Brothers (2008), is often presented as evidence of such conflicts. For example, on September 10, 2008 – the day Lehman Brothers announced its bankruptcy – S&P and Moody's had them rated at A2 and A respectively, and only adjusted the credit ratings down after the bankruptcy announcement.

The entry of investor-paid CRAs (e.g., Egan-Jones Ratings (EJR) and Rapid Ratings) has changed the dynamics of the credit rating industry. These CRAs are paid by the end users of their ratings, such as institutional investors, and the conflict of interests problem is potentially alleviated. Extant literature documents significant evidence of high rating quality of investor-paid CRAs. Cornaggia and Cornaggia (2013) show that Rapid Ratings provides more timely downgrades for defaulting bonds than Moody's downgrades, which results in significant loss avoidance for investors. Xia (2014) considers the entry of EJR as a natural experiment to assess issuer-paid CRAs' reactions to potential competition from a new player. They find that due to reputational concerns, credit ratings issued by S&P tend to become more responsive and informative following the EJR entry. Beaver, Shakespeare, and Soliman (2006), and Bruno, Cornaggia, and Cornaggia (2016) report that EJR's credit ratings are of better quality and timelier than Moody's, even after its successful registration as a Nationally Recognized Statistical Rating Organization (NRSRO) in December 2007.

Given the rise of investor-paid CRAs, the competition they bring about, and the information content of their credit ratings relative to issuer-paid CRAs, it is crucial to understand whether and how financial market participants utilize credit ratings for their benefit. Xia (2014) and Berwart, Guidolin, and Milidonis (2019) find that stocks with downgrade announcements by EJR experience significantly more negative returns than following downgrades by issuer-paid CRAs, whereas EJR upgrades apparently do not trigger a positive response from investors. Investigating the reaction of institutional investors to EJR's rating changes, Bhattacharya, Wei, and Xia (2019) find that these investors are more responsive to its rating announcements than to other trading signals. They also show that institutional investors who follow EJR's credit rating announcements outperform those who ignore these signals. First essay contributes to this strand of literature and examine the value relevance of credit rating changes issued by both types of CRAs.

I argue that investor-paid CRAs cannot completely dominate traditional issuer-paid CRAs who have long-term positions in the credit rating sector. As argued in previous studies, issuer-paid CRAs only tend to delay negative credit rating announcements due to potential conflict of interests (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Cornaggia and Cornaggia, 2013). In contrast, issuer-paid CRAs are likely less conservative in issuing rating upgrades since it would be in their interest to cater positive ratings to their clients (e.g., Bolton, Freixas, and Shapiro, 2012; Griffin, Nickerson, and Tang, 2013). Hence, it remains unclear whether institutional investors who have advanced trading skills and knowledge (Puckett and Yan, 2011) show different trading patterns in responding to negative and positive credit rating adjustments from issuer- and investor-paid CRAs. The answer to these questions is important as it provides a better understanding of the relevance and viability of different types of CRAs from the institutional investor perspective.

I use institutional investors' abnormal trading activity around rating announcements as a proxy for market reaction. I consider EJR as a representative of investor-paid CRAs while the "Big Three" CRAs (i.e., S&P, Moody's, and Fitch) are representatives of issuer-paid CRAs. I find that institutional investors abnormally decrease their equity holdings surrounding investor-paid rating downgrades but do not respond to any issuer-paid rating downgrades. On the contrary, they significantly increase their equity holdings around issuer-paid rating upgrades but remain unresponsive to investor-paid rating upgrades. These results suggest that institutional investors consider investor-paid rating downgrades as being timely and informative for their trading as opposed to issuer-paid rating downgrades. Further, they regard issuer-paid rating upgrades as having more value-relevant information than investor-paid rating upgrades. In the main analysis, I use daily institutional trading provided by Abel/Noser Corporation[1] to measure institutional reactions to credit rating adjustments. I also consider quarterly mutual fund (12F) holdings and quarterly institutional (13F) holdings provided by Thompson Reuters[2] as alternative databases to extend the sample period.

I then examine whether investors can profit from trading decisions in response to rating changes. I construct and compare four trading strategies: (1) a 'dynamic' strategy – selling following investor-paid negative signals and buying following issuer-paid positive signals, (2) a 'naïve' strategy – selling following negative signals and buying following positive signals from any rating agency, (3) an 'EJR-based' strategy – selling following negative signals and buying following positive signals announced by EJR, and (4) an 'issuer-paid CRA based' strategy – selling following negative signals and buying following positive signals by any of

[1] I would like to say thank you Dr. Lily Nguyen, University of Queensland, for sharing this data.
[2] I would like to say thank you Associate Professor Hung Do, my co-supervisor from Massey University, for sharing this data by his account from University Technology of Sydney (UTS).

the issuer-paid CRAs. Following Jagolinzer, Larcker, and Taylor (2011), I compute risk-adjusted returns for each trading strategy. The trading strategy analysis is performed in two steps. First, I construct 'notional', or 'market' trading strategies based on publicly available returns. This acknowledges the fact that any market player with access to credit ratings can potentially benefit from these strategies. These results also correspond to equally weighted returns of an investor who trades on every signal consistent with a given strategy. While all four strategies outperform a buy-and-hold strategy, I find that the dynamic strategy produces the highest returns, offering an average difference in annualized risk-adjusted returns of up to 5.11% over the other three strategies for a one-month holding period. Second, I examine institutional investors' actual transactions around credit rating announcements, classifying transactions into strategies based on a cumulative net buy around the announcement date. I thus explicitly acknowledge that an institution can dynamically switch between strategies and potentially follow multiple strategies at a time. The dynamic strategy, again, outperforms all others, recording an average annualized risk-adjusted return of 18.82% compared to the corresponding return of 8.95% across the other strategies for a one-month holding period. This outperformance based on institutional investors' actual trading is considerably higher than that produced by a 'notional' strategy. This is consistent with the argument that institutional investors have advanced trading skills and knowledge (Puckett and Yan, 2011) to exploit the informative announcements in the financial markets.

The essay contributes to the literature in several important ways. First, I add to the knowledge on the relationship between the quality of credit ratings and market participants' behavior. The related literature finds that the high quality of investor-paid CRA ratings creates a reputational concern for issuer-paid CRAs, which motivates them to improve the overall quality of ratings (e.g., Berwart, Guidolin, and Milidonis, 2019; Bruno, Cornaggia, and Cornaggia, 2016). For example, Xia (2014) finds that following EJR's appearance, S&P ratings started to reflect credit risks more accurately. Similarly, Ramsay (2011) discovers that the entry of Rapid Ratings – another investor-paid CRA – motivated major issuer-paid CRAs to improve the quality of credit ratings. However, the impact of rating quality on investors' behavior has been under-examined. The essay fills this gap by examining the role of timeliness of credit rating adjustments – a proxy for rating quality – in driving institutional investors' behavior.

Second, the essay enriches the understanding of how institutional investors, as professional players, analyse and react dynamically to negative and positive rating adjustments obtained from different sources over time. Bhattacharya, Wei, and Xia (2019) find that EJR's institutional followers respond to ratings issued by EJR rather than important equity trading signals such as analyst recommendations, earning announcements, and earning forecast revisions. They also find that institutional investors who persistently follow EJR's credit rating announcements outperform those who do not embrace these signals. The essay extends their findings by providing new evidence that investors with access to rating announcements could dynamically exploit the value-relevant information of negative and positive rating signals provided by both investor-paid and issuer-paid CRAs in making their trading decisions. The results show that while such trading behavior is generally profitable, institutional investors evidently earn the highest abnormal profits.

The remainder of the essay is organized as follows. Section 2 summarizes data collection, variable measurements, and summary statistics. Section 3 presents the methodology and empirical results. Robustness checks are presented in section 4. Section 5 concludes.

2.2. Sample Selection, Variable Measurements, and Summary Statistics

2.2.1. Sample selection

To measure institutional trading, I use transaction-level data provided by the Abel/Noser Corporation, a leading information provider for research purposes associated with institutional trading. Hu, Jo, Wang, and Xie (2018) describe several important features of Abel/Noser's institutional trading data. The dataset covers at least 12% of the total CRSP trading volume, 233 million transactions with $US 37 trillion in traded volume. It also records equity transactions traded by a large number of institutions from January 1999 to September 2011. For each transaction, it includes the transaction date, the traded stock symbol and CUSIP, the number of shares traded, the dollar traded volume, and the side of trade being +1 for a buy or -1 for a sell. Each institutional investor is identified with a unique symbol (*clientcode)*. Three types of institutional investors are covered: plan sponsors, investment managers, and brokers, coded as 1, 2 and 3, respectively. Due to its high level of coverage, several prior studies have used this data to investigate institutional trading behavior[3]. I winsorize institutional trading data at 1st and 99th percentiles to minimize the effect of outliers.

As mentioned above, I focus on two types of CRAs: investor- and issuer-paid. EJR is a representative of investor-paid CRAs, while the "Big Three" represent issuer-paid CRAs. Credit rating data are sourced from Egan-Jones Rating Company[4] and Bloomberg for the period from July 1999 to September 2011 to match with the period of the Abel/Noser trading data (I extend the sample period to December 2017 using quarterly data as discussed in section 3.1.2). The credit rating database includes two types of rating information: rating warning announcements[5] and official rating adjustments[6]. The database also reports the date of each credit rating adjustment. As I am interested in corporate credit ratings, sovereign credit and

[3] Hu, Jo, Wang, and Xie (2018) summarise 55 publications that use this data.
[4] I would like to say thank so much Egan-Jones Rating company for sharing this data.
[5] Based on the data availability, there are two types of rating warning announcements: outlook and developing signals. These signals are normally announced before official rating adjustments.
[6] Official rating adjustments are basically divided into two types: positive and negative signals. These signals can also include single and multiple events. In the essay, a single event is either a one-notch upgrade or downgrade and a multiple event is either a multiple-notch upgrade (downgrade) or a combined event of a rating warning announcement and an official rating adjustment.

asset backed securities (ABS) ratings are excluded. I next match the rating samples with COMPUSTAT and CRSP by using tickers or company names for accounting and stock price information. I then merge these samples with Abel/Noser's data by CUSIPs. My final samples include 1126, 1259, 509 and 420 firms rated by EJR, S&P, Moody's, and Fitch, respectively.

2.2.2. Variable definitions

Since credit ratings are represented by different combinations of letters and numbers (e.g., AAA/Aaa, AA+/Aa1, AA/Aa2, AA-/Aa3), several prior studies follow Gande and Parsley (2005) to construct a unique "comprehensive credit rating" (CCR) scale to quantify alphabetic ratings (Alsakka and ap Gwilym, 2012; Dimitrov, Palia, and Tang, 2015; Chen, Chen, Chang, and Yang, 2016; Drago and Gallo, 2016). Based on the features of credit rating data availability, I follow Joe and Oh's (2018) rating conversion scale. The numeric score for letter rating and warning (single) signals are shown in Appendix A.1[7]. In addition, I also follow the literature (Vu, Alsakla, and ap Gwilym, 2015; Chen, Chen, Chang, and Yang, 2016) to measure the significance of the credit rating event for firm *n* at time *t* as the change in CCR ($\Delta CCR_{n,t}$):

$$\Delta CCR_{n,t} = CCR_{n,t} - CCR_{n,t-1} \tag{1.1}$$

I use institutional investors' abnormal net buy (NB) to measure their response to credit rating announcements. Specifically, I calculate abnormal net buy of stock *n* by institutional investor *i* during an event window of *W* days surrounding each credit rating adjustment as follows:

[7] Gande and Parsley (2005) count positive and negative outlooks as one notch. In our study, to highlight the impacts of official upgrades (downgrades), positive and negative outlooks count as 0.5 notch and positive and negative developments as 0.25.

$$NB_{i,n,W} = \sum_{t=0}^{W} NB_{i,n,t} \tag{1.2}$$

where

$$NB_{i,n,t} = nb_{i,n,t} - average\ nb_{i,n,t} \tag{1.3}$$

Chemmanur, Li, and Hu (2009) measure $nb_{i,n,t}$ as the number of shares bought minus the number of shares sold, then normalized by the total number of shares outstanding in the financial year prior to the event date. Due to the nature of my dataset, I follow Bhattacharya, Wei, and Xia (2019) and use a similar formula to calculate $nb_{i,n,t}$ as dollar volume bought minus dollar volume sold scaled by the stock's one-month-lagged market capitalization.

$$nb_{i,n,t} = \frac{BOUGHT_{i,n,t} - SOLD_{i,n,t}}{MARKET\_CAP_{i,n,t-1}} \tag{1.4}$$

I next calculate $average\ nb_{i,n,t}$ as the average value of $nb_{i,n,t}$ in the period from day *t* - 371 to day *t* - 6 prior to the date *t* of a trading activity.

$$average\ nb_{i,n,t} = \frac{\sum_{k=-6}^{-371} nb_{i,n,t+k}}{365} \tag{1.5}$$

I also follow Chemmanur, Li, and Zhu (2016) to convert $NB_{i,n,W}$ into basis points. I investigate abnormal institutional trading surrounding a stock's credit rating adjustments in the time window [0, 5][8]. The day 0 is the date of a credit rating event. I consider institutions' trading activities up to five days after the credit rating adjustment to account for potentially gradual investors' reactions, while also avoiding confounding effects that can appear in longer windows.

[8] In the essay, I also consider two different time windows [-2, 5] and [-2, 1] for robustness. The purpose is to account for institutional investors' pre-reactions because of potential information leakage (e.g., Bhattacharya, Wei, and Xia, 2019). The results are reported in the Appendix.

2.2.3. *Control variables*

I also follow the related literature (Bernile, Sulaeman, and Wang, 2015; Henry, Nguyen, and Pham, 2017; Bhattacharya, Wei, and Xia, 2019) to control for a vector of firm characteristics related to institutional trading activities. The list of control variables includes profitability, stock idiosyncratic volatility, Z-score, analyst coverage, interest coverage, firm size, profitability growth, firm age, high tech dummy, S&P 500 index inclusion dummy, and leverage. Descriptions of control variables and their sources are presented in Appendix A.2.

2.2.4. Summary statistics

Table 2.1 presents summary statistics of institutional trading in the [0, 5] window surrounding credit rating announcements for each calendar year from 1999 to 2011. The number of institutions that have traded around credit rating announcements has been stable, ranging from a low of 257 in 2011 to a high of 384 in 2002. The number of stocks traded around credit rating events has increased from 256 in 1999 to 522 in 2011. The number of purchase (sell) transactions increased steadily from 3,736 (4,091) transactions in 1999 to 26,464 (31,394) transactions in 2010 before a significant decline in 2011. The total amount of institutional trading volume around credit rating adjustments is, on average, around $US 56 billion per year during the sample period. The total value of purchase transactions is relatively less than that of sell transactions throughout the sample period. The average value per transaction is $US 1.4 million for purchases compared to $US 1.5 million for sales. These significant transaction values suggest that institutional investors are generally quite sensitive to rating announcements, especially negative ones.

Table 2.1: Institutional trading sample statistics

Year	Number of Investors	Number of stocks traded	Number of purchases	Total dollar volume bought (million)	Average dollar volume bought	Number of sells	Total dollar volume sold (million)	Average dollar volume sold
1999	343	256	3,736	5,903	1,580,091	4,091	5,468	1,336,501
2000	351	458	10,301	15,826	1,536,344	11,014	20,247	1,838,319
2001	374	502	16,279	28,233	1,734,338	15,122	22,248	1,471,233
2002	384	505	17,106	22,727	1,328,613	15,641	21,877	1,398,716
2003	318	541	17,304	19,091	1,103,275	15,721	23,970	1,524,700
2004	341	543	18,457	32,146	1,741,651	16,855	38,498	2,284,094
2005	309	597	20,526	32,442	1,580,512	20,972	41,430	1,975,481
2006	330	639	22,297	31,922	1,431,663	23,840	35,697	1,497,338
2007	309	577	20,698	32,686	1,579,181	22,392	40,702	1,817,696
2008	270	579	28,173	46,095	1,636,135	30,887	49,227	1,593,764
2009	320	592	28,835	34,990	1,213,438	29,616	30,879	1,042,638
2010	306	632	26,464	29,922	1,130,669	31,394	34,448	1,097,282
2011	257	522	15,108	16,034	1,061,291	16,901	17,659	1,044,866
Average	324	534	18,868	26,770	1,435,169	19,573	29,411	1,532,510

The table summarises information related to institutional trading activities around credit rating events executed within each calendar year. Number of investors is the total number of unique institutions that trade surrounding credit rating events in each year. Number of stocks traded shows the average number of stocks that institutional investors trade surrounding credit rating announcements. Number of purchases (sells) is the total buy (sell) transactions made by institutional investors around credit rating events. Total dollar volume bought (sold) is the sum of all transaction values by institutional investors in a year. Average US dollar volume bought (sold) is calculated as the total dollar volume bought (sold) divided by the total number of purchases (sells).

Table 2.2 displays summary statistics of credit rating events. The first row of Panel A shows the unique number of firms that each CRA provides credit rating announcements over the sample period of 1999 – 2011. Despite being a newer player in the credit rating industry, EJR provides credit ratings for 1,126 firms which is only slightly fewer than S&P's (1,259 firms) but more than double the coverage by either Moody's (509) or Fitch (420). EJR is also the only CRA that provides developing signals whereas the traditional issuer-paid CRAs do not seem to provide such service during the sample period[9]. I split the rating announcements into negative and positive events, and present them in Panel A, sections 1 and 2. Both sections show that combined events[10] account for the largest proportion of the rating sample. There are 1,808 (1,732), 955 (392), 261 (126) and 141 (43) negative (positive) combined events assigned by EJR, S&P, Moody's and Fitch, respectively. In addition, the sample comprises of 1,317 (1,222), 818 (846), 231 (322) and 417 (376) solo downgrades (upgrades), and 354 (218), 341 (89), 144 (44) and 135 (59) multiple downgrades (upgrades) announced by EJR, S&P, Moody's and Fitch, respectively. Panel A also shows 873 (1,051), 1,220 (547), 320 (213) and 172 (51) negative (positive) outlook signals by these CRAs, respectively.

Panel B of Table 2.2 presents the distribution of credit rating adjustments. The total number of rating events in Panel B shows that EJR issues about 10% more rating changes than all issuer-paid CRAs' events combined. Within each CRA, EJR has more positive than negative rating announcements. This is opposite to the issuer-paid CRAs which announce more negative rating adjustments than positive ones. Regarding the magnitude of rating adjustments, Fitch, on average, seems to provide the boldest adjustments compared to other CRAs. For example, the

[9] EJR derives its "watch" assignments from the difference between the current and projected ratings. No difference between the two results in a "stable" watch, a higher projected rating results in a "positive" or "POS" watch and a lower projected rating results in a "negative" or "NEG" watch. The absence of a projected rating results in a "developing" or "DEV" watch, or no watch being populated. The addition of a POS or NEG is at the discretion of the analyst or Rating Committee and usually results from the direction the rate is expected to move overtime. Source:https://www.eganjones.com/public/download/methodologies/20210510/EJR_Main_Methodologies_V15a.pdf

[10] A combined event is a multiple announcement when a CRA adjusts both credit rating score and outlook (or developing) signal.

mean absolute value of negative rating adjustments is 1.261 for Fitch while that is 1.149, 1.070, and 1.083 for EJR, S&P, and Moody's, respectively. Negative rating adjustments are generally larger in absolute value than positive rating adjustments. The median column in Panel B suggests that S&P is relatively more conservative in their negative rating adjustments: 50% of their respective negative rating events have a median value of 0.5 notch.

Table 2.2: Credit rating sample statistics

Panel A: Rating changes				
	EJR	S&P	Moody	Fitch
Number of firms rated	1,126	1,259	509	420
Section 1: Negative events				
Negative developing	139	-	-	-
Negative outlook	873	1,220	320	172
Negative combined event	1,808	955	261	141
Single downgrade	1,317	818	231	417
Multiple downgrade	354	341	144	135
Section 2: Positive events				
Positive developing	401	-	-	-
Positive outlook	1,051	547	213	51
Positive combined event	1,732	392	126	43
Single upgrade	1,222	846	322	376
Multiple upgrade	218	89	44	59

Panel B: The distribution of rating changes								
	N	Mean nots	STD	P1	P25	Med	P75	P99
EJR negative event	4,487	1.149	0.843	0.25	0.5	1	1.5	4.5
EJR positive event	4,624	1.012	0.805	0.25	0.5	1	1	4
S&P negative event	3,334	1.070	0.964	0.5	0.5	0.5	1	5
S&P positive event	1,873	1.030	1.035	0.5	0.5	1	1	6.5
Moody's negative event	956	1.083	0.756	0.5	0.5	1	1.5	3.5
Moody's positive event	705	0.895	0.464	0.5	0.5	1	1	2.5
Fitch negative event	865	1.261	1.15	0.5	0.5	1	1	6
Fitch positive event	529	1.242	0.991	0.5	1	1	1	5.5

The table presents credit rating events announced by EJR (investor-paid CRA), and S&P, Moody's and Fitch (issuer-paid CRAs). Panel A displays the number of firms rated and the number of rating events (negative and positive separately) announced by each CRA after being merged with COMPUSTAT, CRSP and Abel/Noser institutional trading data. Panel B presents summary statistics for credit rating changes of each CRA, where the magnitude of a rating change is calculated as the total number of notches by which a rating agency changes a firm's credit ratings.

Table 2.3 presents the descriptive statistics of control variables computed around credit rating adjustments. Firms are divided into three groups: group A includes firms rated by EJR and S&P (Panel A), group B includes firms rated by EJR and Moody's (Panel B), and group C includes firms rated by EJR and Fitch (Panel C). The *N* column in Table 2.3 shows the number of firm-investor-rating observations. Firms in group A, in aggregate, have the largest number of observations in the sample, followed by those in groups C and B, respectively. Group C, on average, includes firms with relatively larger market capitalization and older in age than firms in the other two groups. This seems to be consistent with EJR's and Fitch's policy of rating veteran firms. For instance, the mean (median) market capitalization in group C is $US 24,945 ($US 13,484) millions while the number is $US 19,058 ($US 7,983) millions for group A and $US 6,913 ($US 3,431) millions for group B[11]. Firms in group C also have relatively more analysts following them.

The statistics for ROA indicate a relatively left skewed distribution for firms in groups B and C. The median Z-scores are 1.91, 1.71, and 1.64 for group A, B, and C firms respectively, which are very close to the conventional threshold of 1.8 but above the risk levels of a financially normal to healthy firm. Firms across the groups exhibit relatively similar leverage ratios, staying somewhere between 24% and 30%. Finally, the median interest coverage ratio is slightly lower for firms in group B than for firms in groups A and C.

[11] These numbers are obtained by taking the exponential of the means and medians in the Ln (MV) row of the Table 2.3.

Table 2.3: Control variables statistics

Panel A: Characteristics of firms rated by EJR & S&P (group A)						
Control variables	N	Mean	Median	Std.Dev.	P10	P90
Ln(MV)	427,292	9.86	8.98	10.30	7.03	10.73
ROA	429,548	0.03	0.03	0.08	-0.04	0.11
IDIO_RISK	432,992	0.02	0.02	0.02	0.01	0.04
Z-SCORE	327,545	1.91	1.63	1.55	0.41	3.70
ANALYST_COVERAGE	421,400	6.16	5.66	3.08	2.67	9.98
Ln(AGE)	424,820	3.17	3.26	0.86	2.08	4.30
INTEREST_COVERAGE	352,990	11.65	7.32	16.07	1.10	25.38
LEVERAGE	436,364	0.28	0.25	0.20	0.02	0.53
S&P_500	436,364	0.58	1.00	0.49	0.00	1.00
HIGH_TECH	436,364	0.01	0.00	0.10	0.00	0.00
Panel B: Characteristics of firms rated by EJR & Moody's (group B)						
Control variables	N	Mean	Median	Std.Dev.	P10	P90
Ln(MV)	114,302	8.84	8.14	9.10	6.41	9.86
ROA	115,136	0.02	0.04	0.11	-0.10	0.11
IDIO_RISK	115,873	0.02	0.02	0.02	0.01	0.04
Z-SCORE	100,745	1.71	1.42	1.63	0.22	3.40
ANALYST_COVERAGE	112,325	5.37	4.86	2.58	2.36	9.07
Ln(AGE)	113,751	2.76	2.71	0.81	1.79	3.83
INTEREST_COVERAGE	105,937	9.87	5.73	14.51	0.17	24.17
LEVERAGE	116,340	0.30	0.29	0.21	0.00	0.60
S&P_500	116,340	0.34	0.00	0.47	0.00	1.00
HIGH_TECH	116,340	0.01	0.00	0.09	0.00	0.00
Panel C: Characteristics of firms rated by EJR & Fitch (group C)						
Control variables	N	Mean	Median	Std.Dev.	P10	P90
Ln(MV)	209,073	10.16	9.51	10.41	7.63	10.99
ROA	211,368	0.02	0.03	0.08	-0.04	0.10
IDIO_RISK	212,467	0.02	0.01	0.02	0.01	0.04
Z-SCORE	140,921	1.64	1.46	1.27	0.29	3.39
ANALYST_COVERAGE	207,391	6.54	6.04	3.03	3.26	10.12
Ln(AGE)	208,307	3.27	3.47	0.82	2.20	4.32
INTEREST_COVERAGE	168,192	10.31	7.26	12.81	0.76	22.90
LEVERAGE	213,674	0.27	0.24	0.21	0.02	0.53
S&P_500	213,674	0.70	1.00	0.46	0.00	1.00
HIGH_TECH	116,340	0.01	0.00	0.09	0.00	0.00

The table presents the summary statistics of control variables, which are defined in Appendix A.2. Statistics are computed around credit rating announcements.

2.3. Main Results

2.3.1. Institutional responses to issuer- and investor-paid rating adjustments

2.3.1.1. Abnormal trading behavior

I now examine institutional investors' responses to credit rating signals announced by issuer- and investor-paid CRAs. To ensure that reactions are comparable, I construct three paired samples which include firms rated by EJR and each of the major issuer-paid CRAs: EJR and S&P, EJR and Moody's, and EJR and Fitch. I estimate the following regression for each of the paired samples:

$$NB_{i,n,W} = \alpha + \beta_1 NEG_{n,t} + \beta_2 POS_{n,t} + \beta_3 NEG_{n,t} * EJR_{n,t} + \beta_4 POS_{n,t} * EJR_{n,t} + \beta_5 EJR_{n,t} + \sum_1^k \gamma_k \, CONTROLS_{n,t} + \sum_1^t \theta_t \, QuarterFE_t + \sum_1^i \delta_i \, InvestorFE_i + \sum_1^n \varphi_n \, FirmFE_n + \varepsilon_{i,n,W} \quad (2.6)$$

where $NB_{i,n,W}$ is calculated as an abnormal net buy of institution i in firm n in time window W (i.e., [0, 5] days) surrounding a credit rating adjustment. $NEG_{n,t}(POS_{n,t})$ represent the absolute value of a numeric change in the comprehensive credit rating scale, $\Delta CCR_{n,t}$, for firm n around a negative (positive) rating adjustment on date t. $CONTROLS_{n,t}$ represents a set of firm-level control variables suggested in Table 2.3. $QuarterFE_t$ denotes quarter specific dummy variables to control for differences in institutional trading behavior that can be induced by various economic conditions at different quarters. $InvestorFE_i$ ($FirmFE_n$) is used to control for investor- (firm-) specific characteristics that are not captured by $CONTROLS_{n,t}$. In this model, $NEG_{n,t}$ and $POS_{n,t}$ are interacted with a dummy variable, namely, $\text{EJR}_{n,t}$ that equals one if a credit rating announcement is issued by EJR and zero otherwise. $\varepsilon_{i,n,W}$ is a random error.

Results of Eq. (2.6) are presented in Table 2.4. I find significant asymmetries in the abnormal trading of institutional investors surrounding EJR's and issuer-paid CRAs' credit rating announcements. These results are robust to control variables and fixed effect combinations. For firms that are rated by EJR and S&P, Panel A shows that institutional investors significantly increase their net buy after a positive rating adjustment announced by S&P. The *POS* coefficient is positive and highly significant across the four regression specifications. The significance of *POS* on institutional trading is also economically significant. For example, the 0.1655 basis point coefficient in column (4) is equivalent to an average increase of $US 316,914 in abnormal net buy over the [0, 5] days around the S&P's one-notch rating upgrade announcements[12]. Institutional investors, however, significantly react less to positive rating changes issued by EJR than by S&P. The *EJR*POS* interaction coefficient in Panel A is negative and significant across different models. The *F*-test results for the overall impact of rating upgrades by EJR, i.e., the sum of *POS* and *EJR*POS* coefficients, indicate that institutional investors are unresponsive to EJR's positive rating changes.

Regarding rating downgrades, Panel A shows opposite results. Institutional investors seem to find EJR's negative rating adjustments are more informative than S&P's announcements. While the *NEG* coefficient is insignificant in most of the specifications, the *EJR*NEG* is negative and statistically and economically significant across the models. For example, the -0.1191 coefficient of *EJR*NEG* in column (4) shows that a one-notch downgrade announcement by EJR is equivalent to a decrease of $US 228,063 in abnormal institutional net buy over the [0, 5] day window compared to a similar announcement by S&P. The *F*-test results for the overall impact of rating downgrades by EJR, i.e., the sum of *NEG* and *EJR*NEG* coefficients, indicate that the effect also remains relatively strong statistically and economically.

[12] The increase is calculated by multiplying the POS coefficient of 0.1655 by the average market capitalization ($e^{9.86}$ = $US 19,149 million) of group A firms in Panel A of Table 3 and dividing the result by 10,000 (since the net buy is in basis points).

Table 2.4: Institutional investors' abnormal responses to credit rating adjustments in the [0, 5] day window

Panel A: EJR vs. S&P				
	(1)	(2)	(3)	(4)
Intercept	-0.1111	0.3095	-0.5139	-0.4884
	(1.7653)	(1.8238)	(2.1414)	(2.1424)
NEG	0.0529**	0.0470*	0.0602	0.0538
	(0.0247)	(0.0266)	(0.0406)	(0.0408)
POS	0.1361***	0.2450***	0.1624***	0.1655***
	(0.0278)	(0.0300)	(0.0497)	(0.0498)
EJR×NEG	-0.1100***	-0.1014***	-0.1242***	-0.1191**
	(0.0311)	(0.0322)	(0.0478)	(0.0478)
EJR×POS	-0.1562***	-0.2125***	-0.1220**	-0.1232**
	(0.0340)	(0.0360)	(0.0563)	(0.0563)
EJR	0.1674***	0.1316***	0.1297***	0.1254**
	(0.0345)	(0.0365)	(0.0493)	(0.0493)
Control variables:				
ROA			0.0330	0.0729
			(0.1916)	(0.1928)
IDIO_RISK			0.5287	0.8989
			(1.1872)	(1.206)
Z-SCORE			-0.0165	-0.0167
			(0.0121)	(0.0126)
ANALYST_COVERAGE			-0.0232***	-0.0226***
			(0.0059)	(0.0061)
INTEREST_COVERAGE			0.0010	0.0008
			(0.0010)	(0.0011)
Ln (MV)			0.0624***	0.0464***
			(0.0132)	(0.0148)
Ln (AGE)				0.0217
				(0.0160)
HIGH_TECH				0.1425
				(0.1283)
S&P_500				0.0620*
				(0.0329)
LEVERAGE				-0.0206
				(0.1056)
F-tests:				
NEG + EJR×NEG	-0.0572***	-0.0544***	-0.0640**	-0.0654**
	(0.0197)	(0.0209)	(0.0272)	(0.0273)
POS + EJR×POS	-0.0201	0.0325	0.0403	0.0423
	(0.0198)	(0.0216)	(0.0272)	(0.0272)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes

N Observations	429,268	429,268	304,746	304,731
Adj. R-squared	0.003	0.010	0.004	0.004

Panel B: EJR vs. Moody's

	(1)	(2)	(3)	(4)
Intercept	-0.4270	-0.3379	-0.6773	-0.4840
	(4.9337)	(4.9528)	(4.7204)	(4.7255)
NEG	0.2788***	0.0966	0.1062	0.0925
	(0.1075)	(0.1154)	(0.1299)	(0.1302)
POS	0.5434***	0.3324**	0.4239***	0.4078***
	(0.1240)	(0.1319)	(0.1384)	(0.1387)
EJR×NEG	-0.4117***	-0.1984*	-0.2677**	-0.2538*
	(0.1146)	(0.1204)	(0.1340)	(0.1342)
EJR×POS	-0.5730***	-0.2723**	-0.4645***	-0.4453***
	(0.1316)	(0.1387)	(0.1478)	(0.1481)
EJR	0.5415***	0.2429**	0.4244***	0.4005***
	(0.1160)	(0.1234)	(0.1276)	(0.1282)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.1329***	-0.1018**	-0.1616***	-0.1613***
	(0.0440)	(0.0468)	(0.0486)	(0.0487)
POS + EJR×POS	-0.0296	0.0601	-0.0405	-0.0375
	(0.0462)	(0.0496)	(0.0523)	(0.0523)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	114,354	114,354	93,884	93,867
Adj. R-squared	0.009	0.016	0.010	0.01

Panel C: EJR vs. Fitch

	(1)	(2)	(3)	(4)
Intercept	-0.0483	0.8414	-0.3687	-0.4015
	(1.7391)	(1.7814)	(2.0014)	(2.0034)
NEG	0.0186	0.0285	0.0294	0.0259
	(0.0224)	(0.0233)	(0.0448)	(0.0448)
POS	0.0101	0.0740**	0.0827	0.0818
	(0.0328)	(0.0353)	(0.0708)	(0.0711)
EJR×NEG	-0.0310	-0.0295	-0.0658	-0.0636
	(0.0338)	(0.0349)	(0.0567)	(0.0568)
EJR×POS	0.0164	0.0023	-0.0457	-0.0436
	(0.0421)	(0.0443)	(0.0805)	(0.0807)
EJR	0.0642	0.0507	0.0765	0.0744
	(0.0459)	(0.0491)	(0.0737)	(0.0738)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0124	-0.0011	-0.0364	-0.0377
	(0.0263)	(0.0279)	(0.0367)	(0.0369)

POS + EJR×POS	0.0265	0.0763***	0.0370	0.0381
	(0.0264)	(0.0285)	(0.0393)	(0.0393)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	207,587	207,587	133,824	133,788
Adj. R-squared	0.004	0.006	0.008	0.008

The table reports OLS regression results on institutional investors' abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panels A, B, and C report the results for rating changes by EJR and S&P, EJR and Moody's, and EJR and Fitch, respectively. In all panels, the dependent variable is the abnormal institutional net buy as calculated in Eq. (2) in the main text. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

I find similar asymmetric responses by institutional investors to upgrades and downgrades for firms that are rated by EJR and Moody's in Panel B of Table 2.4. Although the magnitude of asymmetric abnormal trading, represented by the size of the coefficient, is substantially larger than in Panel A, it is relatively smaller in economic terms. For example, the *POS* coefficient of 0.4078 in column (4) indicates that abnormal institutional net buy, on average, increases by $US 281,586 over the [0, 5] day window surrounding a credit rating upgrade by Moody's[13]. This result is opposite to the effect of positive rating announcements by EJR. The combined effect of *POS* and *EJR*POS* suggests that institutional investors do not seem to react to EJR's rating upgrades compared to Moody's. However, the results for negative rating announcements support institutional investors' strong responses to EJR's than Moody's downgrades. The *F*-test results for the sum of *NEG* and *EJR*NEG* coefficients in column (4) indicates that EJR's downgrades, on average, are associated with a significant decrease of $US 111,378 in abnormal institutional net buy over the [0.5] day window.

[13] The increase is calculated by multiplying the POS coefficient of 0.4078 by the average market capitalization (e8.84 = $US 6,905 million) of group B firms in Panel B of Table 3 and dividing the result by 10,000 (since the net buy is in basis points).

The results in Panel C of Table 2.4 do not exhibit any robust and significant difference in the response of institutional investors around credit rating changes for firms covered by both EJR and Fitch. All coefficients of interest are statistically insignificant, except for *POS* and the combined effect of *POS* and *EJR*POS*. I further investigate investor reactions to Fitch ratings in section 2.3.4.

Overall, the results in Table 2.4 suggest that institutional investors[14] find that credit rating upgrades are more informative, hence they respond accordingly when they are issued by S&P or Moody's rather than by EJR. In contrast, they find that negative rating adjustments are more value-relevant when they are announced by EJR than by S&P or Moody's. These findings are consistent with the argument that institutional investors are well equipped to assess the informativeness of credit rating announcements. Previous studies have shown that issuer-paid CRAs tend to delay rating downgrades due to conflict of interests (e.g., Cornaggia and Cornaggia, 2013), but still issue timely rating upgrades (e.g., Kedia et al., Rajgopal, and Zhou, 2017). Brogaard, Koski and Siegel (2019) also find that upgrades issued by issuer-paid CRAs do convey new information. In contrast, investor-paid CRAs tend to be more timely in rating downgrade adjustments (e.g., Johnson, 2004; Berwart, Guidolin, and Milidonis, 2016).

2.3.1.2. Alternative institutional trading data

In the main analysis, I use transaction-level data provided by the Abel/Noser Corporation. Although several recent studies related to institutional trading behavior also use these data (e.g., Duong and Meschke, 2020; Eisele, Nefedova, Parise, and Peijnenburg, 2020; Huang, Tan, and

[14] Different from Bhattacharya et al. (2019), I argue that institutional investors, whoever are CRA followers or CRA non-followers, with advanced knowledge and trading skills can capitalize the value-relevant rating information in the financial markets. I next argue that even although I do not restrict the sample of institutional investors as CRA followers, I find significant results as they have dynamic responses to informative credit ratings. Hence, the results are likely stronger with a restricted sample of CRA followers, i.e, EJR subscribers.

Wermers, 2020; Nefedova and Pratobevera, 2020; Busse, Chordia, Jiang, and Tang, 2021; Chemmanur, Hu, Li, and Xie, 2021; Davis, Khadivar, and Walker, 2021; Eaton, Irvine, and Liu, 2021; among others), like me, their sample periods are constrained by data availability of up to 2011 since Abel/Noser no longer provides institutional trading data for research purposes. In order to make my sample more comprehensive and to ensure the robustness of the findings, I consider two quarterly institutional holding databases to extract institutional investors' trading activities: mutual fund (12F) holdings, and institutional (13F) holdings provided by Thompson Reuters. The dataset covers the period from 1999 to 2017.

The mutual fund (12F) holdings database provides data on mutual fund holdings and shares outstanding at the end of each quarter. Similarly, the institutional (13F) holdings database provides quarterly data on institutional investor stock holdings. My analysis includes all U.S. equity mutual funds and institutional investors that have at least 65% of their assets in common stocks (e.g., Cremers and Petajisto, 2009; Amihud and Goyenko, 2013)[15]. The final samples include 8,566 mutual funds and 8,656 institutional investors. Consistent with the main analysis, I use abnormal mutual fund and institutional investors' trading as a proxy for investors' responses, measured by quarterly abnormal net buy ($NB_{i,n,q}$).

$$NB_{i,n,q} = nb_{i,n,q} - average\ nb_{i,n,q} \tag{2.7}$$

where $nb_{i,n,q}$ is quarterly net buy by mutual fund or institutional investor *i* on stock *n* measured as stock holding in quarter q minus quarter q - 1, normalized by the total number of shares

[15] I also consider alternative thresholds such as 50%, 60% and 70% as robustness checks. The results are consistent and available upon request.

outstanding at the end of the quarter q^{16}. I next calculate $average\ nb_{i,n,q}$ as the average value of $nb_{i,n,q}$ in the period from quarter q - 4 to q - 1 as follows:

$$average\ nb_{i,n,q} = \frac{\sum_{k=-1}^{-4} nb_{i,n,t+k}}{4} \tag{2.8}$$

Like the main analysis, I also follow Chemmanur, Li, and Zhu (2016) to convert $NB_{i,n,q}$ into basis points. Since I focus on quarterly trading, I also aggregate credit rating adjustments on a quarterly basis. For instance, in the first quarter of 2000, S&P announces two credit rating adjustments for firm *n*, a single downgrade (i.e., – 1 notch) on the 1st of February 2000, and a double downgrade (i.e., -2 notches) on the 2nd of March 2000, the aggregate credit rating adjustment by S&P for firm *n* in the first quarter of 2000 is -3 notches.

I then replicate the main analysis by estimating Eq. (2.6) using quarterly data. I report the results in Panels A and B of Table 2.5 for mutual fund (12F) holdings and institutional (13F) holdings, respectively. The results are consistent with the main findings. Specifically, mutual funds and institutional investors sell stocks following negative signals from EJR and buy stocks following positive signals from S&P, Moody's, and Fitch. In contrast, they do not significantly respond to rating downgrades from S&P, Moody's, and Fitch, or to rating upgrades from EJR. Panel A shows that for the group of firms that are rated by EJR and S&P, mutual funds significantly increase their stock holdings following S&P's one-notch upgrades, while they show no significant responses to negative signals from S&P. In contrast, mutual funds significantly decrease their stock holdings following EJR's one-notch downgrades, while they show no significant responses to positive signals from EJR. I also find the same patterns with the group of firms that are rated by EJR and Moody's, while I find no significant results for the

[16] This is to follow the merit of Chemmanur, He, and Hu (2009) who estimate institutional net buy based on shares traded and shares outstanding.

group of firms that are rated by EJR and Fitch. Panel B reports robust results for institutional (13F) investors' abnormal responses to credit rating adjustments by issuer- and investor-paid CRAs. Overall, the robust results on quarterly mutual fund (12F) and institutional (13F) holding changes following credit rating adjustments are consistent with the main findings. Institutional investors who have advanced trading skills and knowledge (Puckett and Yan, 2011) follow credit rating adjustments with the highest informational content: negative and positive from investor- and issuer-paid CRAs, respectively.

In addition, I question whether institutional investors' dynamic trading responses differ over time, or whether they have a more significant effect in more recent years. Therefore, I divide the sample of mutual fund (12F) and institutional investor (13F)'s holding data into two separate periods: 1999-2011 (i.e., the main sample period) and 2012-2017 (more recent period), replicate the analysis, and report in T.A3 and T.A4 respectively. Basically, I find the consistent results as institutional investors have dynamic responses: selling with negative signals from investor-paid CRAs and buying with positive signals from issuer-paid CRAs. The results show that our findings are not driven by time periods.

Table 2.5: Mutual fund (12F) and institutional investor (13F)' abnormal responses to credit rating adjustments

Panel A: Mutual Fund (12F) Holdings						
	EJR vs. S&P		EJR vs. Moody's		EJR vs. Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1379***	-0.0856**	0.4049***	-0.3387***	0.1770***	-0.5467***
	(0.0183)	(0.0346)	(0.0445)	(0.0828)	(0.0234)	(0.0481)
NEG	0.0105*	-0.0013	-0.0040	0.0234	0.0211**	0.0286**
	(0.0062)	(0.0073)	(0.0240)	(0.0283)	(0.0090)	(0.0122)
POS	0.0318***	0.0324***	0.0241**	0.0308**	0.0441***	0.0612***
	(0.0087)	(0.0108)	(0.0121)	(0.0123)	(0.0127)	(0.0179)
EJR×NEG	-0.0199***	-0.0103*	-0.0416*	-0.0512*	-0.0139	-0.0187
	(0.0074)	(0.0057)	(0.0253)	(0.0292)	(0.0102)	(0.0135)
EJR×POS	-0.0257***	-0.0262**	-0.0123	-0.0152	-0.0424***	-0.0587***
	(0.0097)	(0.012)	(0.0303)	(0.0337)	(0.0138)	(0.0191)
EJR	-0.2294***	-0.2410***	-0.5808***	-0.6357***	-0.2948***	-0.2884***
	(0.0084)	(0.0099)	(0.0267)	(0.0300)	(0.0124)	(0.0165)

Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	-0.0094**	-0.0115**	-0.0456***	-0.0278***	0.0073	0.0100
	(0.0042)	(0.0050)	(0.0084)	(0.0096)	(0.0051)	(0.0063)
POS + EJR×POS	0.0061	0.0062	0.0118	0.0156	0.0017	0.0025
	(0.0044)	(0.0056)	(0.0083)	(0.0095)	(0.0055)	(0.0072)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N Observations	3,582,992	2,808,671	1,273,265	1,079,231	2,291,401	1,716,964
Adj. R-squared	0.002	0.003	0.003	0.004	0.002	0.002

Panel B: Institutional (13F) Holdings

	EJR vs. S&P		EJR vs. Moody's		EJR vs. Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.6663***	2.0098***	2.4527***	2.7954***	0.2020***	-1.3221***
	(0.0548)	(0.1136)	(0.1483)	(0.2731)	(0.0568)	(0.1378)
NEG	-0.0278	-0.0665***	0.0124	0.0511	-0.0383	0.0785**
	(0.0219)	(0.0257)	(0.0827)	(0.0959)	(0.0234)	(0.0346)
POS	0.0330*	0.0571**	0.1087***	0.0931***	0.0893**	0.1089**
	(0.0181)	(0.0285)	(0.0325)	(0.0224)	(0.0352)	(0.0531)
EJR×NEG	-0.1555***	-0.1368***	-0.2474***	-0.2707***	-0.0083	-0.0624
	(0.0260)	(0.0305)	(0.0875)	(0.0992)	(0.0273)	(0.0387)
EJR×POS	0.0071	-0.0288	-0.0956***	-0.0923***	-0.1045***	-0.1373**
	(0.035)	(0.0433)	(0.0276)	(0.0270)	(0.0390)	(0.0575)
EJR	-0.7735***	-1.0401***	-2.6222***	-2.6376***	-0.3948***	-0.3114***
	(0.0292)	(0.0342)	(0.0974)	(0.1075)	(0.0336)	(0.0466)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	-0.1833***	-0.2034***	-0.2350***	-0.2196***	-0.0467*	0.0162
	(0.0145)	(0.0174)	(0.0305)	(0.0334)	(0.0247)	(0.0189)
POS + EJR×POS	0.0401	0.0283	0.0131	0.0008	-0.0151	-0.0285
	(0.0265)	(0.0207)	(0.033)	(0.0361)	(0.0173)	(0.0238)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N Observations	4,088,703	3,180,369	1,281,861	1,084,625	2,729,378	2,040,834
Adj. R-squared	0.001	0.001	0.002	0.002	0.001	0.001

The table reports OLS regression results on mutual fund (12F) and institutional investor (13F) abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panel A reports the results for mutual fund (12F) holding changes. Panel B reports the results for institutional investor (13F) holding changes. For each panel, I separately consider three pairs: institutional abnormal responses to (1) EJR vs. S&P, (2) EJR vs. Moody's and (3) EJR vs. Fitch. The dependent variable is the abnormal net buy of a mutual fund or an institutional investor in a quarter. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for quarterly rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

2.3.2. Do CRAs behave the way I assume they do?

Bonsall, Koharki and Neamtiu (2021) find that that EJR can potentially be more optimistically biased than issuer paid CRAs. However, the findings in the previous section show that negative signals from investor-paid CRAs, EJR, and positive signals from issuer-paid CRAs are relatively informative since institutional investors who have advanced knowledge and trading skills respond more to positive rating announcements by major issuer-paid CRAs and to negative rating announcements by the investor-paid CRA, EJR. These results suggest a lead-lag in the timeliness of credit rating announcements between these two types of CRAs. I now empirically examine this to validate the findings.

As before, I separately consider three pairs: EJR and S&P, EJR and Moody's, and EJR and Fitch. For each firm rated by each pair of CRAs, the credit rating score is adjusted multiple times by two paired CRAs throughout the sample period. I investigate the lead-lag relationship of each CRA pair for upgrades and downgrades separately. Based on the announcement timeline and the relative magnitude of consecutive rating adjustments, three scenarios are possible. First, when one CRA issues a rating adjustment that is relatively larger in magnitude than the subsequent adjustment announced by the other CRA, the leading CRA is classified as a 'major leader'. Second, when one CRA issues a rating adjustment that is relatively smaller in magnitude than the subsequent adjustment announced by the other CRA, the following CRA is classified as a 'major confirmer'. Third, if a rating adjustment by one CRA is followed by the adjustment of the same magnitude by the other CRA, I classify the leading CRA as an ‘equal magnitude leader’. I then perform a binominal test with the null hypothesis that the frequencies that both CRAs in a pair hold for a specific role are equal.

In Table 2.6, section 1 reports the results for negative events, and section 2 shows the results for the positive events. Panels A, B, and C present the results for EJR and S&P, EJR and Moody’s, and EJR and Fitch, respectively. The results generally confirm my expectations that EJR issues relatively larger rating adjustments than the issuer-paid CRAs when these adjustments are downgrades. For example, EJR’s downgrades are larger than S&P’s subsequent downgrades 56.95% (= 422 / (422 + 319)) of the time, which is statistically higher than 43.05% where of the time when S&P plays the role of a major leader. The comparison is even higher for EJR than Moody’s in Panel B, at 67.14% (= 141 / (141 + 69)) vs. 32.86%. When EJR follows S&P or Moody’s after their respective negative rating adjustments, EJR tends to issue larger negative adjustments more frequently than when the other two CRAs follow EJR’s downgrades with larger magnitudes. The major confirmer row for a negative event confirms these differences statistically. There are no statistical differences between EJR and the other CRAs in the frequency of being an equal magnitude leader. However, I find no evidence of EJR’s leading role compared to Fitch in the issuance of negative signals. Fitch apparently issues larger negative adjustments more frequently than EJR, although these frequency differences are not statistically significant.

2.6: The relative role of issuer- and investor-paid CRAs in negative and positive signals

	Panel A: EJR & S&P			Panel B: EJR & Moody's			Panel C: EJR & Fitch		
	EJR	*S&P*	*Diff test p-value*	*EJR*	*Moody's*	*Diff test p-value*	*EJR*	*Fitch*	*Diff test p-value*
Section 1: Negative events									
Major leader (t)	422 (56.95%)	319 (43.05%)	0.0002	141 (67.14%)	69 (32.86%)	<.0001	124 (46.62%)	142 (53.38%)	0.2697
Major confirmer (t+1)	423 (55.88%)	334 (44.12%)	0.0012	129 (61.14%)	82 (38.84%)	0.0012	111 (44.94%)	136 (55.06%)	0.1117
Equal magnitude leader(t)	303 (52.15%)	278 (47.85%)	0.2997	72 (52.55%)	65 (47.45%)	0.5498	103 (49.05%)	107 (50.95%)	0.7825
Section 2: Positive events									
Major leader (t)	166(38.52%)	265 (61.48%)	<.0001	75 (41.44%)	106 (58.56%)	0.0212	42 (27.27%)	112 (72.73%)	<.0001
Major confirmer (t+1)	172 (36.52%)	299 (63.48%)	<.0001	77 (43.75%)	99 (56.25%)	0.0973	30 (19.23%)	126 (80.77%)	<.0001
Equal magnitude leader(t)	237(50.21%)	235 (49.79%)	0.9267	103 (49.76%)	104 (50.24%)	0.9446	83 (58.04%)	60 (41.96%)	0.0544

The table shows the relative role of issuer- and investor-paid CRAs in positive and negative credit rating announcements. The table includes six pairs: two pairs of negative (section 1) and positive events (section 2) for each of three CRA pairs: EJR and S&P (Panel A), EJR and Moody's (Panel B) and EJR and Fitch (Panel A). Three scenarios are possible for each pair. First, when one CRA issues a rating adjustment that is relatively larger in magnitude than the subsequent adjustment announced by the other CRA, the leading CRA is classified as a 'major leader'. Second, when one CRA issues a rating adjustment that is relatively smaller in magnitude than the subsequent adjustment announced by the other CRA, the following CRA is classified as a 'major confirmer'. If a rating adjustment by one CRA is followed by the adjustment of the same magnitude by the other CRA, I classify the leading CRA as an 'equal magnitude leader'. For each pair, I calculate the relative frequency of each role (e.g., major leader, major confirmer, or equal magnitude leader). The figures show the number of times and the relative frequency (in brackets) that a CRA holds a specific role. I apply a binomial test to compare the relative frequency of each CRA pair in a specific role.

The results for positive events in section 2 of Table 2.6 indicate that all three issuer-paid CRAs tend to issue larger rating upgrades more frequently than EJR. These frequency differences are statistically significant for both cases when these traditional CRAs are major leaders or major confirmers. There are no significant frequency differences in being an equal magnitude leader, except for the EJR and Fitch pair where EJR leads Fitch more often when they issue positive rating adjustments of the same magnitude.

Overall, the findings in this table support the results in Table 2.4 that EJR's negative rating announcements are apparently timelier and value-relevant to institutional investors than those rating downgrades by the other CRAs. However, the issuer-paid CRAs' positive rating announcements are valued more by institutional investors than EJR's rating upgrades.

2.3.3. Profitability of asymmetric trading strategies

2.3.3.1. Notional trading strategies

I investigate whether a trading strategy based on credit rating signals with the highest informational content can generate superior returns. I begin with notional trading strategies constructed using publicly available returns. These returns would be realized by any investor with timely access to credit ratings.

The first strategy I consider is the 'dynamic strategy' – selling following EJR's negative rating signals and buying following issuer-paid CRAs' positive rating signals. This trading strategy is of the main interest. The second one is the 'naïve strategy' – selling following negative signals and buying following positive signals from any rating agency. The third strategy is the 'EJR-based' – selling following negative signals and buying following positive signals announced by EJR. The fourth strategy is the 'issuer-paid CRA-based' – selling following negative signals and buying following positive signals issued by any of the "Big Three" CRAs. I also add a passive strategy as an additional benchmark – investing in the S&P 500 index. I measure the profitability for each trading strategy as follows.

First, I examine various holding windows (e.g., 1, 3, 6, 9 or 12 months) starting from day *t* to day *t* + 5 relative to the rating announcement date *t*. I follow Jagolinzer, Larcker, and Taylor (2011) and estimate abnormal returns after adjusting for common risks. Specifically, for each announcement, risk-adjusted returns are the intercepts (or alphas) from the four-factor Fama and French (1993) and Carhart (1997) model estimated over the holding period:

$$(R_i - R_f) = \alpha + \beta_1 (R_{mkt} - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + e_i \tag{2.9}$$

where R_i is the daily return; R_f is the daily risk-free rate; R_{mkt} is the CRSP value-weighted market return; *SMB*, *HML*, and *UMD* are the size, book-to-market, and momentum factors. If the announcement is for a positive rating adjustment, suggesting a buy signal, the daily risk-adjusted return is a simple weighted average of the alphas during the [0, 5] window. If the announcement is for a negative rating adjustment, which suggests a sell signal, the average daily risk-adjusted return, i.e., alpha, is multiplied by (-1), as in Jagolinzer, Larcker, and Taylor (2011).

I then group these risk-adjusted returns into one of the trading strategies described above and test the statistical significance of each strategy performance across all rating announcements. I also test the mean difference in risk-adjusted returns between strategies with a two-sample *t*-test and report the results in Table 2.7. All returns are annualized. I find that all four strategies outperform the buy-and-hold of the S&P 500 index. In addition, consistent with my expectations, the dynamic strategy yields higher abnormal returns than all other strategies. Over the one-month investment horizon, the dynamic strategy outperforms the other three by an annualized risk-adjusted return ranging from 4.59% to 5.58%. Outperformance is statistically significant for up to 6 months.

Table 2.7: Notional trading strategy profitability

Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.0935***	0.0708***	0.0498***	0.0344***	0.0283
	(0.0105)	(0.0079)	(0.0061)	(0.011)	(0.0248)
(2) Naïve strategy	0.0419***	0.0381***	0.0225***	0.0159**	0.0057
	(0.0076)	(0.0046)	(0.0038)	(0.0068)	(0.0157)
(3) EJR based	0.0377***	0.0356***	0.0363***	0.0162***	0.0169***
	(0.0086)	(0.0042)	(0.003)	(0.0023)	(0.0034)
(4) Issuer-paid CRA based	0.0476***	0.0406***	0.0215***	0.0155	-0.0016
	(0.0134)	(0.0093)	(0.0081)	(0.016)	(0.0359)
(5) B-H of a S&P500 index	0.0011	0.0011	0.0011	0.0011	0.0011
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Difference (1) - (2)	0.0515***	0.0327***	0.0273***	0.0185	0.0225
	(0.0129)	(0.0092)	(0.0072)	(0.0129)	(0.0293)
Difference (1) - (3)	0.0558***	0.0352***	0.0135**	0.0182	0.0113
	(0.0136)	(0.0089)	(0.0068)	(0.0112)	(0.025)
Difference (1) - (4)	0.0459***	0.0302**	0.0283***	0.0189	0.0299
	(0.017)	(0.0122)	(0.0101)	(0.0194)	(0.0436)
Difference (1) - (5)	0.0924***	0.0697***	0.0487***	0.0333***	0.0271
	(0.0106)	(0.008)	(0.0062)	(0.011)	(0.0248)
Difference (2) - (5)	0.0408***	0.0369***	0.0213***	0.0148**	0.0046
	(0.0077)	(0.0048)	(0.004)	(0.0069)	(0.0157)
Difference (3) - (5)	0.0366***	0.0345***	0.0352***	0.0151***	0.0158***
	(0.0087)	(0.0043)	(0.0032)	(0.0026)	(0.0036)
Difference (4) - (5)	0.0464***	0.0395***	0.0204**	0.0144	-0.0027
	(0.0135)	(0.0094)	(0.0082)	(0.0161)	(0.0359)

Table 2.7 compares the performance of the dynamic trading strategy (i.e., my main interest) and other trading strategies based on market notional responses in the window of [0, 5] days surrounding credit rating adjustments announced by issuer- and investor-paid CRAs. These trading strategies include (1) 'dynamic strategy' – selling following EJR's negative rating signals and buying following issuer-paid CRAs' positive rating signals, (2) 'naïve strategy' – selling following negative signals and buying following positive signals from any rating agency, (3) 'EJR-based' – selling following negative signals and buying following positive signals announced by EJR, (4) 'issuer-paid CRA-based' –selling following negative signals and buying following any of the "Big Three" announcements. I also compare the four strategies to a passive buy-and-hold of the S&P 500 index. The trading strategy returns are adjusted for common risks by following Jagolinzer, Larcker, and Taylor (2011). I consider different holding periods (i.e., 1, 3, 6, 9 and 12 months). All returns are annualized. Standard errors of the *t*-test for the mean and difference in means are in parentheses.

2.3.3.2. Institutional trading strategies

I now examine trading strategies based on actual institutional transactions. The returns on notional strategies can be interpreted as equally weighted returns of an institution trading around every credit rating announcement consistent with a certain strategy. By explicitly considering institutional transactions, I acknowledge that institutions may follow multiple strategies at a time and switch in and out of strategies. I compute daily risk-adjusted returns for each transaction as in Eq. (2.9). I then compute equal- and volume-weighted average profits on all transactions in the [0, 5] window for each event for each institutional investor. The average strategy profit results are reported in Table 2.8. Generally, while all four trading strategies provide positive risk-adjusted profits for up to nine months after credit rating announcements, the dynamic strategy that mimics the typical institutional response yields the highest returns. For example, for the one-month investment horizon, Panel A shows that the dynamic strategy outperforms the other three strategies by an annualized risk-adjusted return ranging from 10.01% to 10.33%. Importantly, this outperformance is approximately twice as much as the corresponding outperformance of notional strategies. Although this outperformance decreases with the investment horizon, it is still statistically significant for up to nine months. Among the other three active strategies, following EJR's signals alone apparently generates the best returns whereas following issuer-paid CRAs only yields the least profits. The results for volume-weighted averages in Panel B show similar patterns where the dynamic trading strategy provides the best returns across the holding periods compared to other active strategies. I also compare the four trading strategies to a passive strategy – a buy-and-hold annual return of the S&P 500 index over the sample period. I observe that all trading strategies outperform the index in the one-month and three-month holding periods.

Overall, the results in Table 2.8 confirm my expectations that credit rating announcements have valuable information content and that the most value-relevant announcements are downgrades by the investor-paid EJR and upgrades by the issuer-paid CRAs. The findings illustrate that institutional investors that dynamically change their trading behavior based on advantages and disadvantages of credit rating information are likely to make abnormal profits beyond those of naïve trading strategies.

Table 2.8: Institutional trading strategy profitability

Panel A: Equal-weighted average risk-adjusted returns					
Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.1882***	0.1080***	0.0793***	0.0693**	0.0336
	(0.0219)	(0.0187)	(0.0224)	(0.0331)	(0.0492)
(2) Naïve strategy	0.0866***	0.0543**	0.0444***	0.0168	0.0348
	(0.0316)	(0.0267)	(0.0130)	(0.0235)	(0.0468)
(3) EJR based	0.0881***	0.0603***	0.0558***	0.0117	0.0344
	(0.0110)	(0.0125)	(0.0114)	(0.0220)	(0.0900)
(4) Issuer-paid CRA based	0.0849***	0.0486*	0.0276	0.0170	0.0359
	(0.0298)	(0.0254)	(0.0261)	(0.0265)	(0.0464)
(5) B-H of a S&P500 index	-0.0163	-0.0163	-0.0163	-0.0163	-0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)
Difference (1) - (2)	0.1017***	0.0537*	0.0350**	0.0525*	-0.0012
	(0.0384)	(0.0326)	(0.0172)	(0.0287)	(0.0528)
Difference (1) - (3)	0.1001***	0.0477**	0.0236	0.0576*	-0.0008
	(0.0245)	(0.0225)	(0.0188)	(0.0311)	(0.1025)
Difference (1) - (4)	0.1033***	0.0594**	0.0517*	0.0523*	-0.0023
	(0.0306)	(0.0262)	(0.0276)	(0.0287)	(0.0525)
Difference (1) - (5)	0.2045***	0.1243***	0.0956***	0.0856**	0.0499
	(0.0227)	(0.0194)	(0.0226)	(0.0332)	(0.0493)
Difference (2) - (5)	0.1029***	0.0706***	0.0607***	0.0331	0.0511
	(0.0322)	(0.0272)	(0.0131)	(0.0235)	(0.0468)
Difference (3) - (5)	0.1044***	0.0766***	0.0721***	0.0280	0.0507
	(0.0126)	(0.0136)	(0.0116)	(0.0221)	(0.0900)
Difference (4) - (5)	0.1012**	0.0650*	0.0440	0.0333	0.0522
	(0.0447)	(0.0382)	(0.0435)	(0.0531)	(0.0619)
Panel B: Volume-weighted average risk-adjusted returns					
Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.1826***	0.1226***	0.0858***	0.0759**	0.0491
	(0.0222)	(0.0188)	(0.0224)	(0.0330)	(0.0496)
(2) Naïve strategy	0.0899***	0.0527**	0.0460***	0.0165	0.0192
	(0.0316)	(0.0267)	(0.0129)	(0.0226)	(0.0450)

(3) EJR based	0.1021***	0.0686***	0.0533***	0.0147	0.0132
	(0.0113)	(0.0127)	(0.0114)	(0.0216)	(0.0907)
(4) Issuer-paid CRA based	0.0777***	0.0508**	0.0333	0.0196	0.0376
	(0.0296)	(0.0254)	(0.026)	(0.0264)	(0.0463)
(5) B-H of a S&P500 index	-0.0163	-0.0163	-0.0163	-0.0163	-0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)
Difference (1) - (2)	0.0927**	0.0699**	0.0398**	0.0594**	0.03
	(0.0386)	(0.0327)	(0.017)	(0.028)	(0.0513)
Difference (1) - (3)	0.0805***	0.0539**	0.0325*	0.0612**	0.0360
	(0.0249)	(0.0226)	(0.0188)	(0.0309)	(0.1034)
Difference (1) - (4)	0.1049***	0.0718***	0.0524*	0.0563**	0.0115
	(0.0306)	(0.0262)	(0.0275)	(0.0286)	(0.0525)
Difference (1) - (5)	0.1989***	0.1389***	0.1021***	0.0922***	0.0654
	(0.0230)	(0.0195)	(0.0226)	(0.0332)	(0.0497)
Difference (2) - (5)	0.1062***	0.0690**	0.0623***	0.0328	0.0355
	(0.0322)	(0.0272)	(0.0129)	(0.0227)	(0.045)
Difference (3) - (5)	0.1184***	0.0849***	0.0696***	0.0310	0.0295
	(0.0129)	(0.0137)	(0.0116)	(0.0217)	(0.0908)
Difference (4) - (5)	0.0940**	0.0671*	0.0496	0.0359	0.0539
	(0.0446)	(0.0382)	(0.0434)	(0.0529)	(0.0617)

Table 2.8 compares the performance of the dynamic trading strategy (i.e., my main interest) and other trading strategies based on institutional investors' actual responses in the window of [0, 5] days surrounding credit rating adjustments announced by issuer- and investor-paid CRAs. These trading strategies include (1) 'dynamic strategy' – institutional investors net sell following EJR's negative rating signals and net buy following issuer-paid CRAs' positive rating signals, (2) 'naïve strategy' – institutional investors net sell following negative signals and net buy following positive signals from any rating agency, (3) 'EJR-based' – institutional investors net sell following negative signals and net buy following positive signals announced by EJR, (4) 'issuer-paid CRA-based' – institutional investors net sell following negative signals and net buy following any of the "Big Three" announcements. I also compare the four strategies to a passive buy-and-hold of the S&P 500 index. The trading strategy returns are adjusted for common risks by following Jagolinzer, Larcker, and Taylor (2011). The table reports two panels. Panel A is for equal-weighted average adjusted returns and panel B is for volume-weighted average adjusted returns. I consider different holding periods (i.e., 1, 3, 6, 9 and 12 months). All returns are annualized. Standard errors of the *t*-test for the mean and difference in means are in parentheses.

2.3.4. The case of Fitch ratings

I note that there are no significant differences in the response of institutional investors around credit rating changes for firms covered by both EJR and Fitch. This has prompted me to investigate this further. Fitch has traditionally held a smaller market share relative to Moody's and S&P (Becker and Milbourn, 2011; Livingston and Zhou, 2016). This may have influenced both their rating behavior (Beatty et al., 2019; Hirth, 2014) and investor reaction.

My empirical analysis suggests that Fitch differs in its rating behavior from other issuer-paid CRAs. First, as reported in Table 2.6, not only does Fitch lead EJR in positive events (as expected) but is also the only issuer-paid CRA to lead EJR in negative announcements (although the difference is not statistically significant). Furthermore, Fitch leads S&P and Moody's in both positive and negative announcements[17]. I believe this is consistent with Fitch providing more timely rating announcements to increase their market share.

Second, I look at the information content of Fitch announcements by constructing two additional trading strategies – 'Fitch-based' – buying on Fitch upgrades and selling on Fitch downgrades (for the sake of completeness I also create 'S&P-based' and 'Moody's-based' strategies), and 'modified dynamic' – buying on the Big Three's upgrades and selling on Fitch downgrades. My unreported results show that the Fitch-based strategy not only outperforms a simple buy-and-hold of the S&P 500 index, but also produces better returns than the issuer-paid CRA-based strategy, particularly over longer time periods. This suggests that Fitch's announcements actually have higher information content than other issuer-paid CRAs. The modified dynamic is the second-best performing strategy, suggesting that Fitch's negative announcements have substantial information content. However, the 'dynamic' strategy – buying on positive issuer-paid CRA announcements and selling on EJR's negative announcements – yields the best returns, which is consistent with my main hypothesis.

Finally, I investigate institutional investors' reactions to Fitch's announcements in greater detail. In the main analysis, institutions do not appear to react significantly to either positive or negative announcements in the sample of firms jointly rated by Fitch and EJR, despite evidence that both CRAs' announcements have significant informational content. I posit that

[17] The save space, I do not report these results.

as Fitch actually leads EJR in negative signals (although insignificantly), lack of significant reaction to EJR's negative announcements may be due to dilution of investors' reaction to both Fitch and EJR's announcements. Investors do not react to Fitch's announcements in a significant way (even though these announcements have significant informational content), and this still weakens the investors' reaction to subsequent announcements by EJR. To investigate this, I remove negative announcements led by Fitch. My unreported results are consistent with my expectations, i.e., investors' reaction to EJR's negative announcements becomes negative and significant in three out of four specifications. This is also consistent with results reported in Panels A and B of Table 2.4.

2.4. Robustness Tests

2.4.1. *Alternative event windows*

In the first robustness test, I consider two alternative event windows: [-2, 1] and [-2, 5] days. First, these time windows include the two days prior to credit rating adjustments to control for potential information leakage before official rating adjustments (Bhattacharya, Wei, and Xia, 2019). Second, I also chose short time windows to control for any effect of clusters of rating signals (e.g., Gande and Parsley, 2005; Alsakka and ap Gwilym, 2012; Vu, Alsakka, and ap Gwilym, 2015). In other words, short time windows enable us to avoid any information contamination problems caused by the appearance of other information in financial markets in longer time windows.

The results for the two alternative event windows: [-2, 1] and [-2, 5] are presented in Tables A.5 and A.6 in the Appendix. The results are consistent with the main findings. Institutional investors still exhibit asymmetric trading behaviors to issuer- and investor-paid credit rating signals, abnormally buying with issuer-paid CRAs' positive rating adjustments and abnormally selling with EJR's negative rating adjustments in both alternative time windows. All four active trading strategies earn significant profits in similar patterns as in Table 2.4. They outperform the buy-and-hold return of the S&P 500 index for up to a nine-month horizon. Most importantly, the dynamic trading strategy is the best performer over all other strategies. The robust results of institutional trading strategies constructed surrounding alternative event windows: [-2, 1] and [-2, 5] are reported in Tables A.10 and Table A.11, respectively in the Appendix. I also report the results for notional trading strategies for these alternative windows and the results exhibit similar patterns, as shown in Tables A.12 and A.13 in the Appendix, respectively.

2.4.2. Raw institutional trading

My second robustness check analyses "raw" reactions (i.e., unadjusted for the average trading activities) of institutional investors to credit rating announcements in the same [0, 5] day window as in the main analysis. I present the robust results in Table A.7 in the Appendix. The results are highly consistent with the main findings. After controlling for firm characteristics, and firm, investor, and time fixed effects, I confirm that institutional investors tend to sell stocks of firms with EJR's negative rating announcements but ignore positive ones. The institutional investors' net buy, however, increases substantially surrounding issuer-paid CRAs' positive rating announcements.

2.4.3. 'Big issuer-paid CRA'

In the third robustness check, I create a ‘Big issuer-paid CRA’ by combining S&P, Moody’s, and Fitch together. I investigate institutional investor’s trading activities surrounding negative and positive rating signals by EJR and the ‘Big issuer-paid CRA’. The results are reported in Table A.8 in the Appendix. The results are consistent: Institutional investors tend to abnormally sell stocks surrounding negative signals issued by EJR and abnormally buy stocks surrounding positive signals issued by the ‘Big issuer-paid CRA’. My results remain unchanged after controlling for firm characteristics.

2.4.4. Excluding non-trading observations

In main analysis, abnormal net buy is set at zero if institutional investors have no trading activities surrounding credit rating adjustments. In this fourth robustness check, I exclude these non-trading observations. I report the robust results in Table A.9 in the Appendix. The results are robust. After excluding non-trading observations, institutional investors still have asymmetric responses, abnormally increasing (decreasing) stock holdings surrounding positive (negative) rating signals by issuer- (investor-) paid CRAs. The robustness test confirms my main findings that institutional investors who have advanced trading skills selectively react to credit rating signals from different sources based on the informative values.

2.5. Conclusion

This essay investigates institutional investors’ responses to credit rating adjustments announced by the investor-paid EJR and the Big Three issuer-paid CRAs. In recent years, traditional issuer-paid CRAs have faced criticism regarding lack of timeliness in negative signals in many infamous scandals such as Enron (2001), WorldCom (2002) and Lehman Brothers (2008).

Meanwhile, investor-paid CRAs, particularly EJR, have built a good reputation regarding the timeliness of their negative rating adjustments. As a result, institutional investors with advanced trading skills and sophistication (Puckett and Yan, 2011), are likely to dynamically switch between following investor- and issuer-paid CRAs based on the timeliness of credit rating information.

I document considerable asymmetries in institutional investors' responses to issuer- and investor-paid CRA announcements. They react by abnormally selling following EJR's negative signals and abnormally buying following issuer-paid CRAs' positive signals. The results differentiate my essay from the existing literature. Several prior studies show that institutional investors simply tend to be more sensitive to negative, rather than positive signals. The essay finds that institutional investors, as professional players, have their own responses to the lack of timeliness criticism by following investor-paid CRA's negative signals. They still maintain faith in positive issuer-paid rating announcements due to no evidence of their delays. The results are robust across different databases from which the institutional investors' trading activities were extracted. I also document that a dynamic trading strategy based on selling following the investor-paid CRAs' negative signals and buying following issuer-paid CRAs' positive signals produces superior returns. While any investor can take advantage of these strategies, institutional investors evidently achieve higher returns. I document highly dynamic behavior of institutions in responding to important market signals.

APPENDIX A

FOR ESSAY ONE

Appendix A.1: Numeric transformation of alphanumerical rating codes

Investment grade		Speculative grade		Credit events[18]	
Rating	Score	Rating	Score		Score
AAA (Aaa)	22	BB+ (Ba1)	12	Single upgrade	1
AA+ (Aa1)	21	BB (Ba2)	11	Positive outlook	0.5
AA (Aa2)	20	BB- (Ba3)	10	Positive developing	0.25
AA- (Aa3)	19	B+ (B1)	9	Stable	0
A+ (A1)	18	B (B2)	8	Negative developing	-0.25
A (A2)	17	B- (B3)	7	Negative outlook	-0.5
A- (A3)	16	CCC+ (Caa1)	6	Single downgrade	-1
BBB+ (Baa1)	15	CCC (Caa2)	5		
BBB (Baa2)	14	CCC- (Caa3)	4		
BBB- (Baa3)	13	CC (Ca)	3		
		C	2		
		SD, D	1		

[18] Single upgrade (downgrade) is a credit rating announcement when a rating agency adjusts the firm's credit rating by one letter rating higher (lower) (e.g., up from AA+ to AAA or down from AA+ to AA). A positive (negative) outlook is a credit rating review when a CRA adjusts its short-term expectations about the firm from being stable to positive (negative). A positive (negative) developing is a credit rating signal when a CRA adjusts its long-term expectations about the firm from being stable to positive (negative).

Appendix A.2: Variable definitions and data sources

Variable	Description	Data source
Panel A: Dependent variables		
nb	Institutional net buy measured as the dollar volume of shares purchased by an institutional investor minus the dollar volume of shares sold by that investor, scaled by one-month lagged market capitalization of the stock.	ANCERNO
NB	Abnormal institutional net buy measured as the difference between an institutional net buy on day *t* minus the average institutional net buy over the past 365 days.	ANCERNO
Panel B: Independent variables		
POS	A binary variable that equals one when there is a positive change in comprehensive credit rating and zero otherwise (see more in Appendix A).	Bloomberg & Egan-Jones Ratings
NEG	A binary variable that equals one when there is a negative change in comprehensive credit rating and zero otherwise (see more in Appendix A).	Bloomberg & Egan-Jones Ratings
EJR	A binary variable that takes a value of one if EJR announces a rating adjustment and zero if the rating adjustment comes from issuer-paid CRAs.	Egan-Jones Ratings
Panel C: Control variables		
ROA	The ratio of operating income before depreciation to total assets in the quarter.	COMPUSTAT
Z-SCORE	Alman's Z-score that represents the probability that a firm will go into bankruptcy within two years.	COMPUSTAT
ANALYST_COVERAGE	The average number of analysts covering a firm in the quarter.	CRSP
INTEREST_COVERAGE	The ratio of earnings before interest, tax, and depreciation and amortization to total interest expense in the quarter.	COMPUSTAT
Ln (MV)	The natural log of total market capitalization in the quarter.	CRSP
Ln (AGE)	The natural log of number of years since a firm's first appearance on CRSP database.	CRSP
HIGH_TECH	A binary variable that equals one if a firm's SIC code is between 7370 and 7379 (Herron and Lie, 2009) and zero otherwise.	CRSP
S&P_500	A binary variable that equals one if a firm is included in the S&P 500 list.	S&P 500 Down Jones Index
LEVERAGE	The ratio of sum of long-term debt and debt in current liabilities to total assets in the quarter.	COMPUSTAT
IDIO_RISK	The standard deviation of residual returns from the Fama-French 3-factor model using daily stock returns from day *t* - 31 to day *t* -1.	Kenneth R. French (Data Library) & CRSP

Table A.3: Mutual fund (12F) and institutional investor (13F)' abnormal responses to credit rating adjustments in the sub-period 1999-2011

	Panel A: Mutual Fund (12F) Holdings					
	EJR vs. S&P		EJR vs. Moody's		EJR vs. Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1102***	-0.0977***	0.3037***	-0.3204***	0.1340***	-0.4467***
	(0.0123)	(0.0302)	(0.0657)	(0.0972)	(0.0204)	(0.0581)
NEG	0.0074	-0.0021	0.008	0.0312	0.0208**	0.0274**
	(0.0052)	(0.0061)	(0.014)	(0.0483)	(0.009)	(0.0139)
POS	0.0215**	0.0424***	0.0222**	0.0256**	0.0341***	0.0811***
	(0.0100)	(0.0104)	(0.0115)	(0.0105)	(0.0107)	(0.0165)
EJR×NEG	-0.0183**	-0.0203**	-0.0536**	-0.0678***	-0.0189	-0.0192
	(0.0084)	(0.0097)	(0.0208)	(0.0191)	(0.0132)	(0.0145)
EJR×POS	-0.0254**	-0.0460**	-0.0223	-0.0234	-0.0424***	-0.0887***
	(0.0107)	(0.022)	(0.0203)	(0.0351)	(0.0128)	(0.0181)
EJR	-0.2208***	-0.2215**	-0.4706***	-0.6701***	-0.2848***	-0.2842***
	(0.0074)	(0.0099)	(0.0867)	(0.080)	(0.0144)	(0.0145)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	-0.0109**	-0.0224***	-0.0456***	-0.0366***	0.0019	0.0082
	(0.0054)	(0.008)	(0.0094)	(0.0108)	(0.0061)	(0.0087)
POS + EJR×POS	-0.0039	-0.0036	-0.0001	0.0022	-0.0083	-0.0076
	(0.0057)	(0.0078)	(0.0072)	(0.0083)	(0.0065)	(0.0083)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,782,891	2,116,430	853,272	681,243	1,634,043	1,283,992
R-squared	0.002	0.002	0.004	0.002	0.002	0.002

	Panel B: Institutional (13F) Holdings					
	EJR vs. S&P		EJR vs. Moody's		EJR vs. Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.5349***	1.0178***	2.1203***	2.3210***	0.1902***	-1.1282***
	(0.0848)	(0.1136)	(0.2034)	(0.4031)	(0.0402)	(0.2178)
NEG	-0.0158	-0.0534***	0.0203	0.0401	-0.0278	0.0786**
	(0.0209)	(0.0157)	(0.0627)	(0.0843)	(0.0401)	(0.0334)
POS	0.0421**	0.0602**	0.0934***	0.0701***	0.0789**	0.0891**
	(0.0191)	(0.0284)	(0.0302)	(0.0202)	(0.0352)	(0.0434)
EJR×NEG	-0.1645***	-0.1245***	-0.2106***	-0.2307***	-0.0079	-0.0724
	(0.036)	(0.0405)	(0.0675)	(0.0702)	(0.0301)	(0.0387)

EJR×POS	-0.0371	-0.0502	-0.0876***	-0.0803***	-0.1032***	-0.1065**
	(0.035)	(0.0603)	(0.0176)	(0.0180)	(0.0290)	(0.0565)
EJR	-0.6665***	-1.1243***	-2.0234***	-1.9012***	-0.2302***	-0.2104***
	(0.0382)	(0.0442)	(0.0571)	(0.304)	(0.0236)	(0.0336)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	-0.1487***	-0.1779***	-0.1903***	-0.1906***	-0.0357**	0.0062
	(0.0145)	(0.0194)	(0.0502)	(0.0401)	(0.0147)	(0.0134)
POS + EJR×POS	0.0005	0.0100	0.0058	-0.0102	-0.0243	-0.0174
	(0.0365)	(0.0128)	(0.0112)	(0.0201)	(0.0183)	(0.0203)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,003,348	2,305,891	801,231	798,211	1,901,010	1,401,907
R-squared	0.001	0.001	0.002	0.002	0.001	0.001

The table reports OLS regression results on mutual fund (12F) and institutional investor (13F) abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panel A reports the results for mutual fund (12F) holding changes. Panel B reports the results for institutional investor (13F) holding changes. For each panel, I separately consider three pairs: institutional abnormal responses to (1) EJR vs. S&P, (2) EJR vs. Moody's and (3) EJR vs. Fitch. The dependent variable is the abnormal net buy of a mutual fund or an institutional investor in a quarter. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for quarterly rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.4: Mutual fund (12F) and institutional investor (13F)' abnormal responses to credit rating adjustments in the sub-period 2012-2017

Panel A: Mutual Fund (12F) Holdings						
	EJR vs. S&P		EJR vs. Moody's		EJR vs. Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.1340***	-0.0891***	0.4035***	-0.3709***	0.2012***	-0.3267***
	(0.0232)	(0.0262)	(0.0778)	(0.0772)	(0.0353)	(0.0667)
NEG	0.0089	-0.0090	0.009	0.0489	0.0218**	0.0282**
	(0.0069)	(0.0071)	(0.024)	(0.0467)	(0.0087)	(0.0129)
POS	0.0341**	0.0524***	0.0329**	0.0389***	0.0443***	0.0602***
	(0.0140)	(0.0134)	(0.0155)	(0.0125)	(0.0147)	(0.0165)
EJR×NEG	-0.0235**	-0.0303**	-0.0546**	-0.0848***	-0.0283	-0.0292**
	(0.0104)	(0.0094)	(0.0268)	(0.0231)	(0.0232)	(0.0145)
EJR×POS	-0.0284**	-0.0540**	-0.0283	-0.0324	-0.0428***	-0.0784***
	(0.0147)	(0.024)	(0.0233)	(0.0381)	(0.0158)	(0.0280)
EJR	-0.1906***	-0.3212**	-0.4602***	-0.6501***	-0.3848***	-0.2441***
	(0.0172)	(0.0123)	(0.0982)	(0.180)	(0.0164)	(0.0045)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	-0.0146**	-0.0393***	-0.0456***	-0.0359***	-0.0065	-0.001
	(0.0062)	(0.0102)	(0.0072)	(0.0118)	(0.0071)	(0.0054)
POS + EJR×POS	0.0057	-0.0016	0.0046	0.0065	0.0015	-0.0182
	(0.0082)	(0.0068)	(0.0087)	(0.0081)	(0.0075)	(0.0133)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	800,101	692,241	419,993	397,988	657,358	432,972
R-squared	0.002	0.002	0.004	0.002	0.002	0.002

Panel B: Institutional (13F) Holdings						
	EJR vs. S&P		EJR vs. Moody's		EJR vs. Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.6213***	0.9458***	1.4233***	1.4218***	0.1842***	-1.1387***
	(0.0756)	(0.2235)	(0.4132)	(0.3837)	(0.0302)	(0.3002)
NEG	-0.0172	-0.0431***	0.0223	0.0702	-0.0245	0.0882**
	(0.0309)	(0.0137)	(0.0724)	(0.0643)	(0.0301)	(0.0374)
POS	0.0532***	0.0702**	0.0831***	0.0823***	0.0809**	0.0791**
	(0.0091)	(0.0205)	(0.0242)	(0.0301)	(0.0372)	(0.0404)
EJR×NEG	-0.1542***	-0.1145***	-0.2208***	-0.2217***	-0.0087	-0.0801
	(0.0353)	(0.0365)	(0.0755)	(0.0622)	(0.0401)	(0.0787)

EJR×POS	-0.0476	-0.0602	-0.0866***	-0.0833***	-0.0967***	-0.0865**
	(0.035)	(0.0703)	(0.0216)	(0.0280)	(0.0392)	(0.0385)
EJR	-0.4765***	-0.9263***	-1.0204***	-1.8342***	-0.1802***	-0.1104***
	(0.0382)	(0.0542)	(0.0681)	(0.451)	(0.0437)	(0.0436)
Control variables:	No	Yes	No	Yes	No	Yes
F-tests:						
NEG + EJR×NEG	-0.1714***	-0.1576***	-0.1980***	-0.1515***	-0.0332**	0.0081
	(0.0345)	(0.0301)	(0.0671)	(0.0207)	(0.0157)	(0.0234)
POS + EJR×POS	0.0056	0.0100	-0.0035	-0.001	-0.0158	-0.0074
	(0.0456)	(0.0131)	(0.0213)	(0.0301)	(0.0173)	(0.0253)
Fixed effects:						
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,085,355	874,478	480,630	286,414	828,368	638,927
R-squared	0.003	0.002	0.002	0.002	0.002	0.002

The table reports OLS regression results on mutual fund (12F) and institutional investor (13F) abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panel A reports the results for mutual fund (12F) holding changes. Panel B reports the results for institutional investor (13F) holding changes. For each panel, I separately consider three pairs: institutional abnormal responses to (1) EJR vs. S&P, (2) EJR vs. Moody's and (3) EJR vs. Fitch. The dependent variable is the abnormal net buy of a mutual fund or an institutional investor in a quarter. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for quarterly rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.5 Institutional investor's abnormal responses to credit rating adjustments in the [-2, 1] day window

	Panel A: EJR vs. S&P			
	(1)	(2)	(3)	(4)
Intercept	-0.0874	0.2957	-0.4133	-0.3282
	(1.7617)	(1.8048)	(2.0322)	(2.0329)
NEG	0.0163	0.0158	0.0351	0.0329
	(0.0210)	(0.0227)	(0.0352)	(0.0354)
POS	0.0408*	0.1305***	0.1340***	0.1338***
	(0.0235)	(0.0253)	(0.0433)	(0.0433)
EJR×NEG	-0.0720***	-0.0602**	-0.1057**	-0.1041**
	(0.0265)	(0.0275)	(0.0415)	(0.0415)
EJR×POS	-0.0469	-0.0989***	-0.1215**	-0.1211**
	(0.0288)	(0.0305)	(0.0490)	(0.0491)
EJR	0.1189***	0.0913***	0.1539***	0.1488***
	(0.0293)	(0.0311)	(0.0427)	(0.0428)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0556***	-0.0445**	-0.0706***	-0.0712***
	(0.0168)	(0.0179)	(0.0237)	(0.0237)
POS + EJR×POS	-0.0061	0.0316*	0.0126	0.0127
	(0.0169)	(0.0184)	(0.0236)	(0.0236)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	421,853	421,853	299,630	299,612
Adj. R-squared	0.003	0.009	0.004	0.004
	Panel B: EJR vs. Moody's			
	(1)	(2)	(3)	(4)
Intercept	-0.4401	-0.4411	-0.4864	-0.1786
	(5.1465)	(5.1565)	(5.0251)	(5.0287)
NEG	0.1295	-0.0191	0.0442	0.0455
	(0.0926)	(0.0994)	(0.1143)	(0.1145)
POS	0.4132***	0.2574**	0.3681***	0.3645***
	(0.1063)	(0.1131)	(0.1215)	(0.1218)
EJR×NEG	-0.2809***	-0.1117	-0.2326**	-0.2358**
	(0.0987)	(0.1037)	(0.1179)	(0.1181)
EJR×POS	-0.4109***	-0.2033*	-0.4199***	-0.4172***
	(0.1129)	(0.119)	(0.1299)	(0.1301)
EJR	0.4389***	0.2256**	0.4286***	0.4232***
	(0.0997)	(0.1061)	(0.1121)	(0.1125)
Control variables:	No	No	Yes	Yes

F-tests:				
NEG + EJR×NEG	-0.1515***	-0.1307***	-0.1884***	-0.1903***
	(0.0381)	(0.0405)	(0.0430)	(0.0430)
POS + EJR×POS	0.0022	0.0542	-0.0518	-0.0527
	(0.0399)	(0.0428)	(0.0460)	(0.0460)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	112,075	112,075	92,117	92,102
Adj. R-squared	0.008	0.015	0.008	0.008
Panel C: EJR vs. Fitch				
	(1)	(2)	(3)	(4)
Intercept	-0.0167	0.7738	-0.3291	-0.2532
	(1.6756)	(1.7106)	(1.9228)	(1.9247)
NEG	-0.0015	0.0035	-0.023	-0.0253
	(0.0198)	(0.0205)	(0.0407)	(0.0408)
POS	0.0107	0.0342	0.0286	0.0229
	(0.0288)	(0.031)	(0.0647)	(0.0649)
EJR×NEG	-0.008	-0.0014	-0.0041	-0.0012
	(0.03)	(0.0309)	(0.0519)	(0.0519)
EJR×POS	-0.029	-0.0292	-0.0676	-0.0613
	(0.0372)	(0.039)	(0.0736)	(0.0738)
EJR	0.0343	0.0122	0.0359	0.0294
	(0.0407)	(0.0435)	(0.0675)	(0.0677)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0095	0.0021	-0.0271	-0.0265
	(0.0234)	(0.0248)	(0.0338)	(0.0339)
POS + EJR×POS	-0.0183	0.0049	-0.039	-0.0385
	(0.0234)	(0.0253)	(0.0361)	(0.0362)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	204,198	204,198	131,772	131,744
Adj. R-squared	0.004	0.006	0.006	0.006

The table reports OLS regression results on institutional investors' abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panels A, B, and C report the results for rating changes by EJR and S&P, EJR and Moody's, and EJR and Fitch, respectively. In all panels, the dependent variable is the abnormal institutional net buy as calculated in Eq. (2.2) in the main text. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.6 Institutional investor's abnormal responses to credit rating adjustments in the [-2, 5] day window

	Panel A: EJR vs. S&P			
	(1)	(2)	(3)	(4)
Intercept	-0.1008	0.2601	-0.5815	-0.5380
	(2.0714)	(2.1399)	(2.5448)	(2.546)
NEG	0.0345	0.0330	0.0528	0.0483
	(0.0288)	(0.031)	(0.0481)	(0.0482)
POS	0.1055***	0.2240***	0.2045***	0.2054***
	(0.0322)	(0.0348)	(0.0588)	(0.0588)
EJR×NEG	-0.1038***	-0.0980***	-0.1302**	-0.1271**
	(0.0362)	(0.0376)	(0.0565)	(0.0566)
EJR×POS	-0.1288***	-0.1970***	-0.1771***	-0.1770***
	(0.0395)	(0.0418)	(0.0666)	(0.0666)
EJR	0.1631***	0.1326***	0.1673***	0.1627***
	(0.0402)	(0.0425)	(0.0582)	(0.0583)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0692***	-0.0650***	-0.0774**	-0.0788**
	(0.0229)	(0.0243)	(0.0322)	(0.0322)
POS + EJR×POS	-0.0233	0.0270	0.0275	0.0284
	(0.0231)	(0.0251)	(0.0321)	(0.0321)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	434,476	434,476	308,204	308,186
Adj. R-squared	0.003	0.009	0.004	0.004
	Panel B: EJR vs. Moody's			
	(1)	(2)	(3)	(4)
Intercept	-0.4765	-0.4537	-0.6339	-0.2980
	(5.7659)	(5.7907)	(5.5522)	(5.5582)
NEG	0.2469**	0.0558	0.0590	0.0491
	(0.1249)	(0.1341)	(0.1520)	(0.1523)
POS	0.6643***	0.4404***	0.5460***	0.5300***
	(0.1435)	(0.1526)	(0.1619)	(0.1623)
EJR×NEG	-0.4154***	-0.1967	-0.2691*	-0.2601*
	(0.1332)	(0.1399)	(0.1568)	(0.1571)
EJR×POS	-0.6961***	-0.3999**	-0.6146***	-0.5971***
	(0.1524)	(0.1606)	(0.1729)	(0.1733)
EJR	0.5921***	0.3059**	0.5024***	0.4801***
	(0.1346)	(0.1432)	(0.1492)	(0.1498)

Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.1685***	-0.1409***	-0.2102***	-0.2110***
	(0.0512)	(0.0544)	(0.0569)	(0.0569)
POS + EJR×POS	-0.0318	0.0404	-0.0686	-0.0671
	(0.0536)	(0.0576)	(0.061)	(0.0611)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	115,805	115,805	94,973	94,955
Adj. R-squared	0.009	0.015	0.009	0.009
Panel C: EJR vs. Fitch				
	(1)	(2)	(3)	(4)
Intercept	-0.0521	0.7563	-0.4721	-0.4792
	(2.0614)	(2.1112)	(2.4670)	(2.4697)
NEG	0.0135	0.0229	-0.0025	-0.0063
	(0.0264)	(0.0274)	(0.0546)	(0.0547)
POS	0.0274	0.0776*	0.0682	0.0661
	(0.0385)	(0.0415)	(0.0865)	(0.0868)
EJR×NEG	-0.0321	-0.0299	-0.0299	-0.0282
	(0.0397)	(0.041)	(0.0694)	(0.0695)
EJR×POS	-0.0295	-0.0389	-0.0766	-0.0738
	(0.0495)	(0.052)	(0.0984)	(0.0986)
EJR	0.078	0.0628	0.0539	0.0507
	(0.0541)	(0.0578)	(0.0902)	(0.0904)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0186	-0.0070	-0.0324	-0.0346
	(0.0308)	(0.0327)	(0.0451)	(0.0452)
POS + EJR×POS	-0.0020	0.0387	-0.0084	-0.0077
	(0.0311)	(0.0335)	(0.0481)	(0.0482)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	209,891	209,891	135,202	135,163
Adj. R-squared	0.004	0.006	0.008	0.008

The table reports OLS regression results on institutional investors' abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panels A, B, and C report the results for rating changes by EJR and S&P, EJR and Moody's, and EJR and Fitch, respectively. In all panels, the dependent variable is the abnormal institutional net buy as calculated in Eq. (2.2) in the main text. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.7 Institutional investor's unadjusted responses to credit rating adjustments in the [0, 5] day window

Panel A: EJR vs. S&P				
	(1)	(2)	(3)	(4)
Intercept	-0.1116	0.3021	-0.3720	-0.3095
	(1.7629)	(1.8213)	(2.1348)	(2.1358)
NEG	0.0435*	0.0407	0.0459	0.0408
	(0.0246)	(0.0266)	(0.0405)	(0.0406)
POS	0.1369***	0.2455***	0.1680***	0.1707***
	(0.0277)	(0.0299)	(0.0496)	(0.0496)
EJR×NEG	-0.1067***	-0.1026***	-0.1229***	-0.1188**
	(0.0310)	(0.0322)	(0.0476)	(0.0477)
EJR×POS	-0.1547***	-0.2150***	-0.1291**	-0.1302**
	(0.0340)	(0.0359)	(0.0562)	(0.0562)
EJR	0.1690***	0.1413***	0.1420***	0.1374***
	(0.0344)	(0.0365)	(0.0491)	(0.0491)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0631***	-0.0619***	-0.0771***	-0.0780***
	(0.0196)	(0.0208)	(0.0272)	(0.0272)
POS + EJR×POS	-0.0179	0.0305	0.0390	0.0405
	(0.0198)	(0.0215)	(0.0271)	(0.0271)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	429,268	429,268	304,746	304,731
Adj. R-squared	0.003	0.010	0.004	0.004
Panel B: EJR vs. Moody's				
	(1)	(2)	(3)	(4)
Intercept	-0.4459	-0.3153	-0.6165	-0.4635
	(4.9319)	(4.9506)	(4.7200)	(4.7251)
NEG	0.2631**	0.0619	0.0753	0.0619
	(0.1075)	(0.1153)	(0.1299)	(0.1302)
POS	0.5689***	0.3338**	0.4355***	0.4203***
	(0.1240)	(0.1319)	(0.1384)	(0.1387)
EJR×NEG	-0.4116***	-0.1805	-0.2544*	-0.2406*
	(0.1146)	(0.1203)	(0.1340)	(0.1342)
EJR×POS	-0.6037***	-0.2841**	-0.4809***	-0.4629***
	(0.1316)	(0.1387)	(0.1478)	(0.1481)
EJR	0.5630***	0.2550**	0.4359***	0.4135***
	(0.1160)	(0.1234)	(0.1276)	(0.1281)

Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.1485***	-0.1186**	-0.1791***	-0.1786***
	(0.0440)	(0.0468)	(0.0486)	(0.0487)
POS + EJR×POS	-0.0348	0.0497	-0.0454	-0.0426
	(0.0462)	(0.0496)	(0.0523)	(0.0523)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	114,354	114,354	93,884	93,867
Adj. R-squared	0.009	0.016	0.010	0.010
Panel C: EJR vs. Fitch				
	(1)	(2)	(3)	(4)
Intercept	-0.0529	0.7921	-0.3139	-0.3464
	(1.7362)	(1.7784)	(2.0015)	(2.0035)
NEG	0.0170	0.0266	0.0248	0.0218
	(0.0224)	(0.0232)	(0.0448)	(0.0448)
POS	0.0126	0.0752**	0.0847	0.0836
	(0.0328)	(0.0353)	(0.0708)	(0.0711)
EJR×NEG	-0.0327	-0.0328	-0.0670	-0.0658
	(0.0337)	(0.0348)	(0.0567)	(0.0568)
EJR×POS	0.0176	0.0014	-0.0399	-0.0381
	(0.0421)	(0.0442)	(0.0805)	(0.0807)
EJR	0.0713	0.0590	0.0808	0.0795
	(0.0458)	(0.0490)	(0.0737)	(0.0738)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0157	-0.0063	-0.0422	-0.0439
	(0.0263)	(0.0278)	(0.0367)	(0.0369)
POS + EJR×POS	0.0302	0.0765***	0.0449	0.0455
	(0.0263)	(0.0284)	(0.0393)	(0.0393)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	207,587	207,587	133,824	133,788
Adj. R-squared	0.004	0.006	0.009	0.009

The table reports OLS regression results on institutional investors' 'raw' responses to credit rating adjustments announced by EJR and issuer-paid CRAs. Panels A, B, and C report the results for rating changes by EJR and S&P, EJR and Moody's, and EJR and Fitch, respectively. In all panels, the dependent variable is the institutional net buy unadjusted for the average net buy over the previous year. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.8 Institutional investors' abnormal responses to credit rating adjustments issued by EJR and the 'Big issuer-paid CRA' in the [0, 5] day window

	(1)	(2)	(3)	(4)
Intercept	-0.0902	-0.0012	-0.6348	-0.5566
	(1.5891)	(1.6269)	(1.8786)	(1.8796)
NEG	0.0460***	0.0339*	0.0563*	0.0523*
	(0.0172)	(0.0183)	(0.0298)	(0.0299)
POS	0.1133***	0.1771***	0.1730***	0.1718***
	(0.0217)	(0.0232)	(0.0388)	(0.0388)
EJR×NEG	-0.1043***	-0.0843***	-0.1273***	-0.1234***
	(0.0255)	(0.0262)	(0.0386)	(0.0386)
EJR×POS	-0.1336***	-0.1416***	-0.1370***	-0.1349***
	(0.0292)	(0.0307)	(0.0466)	(0.0466)
EJR	0.1587***	0.1064***	0.1476***	0.1416***
	(0.0298)	(0.0315)	(0.0419)	(0.0419)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0583***	-0.0505**	-0.0711***	-0.0711***
	(0.0194)	(0.0205)	(0.0261)	(0.0262)
POS + EJR×POS	-0.0203	0.0355*	0.0360	0.0369
	(0.0198)	(0.0213)	(0.0263)	(0.0263)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	527,139	527,139	368,827	368,759
Adj. R-squared	0.003	0.010	0.004	0.004

The table reports OLS regression results on institutional investors' abnormal responses to credit rating adjustments announced by EJR and a 'Big issuer-paid CRA' constructed by S&P, Moody's, and Fitch. Panels A, B, and C report the results for rating changes by EJR and S&P, EJR and Moody's, and EJR and Fitch, respectively. In all panels, the dependent variable is the abnormal institutional net buy as calculated in Eq. (2.2) in the main text. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.9 Institutional investors' abnormal responses to credit rating adjustments in the [0, 5] day window (excluding non-trading observations)

	Panel A: EJR vs. S&P			
	(1)	(2)	(3)	(4)
Intercept	-0.3713	0.2232	-1.6952	-1.6456
	(5.5681)	(5.6759)	(8.5235)	(8.5253)
NEG	0.1730**	0.0884	0.1750	0.1568
	(0.0702)	(0.0760)	(0.1210)	(0.1214)
POS	0.5472***	0.6054***	0.4847***	0.4971***
	(0.0973)	(0.1060)	(0.1476)	(0.1477)
EJR×NEG	-0.3196***	-0.2090**	-0.3411**	-0.3267**
	(0.0867)	(0.0904)	(0.1406)	(0.1408)
EJR×POS	-0.6018***	-0.5122***	-0.3472**	-0.3533**
	(0.1119)	(0.1196)	(0.1661)	(0.1662)
EJR	0.5478***	0.3059***	0.3663**	0.3541**
	(0.1003)	(0.1065)	(0.1438)	(0.1440)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.1466***	-0.1206**	-0.1661**	-0.1699**
	(0.0529)	(0.0564)	(0.0775)	(0.0776)
POS + EJR×POS	-0.0546	0.0931	0.1375*	0.1438*
	(0.0563)	(0.0611)	(0.0783)	(0.0784)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	151,066	151,066	105,678	105,666
Adj. R-squared	0.006	0.024	0.009	0.010
	Panel B: EJR vs. Moody's			
	(1)	(2)	(3)	(4)
Intercept	-1.2735	-1.5313	-2.6004	-1.908
	(14.6861)	(14.7313)	(14.1048)	(14.1235)
NEG	0.8316**	0.2185	0.4250	0.3990
	(0.3553)	(0.3823)	(0.4393)	(0.4410)
POS	1.6713***	0.8928**	1.2669***	1.2287***
	(0.3889)	(0.4135)	(0.4448)	(0.4459)
EJR×NEG	-1.1968***	-0.4655	-0.8366*	-0.8127*
	(0.3739)	(0.3969)	(0.4498)	(0.4516)
EJR×POS	-1.7560***	-0.7468*	-1.3572***	-1.3122***
	(0.4085)	(0.4310)	(0.4687)	(0.4699)
EJR	1.6151***	0.6194	1.2514***	1.1935***
	(0.3562)	(0.3795)	(0.4007)	(0.4024)

Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.3652***	-0.2470*	-0.4116***	-0.4137***
	(0.1313)	(0.1393)	(0.1428)	(0.1429)
POS + EJR×POS	-0.0847	0.1461	-0.0903	-0.0836
	(0.1335)	(0.1441)	(0.1493)	(0.1495)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	38,783	38,783	31,686	31,673
Adj. R-squared	0.021	0.038	0.021	0.021
Panel C: EJR vs. Fitch				
	(1)	(2)	(3)	(4)
Intercept	-0.1923	3.4293	-1.1719	-1.2749
	(7.0526)	(7.1486)	(10.5013)	(10.5063)
NEG	0.0419	0.0306	0.1014	0.0924
	(0.0538)	(0.0562)	(0.1116)	(0.1118)
POS	0.0199	0.0127	0.2382	0.2367
	(0.1025)	(0.109)	(0.1917)	(0.1924)
EJR×NEG	-0.0879	-0.0527	-0.2419	-0.2376
	(0.0849)	(0.0877)	(0.1498)	(0.1500)
EJR×POS	0.0435	0.1285	-0.1499	-0.1460
	(0.1257)	(0.1311)	(0.221)	(0.2215)
EJR	0.1895	0.0418	0.2674	0.2623
	(0.1258)	(0.1350)	(0.1991)	(0.1994)
Control variables:	No	No	Yes	Yes
F-tests:				
NEG + EJR×NEG	-0.0460	-0.0221	-0.1405	-0.1452
	(0.0685)	(0.0732)	(0.1049)	(0.1052)
POS + EJR×POS	0.0634	0.1412*	0.0883	0.0907
	(0.0728)	(0.0782)	(0.1129)	(0.1130)
Fixed effects:				
Investor FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
Quarter FE	Yes	Yes	Yes	Yes
N Observations	75,911	75,911	48,259	48,230
Adj. R-squared	0.009	0.016	0.021	0.021

The table reports OLS regression results on institutional investors' abnormal responses to credit rating adjustments announced by EJR and issuer-paid CRAs after excluding non-trading observations by institutional investors. Panels A, B, and C report the results for rating changes by EJR and S&P, EJR and Moody's, and EJR and Fitch, respectively. In all panels, the dependent variable is the abnormal institutional net buy as calculated in Eq. (2.2) in the main text. *EJR* is an indicator variable equal to one for EJR's rating announcements and zero otherwise. *NEG* (*POS*) is equal to one for rating downgrades (upgrades) and zero otherwise. All control variables are defined in Appendix A.2. F-tests account for firm- and quarter-fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and quarter levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.10 Institutional strategy profitability in the [-2, 1] day window

Panel A: Equal-weighted average risk-adjusted returns					
Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.1891***	0.1703***	0.1335***	0.1082***	0.0369
	(0.0349)	(0.0239)	(0.0273)	(0.0322)	(0.065)
(2) Naïve strategy	0.0971***	0.0843***	0.0595***	0.0441	0.0277
	(0.0333)	(0.0276)	(0.016)	(0.0279)	(0.0539)
(3) EJR follower	0.1022***	0.0858***	0.059***	0.0218	0.025
	(0.0162)	(0.0156)	(0.0141)	(0.0195)	(0.0862)
(4) Issuer-paid CRA follower	0.0895***	0.0825***	0.0603*	0.0479	0.0531
	(0.0297)	(0.0257)	(0.0312)	(0.0346)	(0.0613)
(5) B-H of a S&P500 index	-0.0163	-0.0163	-0.0163	-0.0163	-0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)
Difference (1) - (2)	0.092*	0.086**	0.074***	0.0641**	0.0092
	(0.0482)	(0.0365)	(0.021)	(0.0322)	(0.0629)
Difference (1) - (3)	0.0869**	0.0844***	0.0744***	0.0865***	0.0119
	(0.0385)	(0.0286)	(0.023)	(0.029)	(0.108)
Difference (1) - (4)	0.0996***	0.0877***	0.0731**	0.0603*	-0.0162
	(0.0319)	(0.0269)	(0.033)	(0.0363)	(0.0694)
Difference (1) - (5)	0.2054***	0.1866***	0.1498***	0.1245***	0.0532
	(0.0354)	(0.0245)	(0.0275)	(0.0323)	(0.0651)
Difference (2) - (5)	0.1134***	0.1006***	0.0758***	0.0604**	0.044
	(0.0339)	(0.0281)	(0.0161)	(0.0279)	(0.0539)
Difference (3) - (5)	0.1185***	0.1021***	0.0753***	0.0381*	0.0413
	(0.0174)	(0.0164)	(0.0143)	(0.0196)	(0.0863)
Difference (4) - (5)	0.1058**	0.0989**	0.0766	0.0642	0.0694
	(0.0447)	(0.0386)	(0.052)	(0.0693)	(0.0818)

Panel B: Volume-weighted average risk-adjusted returns					
Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.204***	0.1768***	0.1132***	0.0865***	0.0616
	(0.0348)	(0.0239)	(0.0273)	(0.0322)	(0.0535)
(2) Naïve strategy	0.1197***	0.0888***	0.0543***	0.0449*	0.0298
	(0.0333)	(0.0276)	(0.0158)	(0.0273)	(0.0567)
(3) EJR follower	0.1244***	0.0942***	0.05***	0.0309	0.0268
	(0.0162)	(0.0156)	(0.0142)	(0.0193)	(0.0992)
(4) Issuer-paid CRA follower	0.1125***	0.0792***	0.06*	0.059*	0.0397
	(0.0297)	(0.0256)	(0.0311)	(0.0345)	(0.0611)
(5) B-H of a S&P500 index	-0.0163	-0.0163	-0.0163	-0.0163	-0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)

Difference (1) - (2)	0.0844*	0.088**	0.0589***	0.0416	0.0319
	(0.0481)	(0.0365)	(0.0209)	(0.0317)	(0.0627)
Difference (1) - (3)	0.0796**	0.0826***	0.0632***	0.0557*	0.0348
	(0.0384)	(0.0286)	(0.0231)	(0.0289)	(0.1127)
Difference (1) - (4)	0.0915***	0.0976***	0.0532	0.0275	0.0219
	(0.0319)	(0.0269)	(0.033)	(0.0362)	(0.0667)
Difference (1) - (5)	0.2203***	0.1931***	0.1295***	0.1028***	0.0779
	(0.0354)	(0.0245)	(0.0275)	(0.0323)	(0.0536)
Difference (2) - (5)	0.136***	0.1052***	0.0256	0.0612**	0.0461
	(0.0338)	(0.0281)	(0.016)	(0.0273)	(0.0567)
Difference (3) - (5)	0.1407***	0.1105***	0.0663***	0.0472**	0.0431
	(0.0174)	(0.0165)	(0.0143)	(0.0194)	(0.0992)
Difference (4) - (5)	0.1288***	0.0955**	0.0763	0.0753	0.056
	(0.0447)	(0.0386)	(0.0519)	(0.0691)	(0.0815)

Table A.8 compares the performance of the dynamic trading strategy (i.e., my main interest) and other trading strategies based on institutional investors' actual responses in the window of [-2, 1] days surrounding credit rating adjustments announced by issuer- and investor-paid CRAs. These trading strategies include (1) 'dynamic strategy' – institutional investors net sell following EJR's negative rating signals and net buy following issuer-paid CRAs' positive rating signals, (2) 'naïve strategy' – institutional investors net sell following negative signals and net buy following positive signals from any rating agency, (3) 'EJR-based' – institutional investors net sell following negative signals and net buy following positive signals announced by EJR, (4) 'issuer-paid CRA-based' – institutional investors net sell following negative signals and net buy following any of the "Big Three" announcements. I also compare the four strategies to a passive buy-and-hold of the S&P 500 index. The trading strategy returns are adjusted for common risks by following Jagolinzer, Larcker, and Taylor (2011). The table reports two panels. Panel A is for equal-weighted average adjusted returns and panel B is for volume-weighted average adjusted returns. I consider different holding periods (i.e., 1, 3, 6, 9 and 12 months). All returns are annualized. Standard errors of the *t*-test for the mean and difference in means are in parentheses.

Table A.11 Institutional strategy profitability in the [-2, 5] day window

Panel A: Equall-weighted average risk-adjusted returns					
Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.1789***	0.1339***	0.0926***	0.0721**	0.0201
	(0.023)	(0.0186)	(0.0223)	(0.033)	(0.0548)
(2) Naïve strategy	0.0833***	0.0649**	0.0495***	0.0289	0.0158
	(0.0319)	(0.0267)	(0.013)	(0.0235)	(0.0457)
(3) EJR follower	0.0722***	0.061***	0.0566***	0.0299	0.0023
	(0.0118)	(0.0125)	(0.0114)	(0.022)	(0.0868)
(4) Issuer-paid CRA follower	0.0995***	0.068***	0.0435*	0.0281	0.0287
	(0.0299)	(0.0254)	(0.0259)	(0.0265)	(0.0464)
(5) B-H of a S&P500 index	-0.0163	-0.0163	-0.0163	-0.0163	-0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)
Difference (1) - (2)	0.0956**	0.069**	0.0431**	0.0432	0.0043
	(0.0393)	(0.0325)	(0.0171)	(0.0287)	(0.0533)
Difference (1) - (3)	0.1066***	0.073***	0.036*	0.0422	0.0178
	(0.0258)	(0.0224)	(0.0187)	(0.0311)	(0.1027)
Difference (1) - (4)	0.0794**	0.066**	0.0492*	0.044	-0.0086
	(0.0308)	(0.0262)	(0.0274)	(0.0287)	(0.0539)
Difference (1) - (5)	0.1952***	0.1502***	0.1089***	0.0884***	0.0364
	(0.0238)	(0.0193)	(0.0225)	(0.0332)	(0.0549)
Difference (2) - (5)	0.0996***	0.0812***	0.0658***	0.0452*	0.0321
	(0.0325)	(0.0272)	(0.013)	(0.0236)	(0.0458)
Difference (3) - (5)	0.0885***	0.0773***	0.0729***	0.0462**	0.0186
	(0.0133)	(0.0136)	(0.0116)	(0.0221)	(0.0868)
Difference (4) - (5)	0.1158**	0.0843**	0.0598	0.0444	0.045
	(0.0449)	(0.0382)	(0.0433)	(0.053)	(0.0619)
Panel B: Volume-weighted average risk-adjusted returns					
Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.1763***	0.1426***	0.0866***	0.0775**	0.033
	(0.0233)	(0.0187)	(0.0223)	(0.033)	(0.0495)
(2) Naïve strategy	0.0796**	0.0529**	0.051***	0.0247	0.0313
	(0.032)	(0.0268)	(0.0128)	(0.0225)	(0.0448)
(3) EJR follower	0.0772***	0.053***	0.0557***	0.0282	0.0404
	(0.012)	(0.0127)	(0.0114)	(0.0216)	(0.0907)
(4) Issuer-paid CRA follower	0.0988***	0.0503**	0.0438*	0.019	0.025
	(0.0298)	(0.0254)	(0.0259)	(0.0264)	(0.0462)
(5) B-H of a S&P500 index	-0.0163	-0.0163	-0.0163	-0.0163	-0.0163
	(0.0621)	(0.0621)	(0.0621)	(0.0621)	(0.0621)

Difference (1) - (2)	0.0968**	0.0897***	0.0356**	0.0528*	0.0017
	(0.0396)	(0.0327)	(0.017)	(0.0279)	(0.0511)
Difference (1) - (3)	0.0991***	0.0896***	0.0309*	0.0493	-0.0073
	(0.0263)	(0.0226)	(0.0187)	(0.0308)	(0.1033)
Difference (1) - (4)	0.0775**	0.0923***	0.0428	0.0585**	0.0081
	(0.0308)	(0.0262)	(0.0274)	(0.0286)	(0.0524)
Difference (1) - (5)	0.1926***	0.1589***	0.1029***	0.0938***	0.0493
	(0.0242)	(0.0194)	(0.0226)	(0.0331)	(0.0496)
Difference (2) - (5)	0.0959***	0.0692**	0.0673***	0.041*	0.0476
	(0.0326)	(0.0272)	(0.0129)	(0.0226)	(0.0448)
Difference (3) - (5)	0.0935***	0.0694***	0.072***	0.0445**	0.0567
	(0.0135)	(0.0137)	(0.0116)	(0.0217)	(0.0907)
Difference (4) - (5)	0.1151**	0.0666*	0.0601	0.0353	0.0413
	(0.0447)	(0.0382)	(0.0432)	(0.0528)	(0.0617)

Table A.9 compares the performance of the dynamic trading strategy (i.e., my main interest) and other trading strategies based on institutional investors' actual responses in the window of [-2, 5] days surrounding credit rating adjustments announced by issuer- and investor-paid CRAs. These trading strategies include (1) 'dynamic strategy' – institutional investors net sell following EJR's negative rating signals and net buy following issuer-paid CRAs' positive rating signals, (2) 'naïve strategy' – institutional investors net sell following negative signals and net buy following positive signals from any rating agency, (3) 'EJR-based' – institutional investors net sell following negative signals and net buy following positive signals announced by EJR, (4) 'issuer-paid CRA-based' – institutional investors net sell following negative signals and net buy following any of the "Big Three" announcements. I also compare the four strategies to a passive buy-and-hold of the S&P 500 index. The trading strategy returns are adjusted for common risks by following Jagolinzer, Larcker, and Taylor (2011). The table reports two panels. Panel A is for equal-weighted average adjusted returns and panel B is for volume-weighted average adjusted returns. I consider different holding periods (i.e., 1, 3, 6, 9 and 12 months). All returns are annualized. Standard errors of the *t*-test for the mean and difference in means are in parentheses.

Table A.12 Notional trading strategy profitability in the [-2, 1] day window.

Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.1095***	0.1027***	0.0863***	0.0682***	0.0265
	(0.0135)	(0.0106)	(0.0075)	(0.0148)	(0.0327)
(2) Naïve strategy	0.0477***	0.0486***	0.0438***	0.031***	0.0289
	(0.0093)	(0.006)	(0.0046)	(0.009)	(0.0207)
(3) EJR follower	0.069***	0.0485***	0.0439***	0.0298***	0.0056
	(0.0102)	(0.0049)	(0.0035)	(0.0028)	(0.0046)
(4) Issuer-paid CRA follower	0.0446***	0.049***	0.0421***	0.0342	0.0338
	(0.017)	(0.0124)	(0.0098)	(0.0217)	(0.048)
(5) B-H of a S&P500 index	0.0011	0.0011	0.0011	0.0011	0.0011
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Difference (1) - (2)	0.0618***	0.0541***	0.0425***	0.0371**	-0.0024
	(0.0164)	(0.0122)	(0.0088)	(0.0174)	(0.0387)
Difference (1) - (3)	0.0405**	0.0542***	0.0424***	0.0384**	0.0209
	(0.0169)	(0.0117)	(0.0083)	(0.0151)	(0.0331)
Difference (1) - (4)	0.0649***	0.0537***	0.0442***	0.034	-0.0073
	(0.0217)	(0.0163)	(0.0123)	(0.0263)	(0.0581)
Difference (1) - (5)	0.1084***	0.1016***	0.0852***	0.067***	0.0254
	(0.0135)	(0.0107)	(0.0076)	(0.0149)	(0.0328)
Difference (2) - (5)	0.0466***	0.0475***	0.0427***	0.0299***	0.0278
	(0.0093)	(0.0061)	(0.0047)	(0.0091)	(0.0207)
Difference (3) - (5)	0.0679***	0.0473***	0.0428***	0.0287***	0.0045
	(0.0102)	(0.0051)	(0.0037)	(0.0031)	(0.0048)
Difference (4) - (5)	0.0435**	0.0479***	0.041***	0.0331	0.0327
	(0.017)	(0.0125)	(0.0098)	(0.0217)	(0.048)

Table A.10 compares the performance of the dynamic trading strategy (i.e., my main interest) and other trading strategies based on market notional responses in the window of [-2, 1] days surrounding credit rating adjustments announced by issuer- and investor-paid CRAs. These trading strategies include (1) 'dynamic strategy' – selling following EJR's negative rating signals and buying following issuer-paid CRAs' positive rating signals, (2) 'naïve strategy' – selling following negative signals and buying following positive signals from any rating agency, (3) 'EJR-based' – selling following negative signals and buying following positive signals announced by EJR, (4) 'issuer-paid CRA-based' –selling following negative signals and buying following any of the "Big Three" announcements. I also compare the four strategies to a passive buy-and-hold of the S&P 500 index. The trading strategy returns are adjusted for common risks by following Jagolinzer, Larcker, and Taylor (2011). I consider different holding periods (i.e., 1, 3, 6, 9 and 12 months). All returns are annualized. Standard errors of the *t*-test for the mean and difference in means are in parentheses

Table A.13 Notional trading strategy profitability in the [-2, 5] day window

Holding periods	1 month	3 months	6 months	9 months	12 months
(1) Dynamic strategy	0.0951***	0.0757***	0.0339***	0.0385***	0.0249
	(0.0093)	(0.007)	(0.0051)	(0.0098)	(0.022)
(2) Naïve strategy	0.0702***	0.0496***	0.0105***	0.0199***	0.0001
	(0.0066)	(0.0041)	(0.0032)	(0.006)	(0.0137)
(3) EJR follower	0.0714***	0.0586***	0.0221***	0.0256***	0.0235***
	(0.0075)	(0.0036)	(0.0025)	(0.002)	(0.0033)
(4) Issuer-paid CRA follower	0.0685***	0.0427***	0.009	0.0183	-0.0132
	(0.0118)	(0.0083)	(0.0068)	(0.0143)	(0.0315)
(5) B-H of a S&P500 index	0.0011	0.0011	0.0011	0.0011	0.0011
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Difference (1) - (2)	0.0249**	0.0261***	0.0234***	0.0186	0.0248
	(0.0114)	(0.0081)	(0.006)	(0.0115)	(0.0259)
Difference (1) - (3)	0.0237**	0.0171**	0.0118**	0.0129	0.0014
	(0.012)	(0.0079)	(0.0057)	(0.01)	(0.0223)
Difference (1) - (4)	0.0266*	0.033***	0.0249***	0.0202	0.0381
	(0.015)	(0.0108)	(0.0085)	(0.0173)	(0.0384)
Difference (1) - (5)	0.094***	0.0746***	0.0328***	0.0374***	0.0238
	(0.0094)	(0.0071)	(0.0053)	(0.0098)	(0.022)
Difference (2) - (5)	0.069***	0.0485***	0.0094***	0.0188***	-0.001
	(0.0067)	(0.0043)	(0.0034)	(0.0061)	(0.0137)
Difference (3) - (5)	0.0703***	0.0575***	0.021***	0.0245***	0.0224***
	(0.0076)	(0.0038)	(0.0028)	(0.0024)	(0.0035)
Difference (4) - (5)	0.0674***	0.0415***	0.0079	0.0172	-0.0143
	(0.0118)	(0.0083)	(0.0069)	(0.0143)	(0.0315)

Table A.11 compares the performance of the dynamic trading strategy (i.e., my main interest) and other trading strategies based on market notional responses in the window of [-2, 5] days surrounding credit rating adjustments announced by issuer- and investor-paid CRAs. These trading strategies include (1) ‘dynamic strategy’ – selling following EJR’s negative rating signals and buying following issuer-paid CRAs’ positive rating signals, (2) ‘naïve strategy’ – selling following negative signals and buying following positive signals from any rating agency, (3) ‘EJR-based’ – selling following negative signals and buying following positive signals announced by EJR, (4) ‘issuer-paid CRA-based’ –selling following negative signals and buying following any of the “Big Three” announcements. I also compare the four strategies to a passive buy-and-hold of the S&P 500 index. The trading strategy returns are adjusted for common risks by following Jagolinzer, Larcker, and Taylor (2011). I consider different holding periods (i.e., 1, 3, 6, 9 and 12 months). All returns are annualized. Standard errors of the *t*-test for the mean and difference in means are in parentheses.

CHAPTER THREE

Politically Motivated Credit Ratings

ESSAY TWO

This chapter presents the second essay of this thesis. In general, second essay investigates whether credit ratings are impacted by political connections between CRAs and bond issuers. The chapter is organized as follows. Section 3.1 introduces the overview of second essay. Section 3.2 summarizes data collection, variable measurements, and summary statistics. Section 3.3 presents the methodology and empirical results. Robustness checks are presented in section 3.4. Section 3.5 concludes. The essay’s Appendix and References are shown at the end of this chapter and in the references section, respectively.

3.1. Introduction

Understanding credit rating properties is essential. Traditional issuer-paid CRAs have faced criticism regarding the lack of timeliness and accuracy of credit ratings following some high-profile credit events.[19] It is, therefore, important to understand which non-fundamental factors can potentially affect credit ratings.

The literature analysing rating timeliness and accuracy can be classified into three major strands. The first one focuses on CRAs' ability to access information as a factor that impacts rating timeliness and accuracy. Some examples are geographical distance between CRA's and firm's headquarters (Jaggi and Tang, 2017), media coverage of corporate information (Bonsall, Green, and Muller, 2018), personal connections between CRA's and firm's board members (Khatami, Marchica, and Mura, 2016). The second strand focuses on conflict of interest as another factor driving the quality of credit ratings. Such conflict may originate as a result of a business model (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Jiang, Stanford, and Xie, 2012; Cornaggia and Cornaggia, 2013; Baghai and Becker, 2018), conflicts of interest at the analyst level (Isaac and Shapiro, 2011; Cornaggia, Cornaggia, and Xia, 2016), in ownership structure (Kedia, Rajgopal, and Zhou, 2017), and the issuer's size (He, Qian, and Strahan, 2011; Efing and Hau, 2015). The third strand explores competition within the credit rating industry, namely, tendencies to delay negative signals and overestimate positive signals to their clients to gain market share (Güttler and Wahrenburg, 2007; Kisgen and Strahan, 2010; Becker and Milbourn, 2011; Bolton, Freixas, and Shapiro, 2012; Bongaerts, Cremers, and Goetzman, 2012; Kedia, Rajgopal, and Zhou, 2014; Goel and Thakor, 2015).

[19] These include Enron (2001), WorldCom (2002), and Lehman Brothers (2008). For example, on September 10, 2008 – the day Lehman Brothers announced its bankruptcy – S&P and Moody's had them rated at A2 and A respectively, only adjusting their credit ratings after the announcement.

Second essay contributes to the literature by analysing political connections between rating agencies and rated firms and the impact of those connections on credit ratings. I capture political connections as similarity in CRA and bond issuer CEOs' political contributions. Giuli and Kostovetsky (2014) argue that political contributions reflect personal political favours, and CEO's favour is a good proxy for the firm's political inclination. CRAs may potentially support firms with similar political affiliations through favourable credit ratings. The firms might, in turn, have more resources for lobbying, thus potentially resulting in a favourable political environment. As a result, credit ratings may be distorted.

I first examine whether CRAs use favourable credit ratings to support politically connected bond issuers. I find that greater degree of political similarity results in decreases in timeliness and accuracy of negative rating signals prior to default events. On average, S&P, Moody's, and Fitch delay downgrade announcements by 23, 11, and 13 days, respectively, as political similarity increases by 10%. They also assign/maintain ratings significantly further from default prior to credit events. For example, in a year prior to a default event, S&P maintains, on average, rating level one notch further from default as political similarity increases by 10%.[20] Higher degree of political similarity also results in higher levels of Category I error (i.e., missed defaults) by between approximately 4% and 7%.[21]

Interestingly, I do not find evidence of rating favouritism in the sample of non-defaulting bonds. Category II error (false default warnings) does not appear to be affected by political similarity. These results hold even if I match defaulting bonds with non-defaulting ones in

[20] Cantor and Mann (2006) argue that there is an unavoidable trade-off between timeliness and accuracy. The results that credit ratings become both less timely and less accurate are especially interesting.

[21] Category I and II error are conceptually similar to Type I and Type II errors. I present detail construction of these variables in section 3.2.2.

terms of their default propensity using bond and firm characteristics by applying Propensity Score Matching (PSM) method. The findings suggest that politically similar CRAs can identify bonds that are going to fail, and favour those bonds specifically, rather than giving favourable ratings to all politically similar firms.

I then find that CEOs tend to increase the proportion of political donations to the respective parties following favourable credit ratings. This suggests that CRAs successfully use favourable credit ratings as an indirect channel to support their favoured political party via donations by politically connected bond issuers. It is interesting to note that the result is asymmetric – Republican-leaning firms tend to change their donation patterns following favourable ratings, whereas Democrat-leaning firms do not. CRAs' favourable activities are explained by potential benefits in case their favoured political party wins the elections. A vast number of studies reports that the favoured political environment significantly supports corporate business (e.g., Goldman, Rocholl and So, 2009; Faccio, 2010; Boubakri, Guedhami, Mishra and Saffar, 2012).

My results survive a battery of robustness checks. First, it can be argued that political similarity is just another way to measure similarities in personal characteristics, and thus my results simply re-affirm what has already been established in the literature[22]. To address this, I control for similarities in age, nationality, and gender between CRA' and firm' CEOs. The results remain robust. In addition, I find some evidence that the Dodd-Frank Act of 2010, that was partially aimed at tightening regulations of CRAs, moderates the relation between political similarity and rating favouritism. Finally, my main results are highly robust when I apply

[22] Gender differences in US presidential elections, for example, are well established. Gender gap in 2016 presidential elections was as high as 11 percentage points. See http://www.cawp.rutgers.edu/sites/default/files/resources/ggpresvote.pdf

alternative political similarity measures, consider rating levels at different times prior to defaults, employ alternative cut-offs for default signal identification, and consider different time periods.

Second essay adds to the body of knowledge on importance of political connections in corporate finance. The existing literature finds that the political connections have significant effects on various corporate issues such as corporate bailouts (Faccio, Masulis, and McConnell, 2007; Blau, Brough, and Thomas, 2013), innovations (Krammer and Jiménez, 2019), debt restructurings (Halford and Li, 2019), cost of equity (Boubakri, Guedhami, Mishra, and Saffar, 2012; Pham, 2019), and corporate merger activities (Ferris, Houston, and Javakhadze, 2016). However, the importance of political connections between firms and information providers on the value of corporate information is still under-examined. My study is close to Kempf and Tsoutsoura (2021) showing that credit rating analyst's party affiliations impact the credit rating behaviours. My study is different from Kempf and Tsoutsoura (2021). I further find that following favourable ratings, politically connected firms have donations more to the favourable politically party, then they will have more chance to win the election campaigns that potentially create favourable political environment that supports back to the business of CRAs. In other words, my paper concludes that CRAs are successful to use favourable ratings to politically connected firms as an indirect channel to support back their business. I also find that following Dodd Frank Act, CRAs tend to be less biased in the credit ratings to the politically connected firms because they also would like to protect their reputation.

The remainder of the paper is organized as follows. Section 3.2 presents the data and variables. Section 3.3 presents methodology and empirical results. Robustness checks are presented in Section 3.4. Section 3.5 concludes.

3.2. Data Selection, Variable Definitions and Descriptive Statistics

3.2.1. Sample selection

Data is obtained from Mergent Fixed Investment Securities Database (FSID)[23]. Rating information is collected for the period between 20/04/1983 and 27/06/2019, and default information is collected between 20/04/1984 and 27/06/2020. Default information includes date and type (e.g., bankruptcy, covenant, interest and principal default)[24], while credit rating information includes credit rating levels (e.g., AAA/Aaa, CCC+/Caa1) and rating change dates. I consider data on three major CRAs – S&P, Moody's and Fitch. I also include issue specific variables (offering amount, maturity, seniority level, etc.) as control variables.

In main analyses, political similarity between CRAs and firms is measured by the degree of similarity in yearly political contributions of corporate CEOs. BoardEx[25] is my main source of detailed data on corporate CEOs including age, gender, nationality, education, employment history, role at the firm, and independence status. Data on CEOs' political contributions are obtained from the Federal Election Commission's website (www.fec.gov), which provides data from 1979. For each campaign contribution, the FEC database reports donor's name, address, occupation, employment, and the amount of contribution. I also use data on Chairpersons' political contributions as a robustness check.

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[23] I would like to say thank you Dr. Lily Nguyen, my research co-author, from University of Queensland (Australia) for sharing this data.

[24] Approximately 97% of default events are bankruptcies. The unreported results are robust when I include all default events.

[25] I would like to say thank you Associate Professor Hung Do, my co-supervisor from Massey University and University Technology of Sydney (UTS) for sharing this data.

3.2.2. Variable definition

3.2.2.1. Credit rating properties

I use rating timeliness and accuracy prior to default events as key variables in assessing credit rating behaviour. Following Cheng and Neamtiu (2009), I use three measures to assess credit rating timeliness. The first one is the absolute credit rating level maintained/assigned by each CRA to each rated bond at different times (e.g., -270, -180, -90, and -30 days) prior to a default date. I expect higher rating levels (closer to default[26]) to be assigned at different points prior to default in response to negative signals. I use rating levels at 270 days prior to default events in the main analysis and other points in time as robustness checks. The second measure is the time-weighted average rating level over the one-year period leading to default. For example, for a defaulting bond that is rated 17 at day -360 and is then downgraded to 20 on day -100 (with no other rating changes that year), rating level 17 applies for 260 days, and rating level 20 applies for 100 days. The time-weighted average rating level is thus (17*260 + 20*100)/360 = 17.83. The third measure is defined as the number of days between a downgrade date and the default date for each bond divided by 360. In case of multiple downgrades, I include all of them as separate observations by following Cheng and Neamtiu (2009).

To assess rating accuracy, Cheng and Neamtiu (2009) use Type I & II errors. Type I error is defined as a missed default, when a CRA assigns/maintains favourable rating to an issue that will default within a year. It is a dummy variable that is equal to one if a CRA misses a default event and zero otherwise. I introduce a new measure to assess rating accuracy – Category I

[26] Credit rating scores are divided into 22 levels (Aaa/AAA is 1, Aa1/AA+ is 2, and DDD/DD/D is 22, so higher values represent ratings closer to default). See Table B.2 in the Appendix for more details.

error[27]. It is a continuous variable ranging from 0 to 1 reflecting the degree of missed defaults a year prior to the event. The variable is calculated as (22 – average rating score) / (22 – 1), where the average rating score is computed over a year prior to a default event. By construction, Category I error will be zero if a CRA assigns and maintains a default rating (22) a year prior to an actual default event, and one if it assigns/maintains a AAA (1) rating. Having a continuous rather than a binary variable allows us to examine the marginal effects of political similarity effects on rating accuracy.

Cheng and Neamtiu (2009) define Type II error as a false warning where a CRA assigns/maintains unfavourable ratings (at a certain cut-off or higher) to bonds that will not default in a year's time. Similar to Type I, Type II error is a dummy variable. I also introduce a new measurement to assess the degree of false warning signals – namely Category II error[28]. If a CRA assigns/maintains unfavourable ratings (i.e., warning signals) to a bond and it does not default within a year, Category II error is calculated as (rating score at a warning signal – cut-off point) / (22 – cut-off point). In the main analysis, I choose a rating score of 20 as a cut-off point to identify non-warning signals (below 20) and warning signals (20 or above). Having a continuous variable will allow me to measure the degree of false warnings and analyse the extent of political connection impacts. By construction, if rating stays at 20, Category II error is zero. At 22, it is equal to one. Note that unlike Cheng and Neamtiu (2009), I only include bonds that receive a warning signal of 20 or worse. I argue that default warning signals are

[27] For robustness check, I simply follow Cheng and Neamtiu (2009) to use Type I error defined as a missed default, when a CRA assigns/maintains favourable rating to an issue that will default within a year. It is a dummy variable that is equal to one if a CRA misses a default event and zero otherwise. I find the robust results.

[28] For robustness check, I simply follow Cheng and Neamtiu (2009) to use Type II error defined as a false warning where a CRA assigns/maintains unfavourable ratings (at a certain cut-off or higher) to bonds that will not default in a year's time. I find the robust results.

relevant only for bonds that are already in the 'danger zone' of a cut-off point or worse. After all, it is unlikely that an AA-rated bond can receive a default warning signal.

3.2.2.2. Political similarity

I measure political similarity between CRAs and firms by following Giuli and Kostovetsky (2014) and using financial contributions of corporate CEOs[29] to both Democratic and Republican parties in each political campaign. I use BoardEx to identify firm CEOs and match them with the FEC database for political contributions. I then use contributions to define political affiliations of each CEO. CEO D% is the political affiliation of a CEO in a particular firm-year, calculated as the CEO's contributions to the Democratic party (prior to that year) divided by their total contributions to both parties. CEO D% is set to 0.5 if no political contributions are found (Giulu and Kostovetrky, 2014). Political similarity is a continuous variable, calculated as 1 - |firm_CEO_D% - CRA_CEO_D%|. In one of the robustness checks political affiliation is measured as a discreet variable – Democrat if D% is greater than 0.5, Republican if D% is less than 0.5, and non-partisan if it is equal to 0.5. I apply the same process to calculate Chairpersons' political affiliation and their political similarity between firms and CRAs and use this measure as a robustness check.

3.2.2.3. Summary statistics

[29] For robustness check, I also use financial contributions of all corporate employees to both Democratic and Republican parties in each political campaign to measure the political similarity and find the robust results. The robust results are available upon request.

Panel A of Table 3.1 presents summary statistics on political similarities between each of the CRAs and its rated firms. I see that political similarities tend to be quite high across the three CRAs, ranging from 0.8 for Moody's to approximately 0.9 for Fitch. Both CEO and Chairpersons political similarities exhibit the same pattern. Panel B of Table 3.1 presents summary statistics on issue characteristics which I include as control variables, and which potentially determine credit rating properties. Detailed variable definitions are presented in Appendix B.1. Generally, there are not much difference in characteristics of sample bonds rated by the three CRAs.

Table 3.1 Summary Statistics

Panel A: Political similarity between CRA and bond issuer (yearly basis)	S&P			Moody's			Fitch		
	N	MEAN	STD	N	MEAN	STD	N	MEAN	STD
Chief Executive officer (CEO)	96,810	0.865	0.187	96,810	0.808	0.211	96,810	0.885	0.185
Chairmen	103,049	0.835	0.199	103,049	0.779	0.219	103,049	0.878	0.190

Panel B: Bond characteristics	S&P			Moody's			Fitch		
	N	MEAN	STD	N	MEAN	STD	N	MEAN	STD
Size	304,281	10.738	1.926	321,681	10.740	1.972	154,232	10.791	2.339
Asset-backed	304,281	0.003	0.057	321,681	0.003	0.055	154,232	0.001	0.024
Convertible	304,281	0.010	0.099	321,681	0.009	0.094	154,232	0.021	0.143
Senior-secured	304,281	0.029	0.168	321,681	0.027	0.163	154,232	0.033	0.180
Enhanced	304,281	0.059	0.236	321,681	0.063	0.244	154,232	0.066	0.248
Puttable	304,281	0.007	0.084	321,681	0.006	0.077	154,232	0.009	0.093
Redeemable	304,281	0.672	0.470	321,681	0.654	0.476	154,232	0.617	0.486
Maturity	304,281	7.347	7.256	321,681	7.144	7.188	154,232	8.152	8.219

This table presents summary statistics on political similarity between each CRA (S&P, Moody's and Fitch) and their rated bonds (Panel A), and bond characteristics (Panel B). Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year t - 1 divided by his/her total contributions to both parties in the same year. Political similarity for Chairpersons is calculated in the same manner. *Size* is log of a bond issue's size; *Asset-backed* is a binary variable equal to one if the bond is an asset-backed issue, and zero otherwise; *Convertible* is a binary variable equal to one if the bond can be converted to the issuer's common stock (or other security), and zero otherwise; *Senior-secured* is a dummy variable equal to one if the issue is senior secured debt, and zero otherwise; *Enhanced* is a dummy variable equal to one if the issue has the credit enhancement feature, and zero otherwise; *Puttable* is a dummy variable equal to one if the bond has a puttable option, and zero otherwise; *Redeemable* is a dummy variable equal to one if the bond has a redeemable option, and zero otherwise; and *Maturity* is the number of years to the bond's maturity.

Table 3.2 presents summary statistics on rating timeliness and accuracy. The table is divided into three panels: A, B, and C for corporate bonds rated by S&P, Moody's, and Fitch, respectively. As mentioned earlier, rating timeliness is proxied by the rating level 270 days prior to a default event; number of days between a downgrade and a default divided by 360, DAHEAD; and weighted average rating level one year prior to an event, WRATE. Rating accuracy is proxied by Category I and Category II errors.

S&P and Moody's assign/maintain higher (i.e., closer to default – see Table B.2) ratings prior to default than Fitch. S&P and Moody's assign/maintain an average rating of around 13 (corresponding to Ba3/BB-), while Fitch assigns/maintains an average score of around 10 (corresponding to Baa3/BBB-) 270 days prior to default. Fitch also tends to assign/maintain a lower weighted average score of around 11 (BB+/Ba1) in the year prior to default. The WRATE figure is around 14 (B+/B1) for S&P and Moody's. For DAHEAD, on average, Moody's announces downgrades 118 days (-0.328 * 360) prior to default, while the numbers are 127 and 130 days for S&P and Fitch, respectively.

Category I error proxies the degree of missed defaults. On average, Fitch assesses bonds further from default status (i.e., more missed defaults) than S&P and Moody's (0.54 vs. 0.36 and 0.38). Category II error reflects false warnings. On average, S&P tends to give more false warning signals compared to Moody's and Fitch (0.68 vs. 0.52 and 0.36).

Table 3.2 Rating Timeliness and Accuracy Measures

Panel A: Bonds rated by S&P						
	N	MAX	MEAN	MEDIAN	MIN	STD
Rating level (270)	3,218	22.000	13.393	15.000	1.000	5.423
DAHEAD	7,627	0.000	-0.352	-0.300	-1.000	0.285
WRATE	3,501	22.000	14.377	16.000	1.000	5.409
Category I error	3,501	1.000	0.363	0.286	0.000	0.258
Category II error	4,580	1.000	0.680	0.546	0.000	0.467
Panel B: Bonds rated by Moody's						
	N	MAX	MEAN	MEDIAN	MIN	STD
Rating level (270)	3,259	22.000	13.258	15.000	1.000	5.331
DAHEAD	7,031	0.000	-0.328	-0.272	-1.000	0.281
WRATE	3,659	21.000	13.969	16.000	1.000	5.393
Category I error	3,659	1.000	0.382	0.286	0.000	0.257
Category II error	3,331	1.000	0.529	0.504	0.000	0.257
Panel C: Bonds rated by Fitch						
	N	MAX	MEAN	MEDIAN	MIN	STD
Rating level (270)	1,652	22.000	9.879	9.000	1.000	5.444
DAHEAD	4,060	0.000	-0.361	-0.322	-1.000	0.275
WRATE	1,949	22.000	10.714	11.379	1.000	5.797
Category I error	1,949	1.000	0.537	0.506	0.000	0.276
Category II error	3,427	1.000	0.358	0.500	0.000	0.295

This table presents summary statistics for the measures of credit rating timeliness and accuracy. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date of the issuer divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Category I error measures the degree of missing defaults by a CRA and is calculated as (default score – average rating score) / (default score - 1) where default score is 22 (see Table B.2) and average rating score is the average rating level issued by the CRA for the rated bond in one year prior to the default date. Category II error measures the degree of false default warnings and is calculated as (warning score – cut off point) / (default score - cut-off point) where cut-off point is 20. *Rating Level*, *DAHEAD*, and *WRATE* are proxies for rating timeliness while Category I and Category II errors are proxies for rating accuracy.

3.3. Methodology and Empirical Results

3.3.1. Political similarity and credit rating properties

3.3.1.1. Rating timeliness

I now examine how political similarities between rating agencies and bond issuers impact rating timeliness. I construct three samples which include defaulted bonds rated by S&P, Moody's, and Fitch, respectively. I then run the analysis for each sample separately. The model is as follows:

$$Timeliness_{i,t} = \alpha + \beta_1 Political\ Similarity_{i,t\text{-}1} + \gamma_k Controls_{i,t} + \vartheta_1 FE + \varepsilon_{i,t} \qquad (3.1)$$

where $Timeliness_{i,t}$ presents one of the three measures of rating timeliness (Rating Level, DAHEAD, and WRATE as described in section 2.2.1) of a rated bond *i* prior to an official default event on day *t*. $Political\ Similarity_{i,t}$ is calculated as 1 - |firm_CEO_D% - CRA_CEO_D%| with CEO D% being a CEO's contributions to the Democratic party in year *t* - 1 divided by their total contributions to both parties in that year. $Controls_{i,t}$ represent a set of bond characteristics that literature suggests may have an impact on credit rating properties. *FE* includes year and industry fixed effects.

The results are presented in Table 3.3. Panels A, B, and C include bonds rated by S&P, Moody's, and Fitch, respectively. I first find that a higher degree of political similarity leads CRAs to maintain/assign lower ratings (i.e., further from the default rating level) 270 days prior to defaults. On average, S&P assigns/maintains a credit score of 0.368 (-4.68 * 0.1) notches lower for a bond when its CEO and the CEO of the rated bond's company political similarity increases by 10%. The result is significant at the 1% level. The underestimated rating scores for Moody's and Fitch are 0.47 and 0.78 respectively, both also significant at the 1% level. I also find a significant effect of political similarity on DAHEAD – number of days between a downgrade and default date divided by 360 – suggesting that a higher degree of political similarity leads CRAs to delay downgrades. S&P, Moody's, and Fitch, on average, delay their downgrade announcements by 23 (0.64 * 0.1 * 360), 11, and 13 days, respectively when their political similarity with a rate firm increases by 10%. The results are statistically significant at least at the 5% level. I next find similar evidence on WRATE, the measurement of weighted average rating level over the one-year period prior to defaults. S&P maintains, on average, a weighted rating level 0.897 notches lower than the default rating level if political similarity increases by 10%. The result is significant at the 1% level. The result holds for Moody's and Fitch, with the biased weighted rating of 0.777 and 1.522 notches, respectively, both also significant at the 1% level.

My regression results on rating timeliness are consistent with the story that CRAs tend to delay downward adjustments prior to default events for bonds issued by politically similar firms. This is compelling evidence for the existence of politically biased credit ratings.

Table 3.3 Rating Timeliness and Political Similarity

Panel A: S&P						
	Rating Level		DAHEAD		WRATE	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	22.09***	16.08***	-0.61**	-0.57*	27.89***	21.35***
	(1.21)	(1.82)	(0.27)	(0.31)	(1.99)	(2.59)
Political Similarity	-1.82*	-3.68***	0.64***	0.65***	-6.81***	-8.97***
	(1.10)	(1.00)	(0.24)	(0.22)	(1.84)	(1.68)
Bond characteristics:						
Size		0.55***		-0.01		0.55***
		(0.08)		(0.01)		(0.10)
Asset-backed		-1.34*		-0.01		-2.36***
		(0.79)		(0.06)		(0.70)
Convertible		-0.42		0.08		-1.28*
		(0.66)		(0.05)		(0.71)
Senior-secured		-0.21		0.04*		-0.52*
		(0.31)		(0.02)		(0.29)
Enhanced		1.29***		0.00		1.12***
		(0.25)		(0.02)		(0.24)
Puttable		-1.03*		-0.02		-0.26
		(0.59)		(0.06)		(0.58)
Redeemable		1.58***		-0.04		1.74***
		(0.28)		(0.03)		(0.31)
Maturity		-0.02		0.00		-0.04*
		(0.02)		(0.00)		(0.02)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.532	0.591	0.152	0.159	0.511	0.580
N	3,218	3,191	7,627	7,529	3,501	3,469
Panel B: Moody's						
	Rating Level		DAHEAD		WRATE	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	21.24***	12.55***	-0.31***	-0.12	23.91***	15.49***
	(1.13)	(1.90)	(0.11)	(0.14)	(1.56)	(2.252)
Political Similarity	-3.07**	-4.74***	0.24**	0.30***	-6.76***	-7.77***
	(1.19)	(0.94)	(0.09)	(0.10)	(1.95)	(1.911)
Bond characteristics	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.548	0.606	0.200	0.214	0.548	0.609
N	3,259	3,224	7,031	6,942	3,659	3,620

Panel C: Fitch						
	Rating Level		DAHEAD		WRATE	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	17.53***	12.70***	-0.37**	-0.32*	22.56***	15.12***
	(2.55)	(3.31)	(0.15)	(0.17)	(2.50)	(3.245)
Political Similarity	-5.47**	-7.84***	0.28**	0.35**	-13.24***	-15.22***
	(2.14)	(1.83)	(0.13)	(0.15)	(2.40)	(2.136)
Bond characteristics	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.469	0.527	0.276	0.295	0.479	0.549
N	1,652	1,621	4,060	4,019	1,949	1,914

This table presents the regression results of rating timeliness proxies on political similarity and control variables. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. *Size* is log of a bond issue's size; *Maturity* is the number of years to the bond's maturity; and other control variables are binary variables that are equal to one if a bond issue has a certain characteristic, and zero otherwise. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.3.1.2. Rating accuracy

I now turn to the impact of political similarity on rating accuracy. As with the analysis of timeliness, the sample is divided into three parts, rated by S&P, Moody's, and Fitch. The model is as follows:

$$Accuracy_{i,t} = \alpha + \beta_1 Political\ Similarity_{i,t\text{-}1} + \gamma_k Controls_{i,t} + \vartheta_1 FE + \varepsilon_{i,t} \quad (3.2)$$

where $Accuracy_{i,t}$ denotes rating accuracy for bond *i* prior to default on day *t.* Accuracy is measured by Category I and Category II errors, introduced in section 2.2.1. All other variables are defined as in Eq. (3.1).

The results are presented in columns 1 – 4 of Table 3.4. Overall, across all panels (for S&P, Moody's and Fitch), I find that a higher degree of political similarity leads to a higher level of Category I error (missed defaults). For S&P (Panel A), as political similarity increases by 10%, Category I error for default bonds increases by 4.3% (0.43 * 0.1). The result is significant at the 1% level. I find similar results for Moody's and Fitch in Panels B and C, with the corresponding proportions of missed defaults being 3.7% and 7.3% respectively. These results are also significant at the 1% level. As for Category II error (false warnings), I follow Cheng and Neamtiu (2009) and select in the Category II error computation all non-defaulting bonds except those with a rating level better than 20.[30] The results in columns (3) and (4) show a statistically insignificant association between political similarity and accuracy.

Overall, the results suggest that CRAs tend to miss significantly more defaults of politically similar firms. This is yet another piece of evidence of politically biased credit ratings. As mentioned earlier, these results are particularly interesting given a potential trade-off between rating timeliness and accuracy (Cantor and Mann, 2006).

[30] I include all bonds in one of the robustness checks. The unreported results are robust.

Table 3.4 Rating Accuracy and Political Similarity

Panel A: S&P				
	Category I error		Category II error	
	(1)	(2)	(3)	(4)
Intercept	-0.28***	0.03	0.67***	0.15
	(0.10)	(0.12)	(0.11)	(0.18)
Political Similarity	0.32***	0.43***	-0.09	-0.04
	(0.09)	(0.08)	(0.10)	(0.09)
Bond characteristics:				
Size		-0.03***		0.05***
		(0.01)		(0.01)
Asset-backed		0.11***		-0.02
		(0.03)		(0.09)
Convertible		0.06*		-0.05
		(0.03)		(0.08)
Senior-secured		0.03*		0.08***
		(0.01)		(0.03)
Enhanced		-0.05***		-0.01
		(0.01)		(0.02)
Puttable		0.01		0.00
		(0.03)		(0.06)
Redeemable		-0.08***		-0.11*
		(0.02)		(0.06)
Maturity		0.00*		0.00
		(0.00)		(0.00)
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.511	0.580	0.124	0.148
N	3,501	3,469	4,580	4,380

Panel B: Moody's				
	Category I error		Category II error	
	(1)	(2)	(3)	(4)
Intercept	-0.09	0.31***	0.23*	0.29**
	(0.07)	(0.11)	(0.13)	(0.14)
Political Similarity	0.32***	0.37***	0.09	0.12
	(0.09)	(0.09)	(0.12)	(0.12)
Bond characteristics	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.548	0.609	0.368	0.389
N	3,659	3,620	3,331	3,148

Panel C: Fitch				
	Category I error		Category II error	
	(1)	(2)	(3)	(4)
Intercept	-0.03	0.33**	0.47***	0.39*
	(0.12)	(0.16)	(0.16)	(0.22)
Political Similarity	0.63***	0.73***	-0.10	-0.07
	(0.11)	(0.10)	(0.14)	(0.20)
Bond characteristics	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.479	0.549	0.275	0.222
N	1,949	1,914	3,427	2,554

This table presents the regression results of rating accuracy proxies on the political similarity and control variables. Category I error measures the degree of missing a default rating by a CRA and is calculated as (default score – average rating score) / (default score - 1) where default score is 22 and average rating score is the average rating level issued by the CRA for the rated bond in one year prior to the default date. Category II error measures the degree of false default warning by a CRA to a non-defaulting bond and is calculated as (warning score – cut off point) / (default score - cut-off point) where cut-off point is 20. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. *Size* is log of a bond issue's size; *Maturity* is the number of years to the bond's maturity; and other control variables are binary variables that are equal to one if a bond issue has a certain characteristic, and zero otherwise. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.3.2. Non-defaulting bonds: A further investigation

I have so far established a link between political similarity and rating favouritism in a sample of defaulting bonds. In a year prior to a default event, a higher political similarity between a CRA and the issuing firm results in less timely downgrades, higher rating levels, and more missed defaults.

Since there is no default event available for non-defaulting bonds, the favouritism measure using Category II error is limited to the sample of non-defaulting bonds, which is found not to be significantly related to political similarity. To further investigate the relationship between political similarity and favouritism in a sample of non-defaulting bonds, I apply the propensity score matching (PSM) method to match each defaulting bond to a corresponding non-defaulting bond by estimating the logit model for each year as follows:

$$\Pr(Default\_dum_{it} = 1) = a + b_1 Firm\_characteristics_{i,t} + b_2 Bond\_characteristics_{it} + e_{it} \qquad (3.3)$$

where *Default_dum* is equal one if the bond is a defaulting bond (i.e., the main sample) in year *t* and zero if the bond is a non-defaulting bond (i.e., PSM potential control candidates) in year *t*. *Firm_characteristics* is a set of firm characteristics that potentially drive default risk, including profitability, leverage, and stock return volatility, proposed by Tang and Yan (2010), while *Bond_characteristics* is a set of bond characteristics used by Cheng and Neamtiu (2009). I match each defaulting bond to a corresponding control bond by conditions such as (1) the defaulting bond and the corresponding control bond are in the same industry, (2) their difference in political similarity is less than 1%, (3) the difference between their propensity scores is less than 1%, and (4) the control bond has the closest propensity to become a defaulting bond. I then estimate the following model:

$$Rating\_propensity_{i,t} = \alpha + b_1 Political\ Similarity_{i,t-1} + b_2 Political\ Similarity_{i,t} * Default_{i,t} + b_3 Default_{i,t} + b_4 Controls_{i,t} + c_1 FE + e_{it} \qquad (3.4)$$

where *Rating_propensity* is one of the proxies for rating timeliness and accuracy used in the main analysis. *Default* is a dummy variable taking value of one if the bond is a defaulting bond and zero if the bond is a non-defaulting bond[31]. All other variables are defined as in Eq. (3.1). The results are presented in Table 3.5. The relationship between political similarity and rating favouritism remains largely insignificant for non-defaulting bonds. In contrast, the results remain significant for defaulting bonds across proxies for rating timeliness and accuracy and are similar to those in the main analysis. This is an interesting result, as politically similar CRAs appear to be able to correctly identify defaulting bonds based on information other than firm and bond characteristics, and then they give favourable ratings to defaulting bonds only.

[31] For each corresponding control bond (i.e., non-defaulting bonds), I use the default event of the sample firm (i.e., defaulting bonds), and measure the timeliness and accuracy of downgrade prior to default events.

Table 3.5 Rating Properties and Political Similarity - PSM Approach

Panel A: S&P								
	Rating Level		DAHEAD		WRATE		Category I error	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	11.881***	5.395	0.061	0.13	15.336***	7.417**	0.30**	0.68***
	(4.571)	(4.532)	(0.316)	(0.344)	(2.914)	(3.141)	(0.14)	(0.15)
Political Similarity	6.328	5.327	-0.387	-0.405	2.223	1.633	-0.08	-0.05
	(5)	(4.767)	(0.306)	(0.322)	(2.986)	(2.831)	(0.14)	(0.13)
Political Similarity*Default	-8.468*	-9.287*	1.018**	1.053**	-9.159***	-10.614***	0.41***	0.48***
	(5.107)	(4.898)	(0.414)	(0.431)	(3.188)	(3.042)	(0.15)	(0.14)
Default	10.498**	11.098**	-0.71*	-0.744*	12.667***	14.031***	-0.59***	-0.65***
	(4.64)	(4.415)	(0.377)	(0.387)	(2.919)	(2.752)	(0.14)	(0.13)
Bond characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.525	0.583	0.116	0.120	0.508	0.577	0.509	0.577
N	3,298	3,271	9,006	8,900	3,588	3,556	3,588	3,556
Panel B: Moody's								
	Rating Level		DAHEAD		WRATE		Category I error	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	16.28***	6.41	-0.67*	-0.48	11.53**	2.30	0.40*	0.84***
	(4.86)	(5.22)	(0.38)	(0.40)	(4.54)	(4.90)	(0.21)	(0.23)
Political Similarity	-0.21	-0.53	0.53	0.57	5.25	5.21	-0.08	-0.08
	(5.00)	(5.17)	(0.42)	(0.43)	(4.68)	(4.80)	(0.22)	(0.22)
Political Similarity*Default	-2.87	-4.24	-0.18	-0.17	-12.05**	-13.01***	0.40*	0.45*
	(5.10)	(5.22)	(0.44)	(0.45)	(4.90)	(4.99)	(0.23)	(0.23)
Default	4.97	6.22	0.39	0.36	12.38***	13.24***	-0.49**	-0.53**
	(4.90)	(5.02)	(0.36)	(0.37)	(4.70)	(4.82)	(0.22)	(0.23)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bond characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.54	0.597	0.253	0.265	0.541	0.603	0.542	0.604
N	3,328	3,293	8,387	8,283	3,733	3,694	3,733	3,694

Panel C: Fitch

	Rating Level		DAHEAD		WRATE		Category I error	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	17.34***	8.41**	-0.38***	-0.32*	5.55	-5.70	0.48***	1.02***
	(3.50)	(3.51)	(0.15)	(0.17)	(3.68)	(4.00)	(0.16)	(0.17)
Political Similarity	3.02	-0.46	0.09	0.16	7.28	8.56*	0.23	0.17
	(4.75)	(4.13)	(0.18)	(0.19)	(4.73)	(4.93)	(0.18)	(0.18)
Political Similarity*Default	-8.29**	-7.16*	0.19*	0.20**	-20.41***	-23.60***	0.39*	0.54**
	(4.06)	(3.65)	(0.10)	(0.09)	(5.56)	(5.49)	(0.22)	(0.21)
Default	-0.03	3.88	-0.16	-0.39	16.91***	20.75***	-0.50***	-0.69***
	(3.90)	(3.18)	(0.32)	(0.31)	(4.28)	(4.19)	(0.19)	(0.18)
Bond characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.454	0.513	0.275	0.294	0.477	0.543	0.471	0.54
N	1,701	1,670	4,072	4,031	1,998	1963	1,998	1,963

This table presents the results on the impact of political similarity on rating properties for defaulting and non-defaulting bonds. I apply the PSM method to match each defaulting bond to a corresponding non-defaulting bond by firstly estimating a logit model for each year as follows:

$$\Pr(Default\_dum_{it} = 1) = a + b_1 Firm\_characteristics_{i,t} + b_2 Bond\_characteristics_{it} + e_{it} \quad (3)$$

where *Default_dum* is equal one if the bond is a defaulting bond in year t and zero otherwise. *Firm_characteristics* is a set of firm characteristics that potentially drive the default risks, including profitability, leverage and stock return volatility, proposed by Tang and Yan (2010) while *Bond_characteristics* is a set of bond characteristics as in Tables 3 and 4. I then match each defaulting bond to a non-defaulting control bond if they are in the same industry, the difference between political similarities is less than 1%, the difference between their propensity scores is less than 1%, and the corresponding control bond has the closest propensity score to the defaulting bond. For this PSM matched sample, I run the following model:

$$Rating\_propensity_{i,t} = \alpha + b_1 Political\ Similarity_{i,t} + b_2 Political\ Similarity_{i,t} * Default_{i,t} + b_3 Default_{i,t} + b_4 Controls_{i,t} + c_1 FE + e_{it} \quad (4)$$

where *Rating_propensity* is a rating timeliness proxy (*Rating Level*, *DAHEAD*, *WRATE*) or a rating accuracy (*Category I error*) as defined in Tables 3 and 4. *Default* is a dummy variable taking value of one if the bond is a defaulting bond and zero if the bond is a non-defaulting control bond selected from the PSM approach. Other variables are defined as in Table 3.3. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.3.3. Favourable credit ratings and political contributions

I find evidence that CRAs tend to assign/maintain favourable credit ratings to politically similar firms. In this section, I investigate whether such favourable ratings affect political donations of firms' CEOs. In other words, I am investigating whether favourable ratings actually benefit the political party that CRAs lean towards. I estimate the following model:

$$Donation_{i,t} = \alpha + \beta_1 REP_{i,t\text{-}1} + \beta_2 DEM_{i,t\text{-}1} + \beta_3 REP_{i,t\text{-}1}{*}Favour_{i,t\text{-}1} + \beta_4 DEM_{i,t\text{-}1}{*}Favour_{i,t\text{-}1} + \beta_5 Favour_{i,t\text{-}1} + \gamma_k Controls_{i,t} + \vartheta_1 FE + \varepsilon_{i,t} \quad (3.5)$$

The dependent variable, $Donation_{i,t}$, is the proportion of a firm CEO's political contributions to the Democratic party, CEO D%, in year t after favourable credit rating assigned by the CRA to the firm's bond in year t - 1. $REP_{i,t\text{-}1}$ ($DEM_{i,t\text{-}1}$) is a dummy variable taking value of one if both the CRA and the bond issuer are Republican (Democrat) supporters in year t - 1, and zero otherwise. Firms and CRAs are classified as Republican (Democrat) supporters if the CEO D% is less than 0.5 (more than 0.5) (Giuli and Kostovetsky, 2014). $Favour_{i,t\text{-}1}$ is constructed as a continuous variable ranging from 0 to 1, showing the degree of rating bias (i.e., rating favouritism) in year t - 1. In the essay, $Favour_{i,t}$ is proxied by the degree of rating accuracy (Category I error), and rating timeliness (DAHEAD), and constructed as follows:

$$Favour_{i,t} = Category\ I\ error_{i,t} \quad (3.6a)$$

$$Favour_{i,t} = \text{Min}\ (DAHEAD_{i,t} + 1, 1) \quad (3.6b)$$

Category I error would be equal to zero if a CRA maintains a weighted average rating of 22 (default) prior to the default event, and one if it maintains a weighted average of 1 (AAA, corresponding to a most favourable rating). Similarly, the timeliness measure will be equal to zero if a downgrade is announced a year ahead of a default event, and one if a downgrade is announced on the default date or later. Hence, I argue that Eq. (3.6a) and Eq. (3.6b) are reliable proxies to reflect the degree of rating favouritism. I also add some control variables in the regressions (See Panel C of Appendix B.1).

The results are presented in Table 3.6. Unsurprisingly, and by definition, the coefficients on REP and DEM variables are negative and positive, correspondingly. The coefficients of interest are the ones on the interaction terms between political similarities and rating favouritism. The results are interesting. Republican firms substantially decrease the proportion of donations to the Democratic party (thus increasing donations to the Republican party) following favourable ratings by politically similar CRAs. The result holds for both timeliness and accuracy favouritism measures, with one exception (Fitch, timeliness measure with control variables). Interestingly, no such pattern is detected for Democrat-leaning firms. These firms do not appear to change their donation patterns following favourable credit ratings. This is an interesting result. Explaining the nature of this asymmetry goes beyond the scope of this paper and could be one of the avenues of future research.

The results in this section suggest that CRAs successfully use favourable credit ratings as an indirect channel to support their favoured political party via more donations by politically connected bond issuers. CRAs' favourable activities are motivated by potential benefits in case their favoured political party wins the elections following more financial supports[32]. A vast

[32]We collect total political contribution to Democrat and Republic in each election season from 1980 to 2016 (source: from the Federal Election Commission's website: www.fec.gov), and find that 7 out of 9 election seasons

number of studies reports that the favoured political environment significantly increases the firm values (e.g., Goldman, Rocholl and So, 2009), decreases cost of capital (e.g., Faccio, 2010; Boubakri, Guedhami, Mishra and Saffar, 2012).

Table 3.6 *Political Donations and Credit Rating Favouritism*

Panel A: Favour credit ratings (Accuracy proxy)						
	S&P		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.47***	0.47***	0.48***	0.49***	0.50***	0.50***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.06)
REP	-0.13***	-0.14***	-0.11***	-0.11***	-0.34***	-0.33***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
DEM	0.03**	0.03**	0.07**	0.08**	0.00	0.00
	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)
REP*Favour	-0.38***	-0.36***	-0.33***	-0.31***	0.00	0.03
	(0.07)	(0.07)	(0.10)	(0.10)	(0.09)	(0.10)
DEM*Favour	0.04	0.04	0.11**	0.09*	0.11	0.12
	(0.03)	(0.03)	(0.05)	(0.05)	(0.08)	(0.09)
Favour	-0.03	-0.06**	-0.12**	-0.16***	-0.12*	-0.16**
	(0.02)	(0.03)	(0.05)	(0.05)	(0.07)	(0.08)
Control variables:						
REP-to-DEM		0.03**		0.03**		0.02
		(0.01)		(0.01)		(0.02)
DEM-to-REP		0.01		0.01		0.07
		(0.01)		(0.01)		(0.05)
High rating score		0.03*		0.05***		0.02*
		(0.01)		(0.02)		(0.01)
Medium rating score		0.02*		0.03***		0.01
		(0.01)		(0.01)		(0.01)
Democratic President		-0.02		-0.01		-0.04
		(0.01)		(0.01)		(0.03)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.614	0.619	0.636	0.645	0.834	0.844
N	3,535	3,534	3,684	3,683	1,963	1,962
F-tests						
REP*Favour + Favour	-0.41***	-0.42***	-0.44***	-0.47***	-0.12**	-0.13**
	(0.06)	(0.06)	(0.08)	(0.08)	(0.06)	(0.06)
DEM*Favour + Favour	0.02	-0.03	0.00	-0.07	-0.01	-0.04
	(0.02)	(0.03)	(0.02)	(0.06)	(0.03)	(0.05)

(i.e., 1980, 1984, 1988, 1992, 2000, 2004, 2008), Democratic/Republican candidates win the president office within more political donations. The numbers are on upon request.

Panel B: Favour credit ratings (Timeliness proxy)						
	S&P		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.44***	0.48***	0.61***	0.60***	0.78***	0.84***
	(0.04)	(0.04)	(0.06)	(0.06)	(0.12)	(0.11)
REP	-0.06	-0.10*	-0.12*	-0.13*	-0.17**	-0.20**
	(0.05)	(0.06)	(0.06)	(0.07)	(0.09)	(0.08)
DEM	0.34***	0.31***	0.28***	0.28***	0.19	0.12
	(0.03)	(0.03)	(0.03)	(0.03)	(0.14)	(0.11)
REP* Favour	-0.07*	-0.07*	-0.06*	-0.05*	-0.07***	-0.02
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
DEM* Favour	-0.05*	-0.03	0.04	0.04	-0.01	0.07
	(0.03)	(0.03)	(0.04)	(0.03)	(0.17)	(0.14)
Favour	0.02	0.02	-0.02	-0.03	0.05***	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Control variables:	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.828	0.833	0.805	0.807	0.808	0.814
N	7,655	7,655	7,048	7,048	4,065	4,065
F-tests						
REP*Favour + Favour	-0.05*	-0.05*	-0.08**	-0.09**	-0.02	0.00
	(0.03)	(0.03)	(0.04)	(0.04)	(0.02)	(0.04)
DEM*Favour + Favour	-0.03	-0.01	0.02	0.01	0.04	0.09
	(0.02)	(0.01)	(0.01)	(0.01)	(0.17)	(0.14)

This table reports the regression results about how firm CEOs allocate their contributions to political parties following favour credit ratings. The dependent variable is a firm CEO D% representing the proportion of the CEO's total campaign contributions to Democrats in year *t* divided by their total contributions to both parties in the same year. $REP_{i,t-1}$ ($DEM_{i,t-1}$) is a dummy variable equal to one if both CRA and firm CEOs are Republican (Democratic) supporters in year *t* -1, and zero otherwise. A firm or a CRA is classified as a Republican (Democratic) supporter if the CEO D% is less than 0.5 (more than 0.5). $Favour_{i,t}$ is either Category I error or Min ($DAHEAD_{i,t}$ + 1, 1). *REP-to-DEM* (*DEM-to-REP*) is a dummy variable that equals one if in year *t* a Republican (Democratic) President is replaced by a Democratic (Republican) President, and zero otherwise. *Democratic President* is a dummy variable equal to one if the President in year *t* is a Democrat, and zero otherwise. High (medium) rating score is a dummy variable that takes a value of one if an issue's credit rating in year *t* is between AAA/Aaa to A1/A+ (A2/A and B1/B+), and zero otherwise. All regressions include industry and time fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4. Robustness Tests

3.4.1. Controlling for personal characteristics

One could argue that the results are driven by systematic differences in personal characteristics of CEOs supporting different political parties. For instance, gender gap in 2016 US presidential elections was estimated at 11%. Some polls have estimated gender gap at as high as 31% in the 2020 election.[33] Therefore, it is possible that political similarity measure I employ is simply an alternative proxy for similarity in personal characteristics.

To address this, I introduce three dummy control variables. The first one is equal to one if CRA and firm's CEOs have the same gender and zero otherwise. The second and third dummy variables are defined similarly to control for nationality and age bracket. Results are presented in Table B.3 in the Appendix. All results for rating timeliness are robust. As for accuracy, most results are significant. As a matter of fact, there is some evidence of rating favouritism in terms of Category II error for Moody's and Fitch.

3.4.2. Impact of Dodd-Frank Act (2010)

Dodd-Frank Act of 2010 (in particular, sections 932, 936, 938, and 939) was, in part, aimed at increasing institutional standards and tightening regulation of CRAs[34]. Thus, *ceteris paribus*, I should expect the extent of rating favouritism to decrease following the implementation of the Act. The results are presented in Table B.4 in the Appendix. They are consistent with my

[33] https://cawp.rutgers.edu/presidential-poll-tracking-2020#NPGR
[34] https://www.sec.gov/spotlight/dodd-frank.shtml#

expectations. The results are also consistent with Dimitrov, Palia, and Tang (2015). They find that due to CRAs becoming more protective to their reputation after the adoption of Dodd-Frank Act, credit rating quality has improved. Favouritism diminishes in 9 out of 15 specifications, especially for Fitch whose market share is relatively smaller than S&P and Moody's.

3.4.3. Political similarity dummy

In the main analysis, political similarity is a continuous variable measured as 1 - |firm_CEO_D% - CRA_CEO_D%|. As an alternative measure, I use a dummy variable that is equal to one if a firm's and a CRA's CEOs have the same political leaning (Democratic, Republican, or non-partisan). For example, both firm and CRA are classified as Republican (Democratic) supporters if the CEO D% of their CEOs is less than 0.5 (more than 0.5). The results presented in Tables B.5 in the Appendix are qualitatively similar to those in Tables 3.3 and 3.4.

3.4.4. Rating levels at different times prior to default events

In the main analysis, one of the measures of rating timeliness is rating level 270 days prior to a default event. In this robustness test I use alternative values of 180, 90, and 30 days. The results are presented in Table B.6 in the Appendix. The results are robust across all specifications.

3.4.5. Alternative cut-off points for Category II error computation

In the main analysis, I use a rating score of 20 as a cut-off point to identify warning signals in the measurement of Category II error. As an alternative, I select 17, 18, 19, and 21. The results are reported in Table B.7 in the Appendix. There is virtually no evidence of rating favouritism, which is consistent with the main results.

3.4.6. Alternative time periods for measuring Category I and II errors

In the main analysis, Category I and Category II errors are computed over a period of 12 months. In this robustness check, I use alternative time windows of 18, 9, and 6 months. The results presented in Table B.8 in the Appendix and are consistent with the main findings of a positive relation between political similarity and missed defaults, but the effect of political similarity on false warnings is not statistically significant.

3.4.7. Excluding non-contributing firms from the analysis

In the main analysis, firms with no recorded stakeholder contributions have their CEO D% variable set at 0.5 by following Giuli and Kostovetsky (2014). In this robustness check, I exclude these firms from the analysis. The results are presented in Table B.9 in the Appendix. Despite smaller sample sizes, the results are robust for all rating timeliness proxies and the rating accuracy proxy of Category I error. There is evidence of favouritism in Category II error for the sample of Moody's-rated bonds.

3.4.8. Evidence of political similarity based on Chairpersons' political contributions

Instead of computing political similarity using the proportion of Democratic contributions by CEOs, I use political contributions by Chairperson as an alternative measure. Therefore, political similarity between a CRA's and a firm's Chairperson is calculated as 1 – |firm_Chairperson_D% - CRA_Chairperson_D%| where D% represents the proportion of the Chairman's total campaign contributions to Democrats in year t - 1 divided by their total contributions to both parties in the same year. The effect of political similarity on rating timeliness and accuracy is reported in Table B.10 in the Appendix. The results exhibit similar pattern as in Tables 3.3 and 3.4 for CEO-based political similarity. However, the significantly positive effect of political similarity on false warnings for the S&P's non-defaulting sample is of the wrong sign. I also report the results for the effect of rating favouritism on firm Chairpersons' political donations in the following year. I find consistent, albeit weaker, results for Chairpersons in Table B.11 in the Appendix compared to those for CEOs in Table 3.6.

3.4.9. CEO Turnover

In this robustness check, I restrict the sample by years that the position of CEO is changed. Results are presented in Table B.12 and B.13 in the Appendix. All results for rating timeliness and rating accuracy are robust. These tests will provide more insights into the relation between politics and credit risk assessment. More importantly, the tests can address some omitted variable concerns regarding the relationship between political connections and rating bias.

3.5. Conclusion

I document that political similarity between CRAs and bond issuers significantly impacts two main credit rating properties: timeliness, and accuracy. For rating timeliness, higher political similarity leads CRAs to downgrade defaulting bonds later and maintain/assign ratings further from default prior to credit events. For rating accuracy, I find that higher political similarity between CRAs and bond issuers leads to higher level of Category I error (i.e., more missed defaults). Interestingly, the findings are confined to a set of defaulting bonds, as I find very limited evidence of reduction of Category II error (false warnings) for a sample of non-defaulting bonds. Overall, the results show that CRAs tend to bias in credit ratings by favouring politically similar firms.

I also show that firms' CEOs change their donation behaviour following favourable credit ratings. Interestingly, this result is almost exclusively observed in the sample of Republican supporters. The results survive a battery of robustness checks, such as addressing potential endogeneity concerns and altering variable definitions. I believe the findings contribute to understanding of the importance of political connections in corporate finance, particularly through the credit information channel.

APPENDIX B

FOR ESSAY TWO

Table B.1: Variable Definitions

Panel A: Credit rating properties

Measurement	**Proxy**	**Description**	**Type of variable**
Rating timeliness	Rating level	Absolute credit rating score issued by the CRA (e.g., S&P, Moody's and Fitch) to each rated bond at different times (e.g., -270, -180, -90 and -30) prior to a default date.	Continuous variable
	DAHEAD	The number of days between a downgrade date and the default date for each bond divided by 360. For example, S&P announces a downgrade to a defaulting bond 90 days before the default event, then DAHEAD is calculated as -90/360= -0.25 year.	Continuous variable
	WRATE	The time-weighted average rating level over the one-year period leading to default	Continuous variable
Rating accuracy	Category I error	The variable is calculated as (22 – average rating score) / (22 – 1), where the average rating score is computed over a year prior to a default event.	Continuous variable
	Category II error	If a CRA assigns/maintains unfavourable ratings (i.e., warning signals) to a bond and it does not default within a year, Category II error is calculated as (rating score at a warning signal – cut-off point) / (22 – cut-off point).	Continuous variable

Panel B: Political environment

Measurement	**Proxy**	**Description**	**Type of variable**
Internal political environment	CEO's political contribution	The CEO’s contributions to the Democratic party (prior to that year) divided by their total contributions to both parties.	Continuous/ dummy variable
	Chairmen's political contribution	The Chairmen’s contributions to the Democratic party (prior to that year) divided by their total contributions to both parties.	Continuous/ dummy variable

Panel C: Control variables

Measurement	**Proxy**	**Description**	**Type of variable**

Issue characteristics	Size	Log of issue size. Rating agencies may have greater incentives to provide early warnings for larger size debt (White, 2001). At the same time, rating agencies might not monitor as closely large issues, if they are related with lower risk.	Continuous variable
	Assetb	Indicator variable that takes a value of 1 if the issue is an asset-backed issue, 0 otherwise. Asset-backed issues may be different from other types of issues with respect to risk characteristics.	Dummy variable
	Conv	Indicator variable that takes a value of 1 if the issue can be converted to the common stock (or other security) of the issuer, 0 otherwise. Other things equal, the convertible feature is associated with lower risk for the bondholders. I expect that rating agencies monitor less closely lower risk issues.	Dummy variable
	Ss	Indicator variable that takes a value of 1 if the issue is senior secured debt, 0 otherwise. Senior secured issues are less risky for the bondholders. I expect that rating agencies monitor less closely senior secured issues.	Dummy variable
	Enhance	Indicator variable that takes a value of 1 if the issue has the credit enhancement feature, 0 otherwise. Theenhancement feature is associated with lower risk for the bondholders. I expect that rating agencies monitorless closely issues with credit enhancement features.	Dummy variable
	Put	Indicator variable that takes a value of 1 if the bondholder has the option, but not the obligation, to sell the security back to the issuer under certain circumstances, 0 otherwise. A put feature is usually associated with lower risk for the bondholders, I expect that rating agencies monitor less closely issues with a put feature.	Dummy variable
	Redeem	Indicator variable that takes a value of 1 if the issue is redeemable under certain circumstances, 0 otherwise. If redeemable debt issues are associated with lower risk for the bondholders, I expect that rating agencies monitor less closely redeemable issues.	Dummy variable
	Maturity	Number of years to maturity. The longer the time to maturity, the higher the risk exposure of an issue and thus the more likely the agencies are to closely monitor the issue.	Continuous variable

External political environments	REP-to-DEM	Dummy variable that takes one if in year t+1, a Republican president is replaced by a Democratic president and zero otherwise.	Dummy variable
	DEM-to-REP	Dummy variable that takes one if in year t+1, a Democratic president is replaced by a Republican president and zero otherwise.	Dummy variable
	High rating score	Dummy variable that takes one if credit rating at year t is high score from AAA/Aaa to A1/A+, and zero otherwise.	Dummy variable
	Medium rating score	Dummy variable that takes one if credit rating at year t is high score from A2/A to B1/B+, and zero otherwise.	Dummy variable
	Democratic party	Dummy variable taking value of one if President is Democratic in year t+1 and zero otherwise.	Dummy variable

Table B.2
Credit Rating Levels and Conversion Codes

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

This table summarizes the conversion of the letter grades of credit ratings issued by the three CRAs (Moody’s, S&P, and Fitch) to the numerical scores used in my analyses.

Table B.3
Rating Properties and Political Similarity - Controlling for CEO characteristics

Panel A: S&P

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	13.19***	-0.63*	19.74***	0.11	0.21
	(2.20)	(0.34)	(2.83)	(0.14)	(0.25)
Political Similarity	-3.55***	0.80***	-9.50***	0.45***	-0.09
	(1.04)	(0.22)	(1.84)	(0.09)	(0.11)
CEOs' characteristics	Yes	Yes	Yes	Yes	Yes
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.596	0.199	0.582	0.58	0.148
N	2,939	6,956	3,215	3,469	4,380

Panel B: Moody's

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	13.92***	-0.38	15.66***	0.30**	-0.02
	(2.71)	(0.29)	(2.98)	(0.14)	(0.18)
Political Similarity	-4.69***	0.36***	-7.77***	0.37***	-0.01
	(1.00)	(0.09)	(2.15)	(0.10)	(0.07)
CEOs' characteristics	Yes	Yes	Yes	Yes	Yes
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.606	0.219	0.609	0.609	0.405
N	3,224	6,942	3,620	3,620	3,148

Panel C: Fitch

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	13.21***	-0.21	15.11***	0.33**	0.31
	(3.43)	(0.18)	(3.40)	(0.16)	(0.21)
Political Similarity	-7.45***	0.53***	-15.14***	0.72***	-0.23
	(2.01)	(0.15)	(2.23)	(0.11)	(0.17)
CEOs' characteristics	Yes	Yes	Yes	Yes	Yes
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.529	0.309	0.548	0.548	0.256
N	1,621	4,019	1,914	1,914	2,554

This table presents the regression results of rating properties (i.e., rating timeliness and rating accuracy) on political similarity after controlling for CEO characteristics and other controls including bond characteristics, industry fixed effects and time fixed effects. Rating timeliness is proxied by three measures: Rating Level, DAHEAD and WRATE. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date of the issuer divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Rating accuracy is proxied by two measures: Category I and II. Category I and II are a continuous variable representing the missed default information and false warning signal, respectively. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.4
Rating Properties and Political Similarity - Dodd-Frank Effect

Panel A: S&P

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	13.57***	-0.38	20.14***	0.09	0.15
	(1.86)	(0.35)	(2.66)	(0.13)	(0.18)
Political Similarity	-5.04***	0.72***	-11.19***	0.53***	-0.04
	(1.10)	(0.23)	(1.80)	(0.09)	(0.09)
Political Similarity*Dodd-Frank	2.19	-0.30	2.11	-0.13	0.08
	(1.87)	(0.30)	(2.24)	(0.11)	(0.07)
Dodd-Frank	1.35	0.38	-4.73**	0.23**	0.04
	(1.83)	(0.32)	(2.12)	(0.10)	(0.06)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.617	0.167	0.605	0.605	0.148
N	3,191	7,529	3,469	3,469	4,380

Panel B: Moody's

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	11.69***	-0.07	17.77***	0.20	0.29**
	(1.93)	(0.24)	(2.74)	(0.13)	(0.14)
Political Similarity	-6.80***	0.32***	-10.68***	0.51***	0.12
	(0.90)	(0.11)	(1.66)	(0.08)	(0.12)
Political Similarity*Dodd-Frank	2.18	-0.15	4.68	-0.20	0.04
	(1.30)	(0.25)	(3.30)	(0.16)	(0.07)
Dodd-Frank	-1.12	0.07	-9.68***	0.46***	0.06
	(1.26)	(0.31)	(3.28)	(0.16)	(0.06)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.643	0.214	0.647	0.647	0.389
N	3,224	6,942	3,620	3,620	3,148

Panel C: Fitch

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	7.67***	0.21	12.63***	0.45***	0.39*
	(2.89)	(0.20)	(3.08)	(0.15)	(0.22)
Political Similarity	-9.39***	0.41***	-16.70***	0.80***	-0.07
	(1.55)	(0.15)	(1.96)	(0.09)	(0.20)

Political Similarity*Dodd-Frank	2.01	-0.13	2.91	-0.11	0.06
	(2.72)	(0.21)	(2.96)	(0.14)	(0.07)
Dodd-Frank	1.17	0.45**	-8.65***	0.41***	0.08
	(2.64)	(0.21)	(2.86)	(0.14)	(0.06)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.589	0.301	0.589	0.589	0.222
N	1,621	4,019	1,914	1,914	2,554

This table presents the regression results of rating properties on political similarity considering the effect of the Dodd-Frank Act. Rating timeliness is proxied by three measures: Rating Level, DAHEAD and WRATE. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date of the issuer divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Rating accuracy is proxied by two measures: Category I and II. Category I and II are a continuous variable representing the missed default information and false warning signal, respectively. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. D-Frank is a dummy variable that takes one if the observation is after Dodd Frank approval (2010) and zero otherwise. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.5
Rating Properties and Dummy of Political Similarity

Panel A: S&P	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	13.18***	0.01	13.69***	0.40***	0.11
	(1.48)	(0.20)	(1.67)	(0.08)	(0.16)
Political Similarity	-0.64	0.24***	-2.93***	0.14***	0.00
	(0.45)	(0.09)	(0.65)	(0.03)	(0.04)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.587	0.156	0.578	0.578	0.148
N	3,191	7,529	3,469	3,469	4,380

Panel B: Moody's	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	9.27***	0.01	10.12***	0.57***	0.34***
	(1.57)	(0.12)	(1.64)	(0.08)	(0.10)
Political Similarity	-1.80***	0.12***	-3.36***	0.16***	0.06
	(0.35)	(0.04)	(0.67)	(0.03)	(0.05)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.607	0.214	0.62	0.62	0.389
N	3,224	6,942	3,620	3,620	3,148

Panel C: Fitch	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	4.89**	0.00	0.44	1.03***	0.25*
	(2.37)	(0.16)	(1.91)	(0.09)	(0.13)
Political Similarity	-2.87***	0.15***	-5.32***	0.25***	0.04
	(0.52)	(0.05)	(0.67)	(0.03)	(0.07)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.537	0.296	0.565	0.565	0.223
N	1,621	4,019	1,914	1,914	2,554

This table presents the regression results of rating properties on political similarity with political similarity is captured as a dummy variable. Rating timeliness is proxied by three measures: Rating

Level, DAHEAD and WRATE. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date of the issuer divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Rating accuracy is proxied by two measures: Category I and II. Categories I and II are a continuous variable representing the missed default information and false warning signal, respectively. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.6
Rating Levels at Different Times Before Default

Panel A: S&P

	180 Days	90 Days	30 Days
	(1)	(2)	(3)
Intercept	19.89***	30.64***	27.30***
	(2.27)	(4.43)	(4.45)
Political Similarity	-6.48***	-17.87***	-17.47***
	(1.32)	(3.36)	(3.31)
Bond characteristics	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adj. R^2	0.567	0.428	0.470
N	3,325	3,395	3,425

Panel B: Moody's

	180 Days	90 Days	30 Days
	(1)	(2)	(3)
Intercept	15.66***	21.76***	22.36***
	(2.12)	(3.55)	(3.40)
Political Similarity	-8.91***	-18.49***	-16.83***
	(1.46)	(3.48)	(3.28)
Bond characteristics	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adj. R^2	0.585	0.488	0.522
N	3,419	3,517	3,569

Panel C: Fitch

	180 Days	90 Days	30 Days
	(1)	(2)	(3)
Intercept	18.88***	30.42***	28.27***
	(3.93)	(4.75)	(4.95)
Political Similarity	-11.97***	-32.53***	-31.63***
	(2.09)	(3.45)	(3.60)
Bond characteristics	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adj. R^2	0.504	0.474	0.485
N	1,699	1,789	1,800

This table presents the regression results of rating levels at different time before defaults on political similarity. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 180, 90, and 30 days prior to the bond issuer's default date. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.7
Category II Error for Different Cut-Off Points

Panel A: S&P				
	17	18	19	21
	(1)	(2)	(3)	(4)
Intercept	0.26***	-0.23	-0.03	1.57***
	(0.10)	(0.15)	(0.20)	(0.25)
Political Similarity	0.02	0.05	0.05	-0.30**
	(0.05)	(0.10)	(0.09)	(0.13)
Bond characteristics	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.096	0.083	0.059	0.112
N	15,354	6,809	3,565	1,196
Panel A: Moody's				
	17	18	19	21
	(1)	(2)	(3)	(4)
Intercept	0.42***	0.34***	0.76***	-0.40
	(0.09)	(0.10)	(0.15)	(0.33)
Political Similarity	0.01	0.03	-0.15	-0.10
	(0.04)	(0.06)	(0.10)	(0.11)
Bond characteristics	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.155	0.425	0.478	0.213
N	14,339	4,853	3,161	443
Panel C: Fitch				
	17	18	19	21
	(1)	(2)	(3)	(4)
Intercept	0.67***	0.45**	0.35**	-0.13
	(0.16)	(0.18)	(0.16)	(0.11)
Political Similarity	-0.12	-0.22	-0.05	0.07
	(0.10)	(0.14)	(0.15)	(0.10)
Bond characteristics	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.239	0.187	0.267	0.461
N	5,821	3,167	1,977	737

This table presents the OLS regression results of Category II with different choices of cut-off points on political similarity. Category II is a continuous variable representing the false warning signal. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.8
Category I and II Errors for Different Time Periods Before Default

Panel A: S&P

	Category I error			Category II error		
	18 months	9 months	6 months	18 months	9 months	6 months
Intercept	0.15	-0.06	-0.18	0.15	0.15	0.15
	(0.11)	(0.14)	(0.17)	(0.18)	(0.18)	(0.18)
Political Similarity	0.31***	0.51***	0.65***	-0.04	-0.04	-0.04
	(0.07)	(0.10)	(0.12)	(0.09)	(0.09)	(0.09)
Bond characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.607	0.556	0.517	0.148	0.148	0.148
N	3,469	3,469	3,469	4,380	4,380	4,380

Panel B: Moody's

	Category I error			Category II error		
	18 months	9 months	6 months	18 months	9 months	6 months
Intercept	0.37***	0.25**	0.16	0.29**	0.29**	0.29**
	(0.10)	(0.12)	(0.14)	(0.14)	(0.14)	(0.14)
Political Similarity	0.27***	0.45***	0.58***	0.12	0.12	0.12
	(0.08)	(0.11)	(0.14)	(0.12)	(0.12)	(0.12)
Bond characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.632	0.586	0.551	0.389	0.389	0.389
N	3,620	3,620	3,620	3,148	3,148	3,148

Panel C: Fitch

	Category I error			Category II error		
	18 months	9 months	6 months	18 months	9 months	6 months
Intercept	0.47***	0.18	-0.02	0.39*	0.39*	0.39*
	(0.13)	(0.17)	(0.20)	(0.22)	(0.22)	(0.22)
Political Similarity	0.54***	0.89***	1.13***	-0.07	-0.07	-0.07
	(0.09)	(0.12)	(0.14)	(0.20)	(0.20)	(0.20)
Bond characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.577	0.534	0.521	0.222	0.222	0.222
N	1,914	1,914	1,914	2,554	2,554	2,554

This table presents the OLS regression results of Categories I and II on political similarity for different time periods before default. Categories I and II are a continuous variable representing the missed default information and false warning signal, respectively. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year t - 1 divided by his/her total contributions to both parties in the same year. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.9
Rating Properties and Political Similarity- Excluding Non-Donating CEOs

Panel A: S&P

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	11.01***	-0.53**	14.10***	0.38***	0.35
	(2.37)	(0.27)	(2.83)	(0.14)	(0.34)
Political Similarity	-3.39***	0.50**	-5.55***	0.26***	-0.11
	(1.13)	(0.21)	(1.58)	(0.08)	(0.12)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.798	0.40	0.661	0.661	0.133
N	861	2,381	893	893	743

Panel B: Moody's

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	10.40***	-0.14	11.18***	0.52***	0.18
	(2.04)	(0.10)	(2.24)	(0.11)	(0.17)
Political Similarity	-2.27*	0.19**	-4.36**	0.21**	-0.07
	(1.24)	(0.09)	(1.88)	(0.09)	(0.09)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.811	0.365	0.681	0.681	0.173
N	828	1,871	872	872	320

Panel C: Fitch

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	10.26***	-0.36	15.98***	0.29**	0.06
	(1.60)	(0.21)	(2.34)	(0.11)	(0.35)
Political Similarity	-7.92***	0.53*	-14.84***	0.71***	-0.15
	(2.03)	(0.27)	(2.72)	(0.13)	(0.10)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.806	0.165	0.701	0.701	0.513
N	437	1,375	449	449	555

This table presents the regression results of rating properties on political similarity. I exclude missing political donations when I measure political similarity. Rating timeliness is proxied by three measures: Rating Level, DAHEAD and WRATE. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date of the issuer divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Rating accuracy is proxied by two measures: Categories I and II. Categories I and II are a continuous variable representing the missed default information and false warning signal, respectively. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.10
Rating Properties and Chairpersons Political Similarity

Panel A: S&P

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	16.52***	-0.53*	21.77***	0.01	-0.01
	(1.64)	(0.28)	(2.34)	(0.11)	(0.18)
Political Similarity	-3.95***	0.58***	-8.88***	0.42***	0.13
	(0.86)	(0.20)	(1.42)	(0.07)	(0.09)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.598	0.178	0.588	0.586	0.148
N	2,919	6,956	3,215	3,469	4,381

Panel B: Moody's

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	12.05***	-0.20	15.36***	0.32***	0.37***
	(1.89)	(0.13)	(2.17)	(0.10)	(0.11)
Political Similarity	-3.67***	0.35***	-7.45***	0.36***	0.04
	(1.09)	(0.10)	(1.64)	(0.08)	(0.06)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.604	0.22	0.612	0.612	0.387
N	3,224	6,942	3,620	3,620	3,149

Panel C: Fitch

	Rating Level	DAHEAD	WRATE	Category I error	Category II error
	(1)	(2)	(3)	(4)	(5)
Intercept	11.72***	-0.26	13.51***	0.40***	0.45**
	(3.09)	(0.17)	(2.88)	(0.14)	(0.18)
Political Similarity	-6.95***	0.28**	-13.58***	0.65***	-0.12
	(1.55)	(0.14)	(1.71)	(0.08)	(0.13)
Bond characteristics	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.528	0.295	0.553	0.553	0.233
N	1,621	4,019	1,914	1,914	2,606

This table presents the regression results of rating properties on political similarity, including other controls, such as bond characteristics, industry fixed effects and time fixed effects. Rating timeliness is proxied by three measures: Rating Level, DAHEAD and WRATE. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date of the issuer divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Rating accuracy is proxied by two measures: Categories I and II. Categories I and II are a continuous variable representing the missed default information and false warning signal, respectively. Political similarity between a CRA's and a firm's Chairperson is calculated as 1 – |firm_Chair_D% - CRA_ Chair _D%| where D% represents the proportion of the Chairmen 's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.11
Chairpersons Political Donations and Credit Rating Favouritism

Panel A: Favour credit ratings (Accuracy proxy)

	S&P	Moody's	Fitch
	(1)	(2)	(3)
Intercept	0.42***	0.47***	0.43***
	(0.03)	(0.02)	(0.08)
REP	-0.25***	-0.20***	-0.34***
	(0.03)	(0.04)	(0.04)
DEM	-0.02	0.04	-0.03
	(0.03)	(0.02)	(0.03)
REP*Favour	-0.09	-0.01	0.10
	(0.08)	(0.11)	(0.11)
DEM*Favour	0.08	0.24***	0.14
	(0.06)	(0.07)	(0.11)
Favour	-0.08*	-0.25***	-0.13
	(0.05)	(0.07)	(0.10)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj. R^2	0.590	0.582	0.793
N	3,534	3683	1,962
F-tests			
REP*Favour + Favour	-0.17***	-0.26***	-0.04
	(0.06)	(0.07)	(0.06)
DEM*Favour + Favour	0.01	-0.01	0.01
	(0.02)	(0.02)	(0.03)

Panel B: Favour credit ratings (Timelines proxy)

	S&P	Moody's	Fitch
	(1)	(2)	(3)
Intercept	0.45***	0.46***	0.73***
	(0.04)	(0.05)	(0.22)
REP	-0.16	-0.14	-0.12
	(0.11)	(0.09)	(0.09)
DEM	0.25***	0.26***	0.38***
	(0.03)	(0.02)	(0.09)
REP*Favour	-0.21*	-0.23*	-0.19*
	(0.13)	(0.12)	(0.10)
DEM*Favour	0.00	0.02	-0.19
	(0.03)	(0.03)	(0.18)
Favour	0.03	-0.01	0.02
	(0.03)	(0.03)	(0.02)

Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj. R^2	0.728	0.739	0.748
N	8,989	8,359	4,819
F-tests			
REP*Favour + Favour	-0.18*	-0.23*	-0.17*
	(0.11)	(0.13)	(0.10)
DEM*Favour + Favour	0.03	0.01	-0.17
	(0.02)	(0.01)	(0.18)

This table reports the regression results on how firm Chairpersons allocate their contributions to political parties following favourable credit ratings. The dependent variable is a firm Chairperson D% representing the proportion of the Chairperson's total campaign contributions to Democrats in year *t* divided by his/her total contributions to both parties in the same year. $REP_{i,t-1}$ ($DEM_{i,t-1}$) is a dummy variable equal to one if both CRA and firm Chairperson are Republican (Democratic) supporters in year *t* -1, and zero otherwise. A firm or a CRA is classified as a Republican (Democratic) supporter if the Chairperson D% is less than 0.5 (more than 0.5). $Favour_{i,t}$ is either Category I error or Min ($DAHEAD_{i,t}$ + 1, 1). *REP-to-DEM* (*DEM-to-REP*) is a dummy variable that equals one if in year *t* a Republican (Democratic) President is replaced by a Democratic (Republican) President, and zero otherwise. *Democratic President* is a dummy variable equal to one if the President in year *t* is a Democratic, and zero otherwise. High (medium) rating score is a dummy variable that takes a value of one if an issue's credit rating in year *t* is between AAA/Aaa to A1/A+ (A2/A and B1/B+), and zero otherwise. All regressions include industry and time fixed effects. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.12
Rating Timeliness and Political Similarity (CEO Turnover)

Panel A: S&P

	Rating Level		DAHEAD		WRATE	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	15.936***	13.179***	-0.175	-0.21	19.11***	18.142***
	(1.326)	(1.792)	(0.179)	(0.172)	(1.237)	(1.488)
Political Similarity	-4.708***	-2.459**	0.097	0.087	-2.245**	-2.016**
	(1.256)	(1.1)	(0.09)	(0.094)	(0.933)	(0.863)
Bond characteristics:						
Size		0.312***		-0.001		0.122
		(0.098)		(0.002)		(0.081)
Asset-backed		-1.511		0.1		-2.186**
		(1.102)		(0.064)		(1.074)
Convertible		1.279		0.057***		1.01
		(1.09)		(0.013)		(1.082)
Senior-secured		0.111		0.09***		-0.185
		(0.392)		(0.028)		(0.337)
Enhanced		1.109***		0.007		0.862***
		(0.256)		(0.02)		(0.215)
Puttable		-0.818		0.037		0.191
		(0.608)		(0.033)		(0.667)
Redeemable		0.292		-0.009		0.423
		(0.346)		(0.012)		(0.277)
Maturity		0.039		0.002*		0.012
		(0.029)		(0.001)		(0.025)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.628	0.673	0.36	0.369	0.441	0.486
N	1,029	1,016	3,276	3,235	1,060	1,047

Panel B: Moody's

	Rating Level		DAHEAD		WRATE	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	14.409***	10.345***	-0.281*	-0.293*	16.266***	14.795***
	(1.169)	(1.667)	(0.156)	(0.158)	(0.982)	(1.302)
Political Similarity	-6.485***	-4.531***	0.283***	0.286***	-4.14***	-3.598***
	(1.275)	(1.088)	(0.095)	(0.1)	(0.911)	(0.91)
Bond characteristics	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.64	0.67	0.198	0.199	0.49	0.518
N	1,000	987	2,379	2,361	1,030	1,017

Panel C: Fitch

	Rating Level		DAHEAD		WRATE	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	4.432	6.864**	-0.55***	-0.574***	5.72***	5.429**
	(2.848)	(3.28)	(0.17)	(0.173)	(2.102)	(2.416)
Political Similarity	-7.511***	-5.266**	0.286**	0.287*	-3.591*	-2.902*
	(2.205)	(2.231)	(0.142)	(0.158)	(1.825)	(1.757)
Bond characteristics	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.667	0.699	0.128	0.132	0.508	0.536
N	618	602	1,735	1,721	629	613

This table presents the regression results of rating timeliness proxies on political similarity and control variables. *Rating Level* is the absolute credit rating score issued by a CRA to a bond at 270 days prior to the bond issuer's default date. *DAHEAD* is the difference between a downgrade date of an issue and the default date divided by 360. *WRATE* is the time-weighted average rating level over the 1-year period leading to default. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. *Size* is log of a bond issue's size; *Maturity* is the number of years to the bond's maturity; and other control variables are binary variables that are equal to one if a bond issue has a certain characteristic, and zero otherwise. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.13
Rating Accuracy and Political Similarity (CEO Turnover)

Panel A: S&P

	Category I error		Category II error	
	(1)	(2)	(3)	(4)
Intercept	0.138**	0.184***	0.971***	0.971***
	(0.059)	(0.071)	(0.22)	(0.22)
Political Similarity	0.107**	0.148***	-0.101	-0.101
	(0.044)	(0.041)	(0.096)	(0.096)
Bond characteristics:				
Size		-0.006		0.008
		(0.004)		(0.007)
Asset-backed		0.104**		0.156***
		(0.051)		(0.046)
Convertible		-0.048		-0.152
		(0.052)		(0.255)
Senior-secured		0.009		-0.034
		(0.016)		(0.041)
Enhanced		-0.041***		-0.039
		(0.01)		(0.028)
Puttable		-0.009		0.18***
		(0.032)		(0.054)
Redeemable		-0.02		-0.013
		(0.013)		(0.025)
Maturity		-0.001		-0.005*
		(0.001)		(0.002)
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.441	0.486	0.091	0.091
N	1,060	1,047	994	994

Panel B: Moody's

	Category I error		Category II error	
	(1)	(2)	(3)	(4)
Intercept	0.273***	0.343***	1.429***	1.429***
	(0.047)	(0.062)	(0.165)	(0.165)
Political Similarity	0.197***	0.171***	-0.313***	-0.313***
	(0.043)	(0.043)	(0.094)	(0.094)
Bond characteristics	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.49	0.518	0.058	0.058
N	1030	1017	975	975

Panel C: Fitch

	Category I error		Category II error	
	(1)	(2)	(3)	(4)

Intercept	0.775***	0.789***	1.105***	1.105***
	(0.1)	(0.115)	(0.256)	(0.256)
Political Similarity	0.171*	0.191**	-0.408**	-0.408**
	(0.087)	(0.084)	(0.18)	(0.18)
Bond characteristics	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.508	0.536	0.23	0.23
N	629	613	593	593

This table presents the regression results of rating accuracy proxies on the political similarity and control variables. Category I error measures the degree of missing a default rating by a CRA and is calculated as (default score – average rating score) / (default score - 1) where default score is 22 and average rating score is the average rating level issued by the CRA for the rated bond in one year prior to the default date. Category II error measures the degree of false default warning by a CRA to a non-defaulting bond and is calculated as (warning score – cut off point) / (default score - cut-off point) where cut-off point is 20. Political similarity between a CRA's and a firm's CEOs is calculated as 1 – |firm_CEO_D% - CRA_CEO_D%| where D% represents the proportion of the CEO's total campaign contributions to Democrats in year *t* - 1 divided by his/her total contributions to both parties in the same year. *Size* is log of a bond issue's size; *Maturity* is the number of years to the bond's maturity; and other control variables are binary variables that are equal to one if a bond issue has a certain characteristic, and zero otherwise. Standard errors in parentheses are adjusted for heteroskedasticity and clustering at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

CHAPTER FOUR

Natural Disasters and Credit Ratings

ESSAY THREE

This chapter presents the third essay of this thesis. In general, the third essay investigates whether natural disasters have an impact on CRAs rating behaviours. The chapter is organized as follows. Section 4.1 provides an overview of second essay. Section 4.2 summarizes data collection, variable measurements, and summary statistics. Section 4.3 presents the methodology and empirical results. Section 4.4 concludes. The essay's Appendix and References are shown at the end of this chapter and in the references section, respectively.

4.1. Introduction

The increasing frequency and unpredictability of natural disasters are currently attracting the attention of the public,[35] particularly large-scale events such as Hurricanes Katrina and Harvey. Natural disasters are exogenous and negative shocks to the communities where they affect because they not only result in property damage including damages to homes, businesses, and automobiles, but also psychological damage (Barth, Sun and Zhang, 2019). Specifically, Kousky (2014) estimates that the average annual damage caused by natural disasters ranged between $US 94 to 130 billion from 2000 to 2012. Further, the consequence of natural disasters is transmitted to the global economy (Emanuel, 2017; Burke, Hsiang and Miguel, 2015; Dietz, Bowen, Dixon and Gradwell, 2016). Hsiang and Jina (2014) estimate that natural disasters have the same effect on income per capita as a banking crisis, and state that these events could have a long-term economic impact. Similarly, BlackRock (2019) also predicts that in the future extreme climatic events are set to cost at least 1% of GDP in the U.S.

Therefore, policy makers are increasingly interested in understanding how the effects of natural disasters transmit to the worldwide economy, in general, and financial markets in particular[36]. To understand this, an investigation is needed into how key market members, important transmission mechanisms, respond to natural disasters. The current literature focuses on investigating the reactions of those market participants who have been fundamentally affected by the disaster such as investors (De Bondt and Thaler, 1985; Alok, Kumar and Wermers,

[35] A poll conducted in the U.S shows that more than 60% people asked believes that the global weather is getting worse and worse and the climate change results in the severity of several current natural disasters (Leiserowitz, Maibach, Renouf and Hmielowski, 2012).
[36] Ban Ki-Moon, United Nations (UN) Secretary General, shows that “investors need to know how the impacts of climate change can affect specific companies, sectors and financial markets as a whole” at the UN Foundation Investor Summit on Climate Risk. The Institutional Investors Group on Climate Change (IIGCC) managing over $US 13 trillion argue that “climate risk needs to be better reflected in the price of risk so that a shift in capital can be encouraged.”

2020; Huynh and Xia, 2021), banks (Chavaz, 2016; Noth and Schuwer, 2018; Brown, Gustafson & Ivanov, 2021), and insurance firms (Massa & Zhang, 2021). In general, the previous study find that fundamentally affected participants tend to either over- or underreact to the climatic disaster risks due to their huge loss following the natural disasters. However, no research investigates how "natural disaster" fundamentally unaffected providers account for the effect of natural disasters in information supplied to financial markets. The third essay addresses the gap in the literature by investigating how CRAs, information contributors in financial markets, make rating changes following natural disasters.

I first examine the direct responses of CRAs to natural disasters. I find that firms located in natural disaster affected-states (affected firms hereafter) are downgraded by 0.030-0.050 notch by major traditional CRAs, S&P, Moody's and Fitch, in the month of the event. The analysis is then extended to three months before and after the disaster events. There is no significant change in credit ratings during the three months before disasters. It is because natural disasters are unpredictable events and as such cannot lead the response of CRAs in the pre-periods. However, I find that credit ratings continue to be downgraded by 0.020-0.030 notch during the month following the disasters. These findings are consistent with initial expectations that CRAs slowly adjust their credit ratings since they need some time to observe the consequence of natural disasters. I next investigate the market responses to natural disasters. In this essay, I use market's reactions to natural disasters as a benchmark to investigate whether CRAs' rating actions are driven by firm's fundamental factors. Specifically, I find that the stock price of affected firms, a proxy for market's reactions to natural disasters, decreases in the month of the event and the months post-event. The results are significant evidence to hypothesise that CRA rating changes following natural disasters are driven by firm's fundamental changes.

I further investigate whether the affected firms' rating changes by natural disasters triggers linked firms' rating changes through different spill-over channels. Since one might concern that rating changes are potentially caused by fundamental factors beyond natural disasters, I apply instrumental variable (IV) analysis to extract the rating changes of firms affected by natural disasters. The linked firms are divided into connected firms and competitive firms, and I separately test the spill-over effects. In this essay, I define connected firms based on their fundamental similarities and/or economic relations to affected firms but located in different states[37]. I define industrial peers of the affected firms as the first type of connected firms (Moskowitz and M. Grinblatt, 1999; Cohen and Lou, 2012). Second, following research by Parsons, Sabbatucci and Titman (2016) and Jannati (2020), I identify the second type of connected firms as firms headquartered in the state that shares borders with states where affected firms are located. Third, I identify the second type of connected firms with a linkage along the supply chain with the affected firms (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Ali and Hirshleifer, 2020). Generally, I find that rating changes of affected firms caused by natural disasters leads to the same directional rating changes for connected firms. The results are consistent with initial expectations that they are fundamentally linked, which might generate a spill-over mechanism. Next, I investigate the spill-over effects from affected firms to their competitors. Conversely, the rating changes of affected firms caused by natural disasters lead to the opposite directional rating changes for competitive firms [38]. In both samples, the spill-over effects appear in the event month and one-month post-event. Further, this essay questions the degree to which CRAs are sensitive to natural extreme events. To answer this question, I use market sensitivity to natural disasters as a benchmark. Specifically, I apply the same process to test the spill-over effect of natural disasters on stock price changes, a proxy for market reactions. I find that the change in stock price of affected firms does not

[37] Since the natural disasters are clustered at state levels, connected firms located in different states from affected firms are selected to avoid the compounding effects.
[38] I would like to say thank you Gerard Hoberg and Gordon Phillips for making the data available on their website: http://hobergphillips.tuck.dartmouth.edu/industryclass.htm

lead to changes in stock prices of linked firms in the event-month, but the changes appear in the month following the natural disasters. The findings confirm that the contagious reactions of CRAs to natural disasters are timelier than those of the market. This is significant evidence of CRA sensitivity to natural extreme events.

The essay first contributes to the climate finance literature which currently follows two main strands. The first strand focuses on the effects of climate change risks. Various studies explore the impact of climate change risks on corporates such as carbon risk, social costs of carbon emissions and the return premium of carbon-intensive firms (Barnett, Brock and Hansen, 2020; Bolton and Kacperczyk, 2021; Choi, Gao and Jiang, 2020; Hsu, Li and Tsou, 2020). Others also investigate the impacts of climate regulatory risk as well as the relationships between corporate risks and social outcomes (Hoepner, Oikonomou, Sautner, Starks and Zhou, 2020; Seltzer, Starks and Zhu, 2021). The second strand concentrates on the effects of natural disasters, extreme climatic events caused by climate changes, and on financial market reactions and corporate outcomes (Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Hsu, Lee, Peng and Yi, 2018; Alok, Kumar and Wermers, 2020; Brown, Gustafson and Ivanov, 2021; Massa and Zhang, 2021). Generally, they conclude that market participants such as corporates, banks and insurance firms fundamentally impacted by natural disasters underestimate the effect of these extreme events since they lack informational sources to assess the consequences. However, the responses of information providers fundamentally unaffected by natural disasters is relatively under-examined. This essay aims to address this issue by investigating how CRAs, an important information contributor in financial markets, adjust their credit ratings following natural disasters.

The second contribution of this essay is to the literature related to corporate credit ratings. The literature currently consists of two main strands. The first strand contributes to the knowledge about conflict of interest in credit ratings. Many studies find sources of conflict of interest that distort the timeliness and accuracy of credit rating quality. These sources include the ability of CRAs to access information (Jaggi and Tang, 2017; Bonsall, Green, and Muller, 2018; Khatami, Marchica, and Mura, 2016), business model (Skreta and Veldkamp, 2009; He, Qian, and Strahan, 2012; Jiang, Stanford, and Xie, 2012; Cornaggia and Cornaggia, 2013; Baghai and Becker, 2018), ownership structure (Kedia, Rajgopal, and Zhou, 2017), and the issuer’s size (He, Qian, and Strahan, 2011; Efing and Hau, 2015).

The second strand, conversely, focuses on the traditional direction. The current literature investigates the content of rating adjustments (Bhattacharya, Wei, and Xia, 2019; Brogaard, Koski and Siegel, 2019). The essay differs from previous studies by investigating how rating agencies respond to exogenous shocks such as natural disasters via their rating adjustments of the affected firms. More importantly, the findings extend to the spill-over effects of rating changes for the affected firms triggered by the effect of natural disasters on the linked firms. To the best of my knowledge, this essay is the first research that explores spill-over effects in credit rating adjustments following extreme climate events.

The remainder of the paper is organized as follows. Section 2 summarizes data collection, variable measurements, and summary statistics. Section 3 presents methodology and empirical results. Section 4 concludes.

4.2. Sample Selection, Variable Measurements, and Summary Statistics

By using spatial hazard events and losses database for the United States (SHELDUS), I identify natural disaster events. The database provides monthly adjusted crop and property damages and monthly injured and deceased people as a result of natural disasters across 50 U.S states. In the essay, I calculate monthly adjusted damage as aggregate crop and property damages (unit: $US million) and monthly affected people as aggregate injured and dead people (unit: 100 people). I then based on these aggregate measures to identify disaster and non-disaster months across 50 U.S states from 1999 to 2015.

Specifically, I report the statistics on natural disaster months across 50 U.S states from 1999 to 2015 in Table 4.1. The table is organized by two panels. Panel A summarizes the number of disaster months identified by monthly adjusted damages. In my main analysis, I use monthly adjusted damages with the threshold of $US 5M to identify disaster months. Specifically, if I choose $US 5M as a threshold (i.e., >= $US 5M), there are 631 disaster months across 50 U.S. states from 1999 to 2015. The figures for the thresholds of $US 10M and $US 100M are 404 and 66 disaster months respectively[39]. Panel A also presents the statistics on monthly adjusted damage. On average, natural disasters result in adjusted damage of $US 5.775M during each month in each state. The maximum monthly adjusted damage caused by natural disasters is $US 7,313.36M. Panel B summarizes the number of disaster months identified by monthly affected people. In robustness checks reported in Table C.3-C.5 in the Appendix, I use monthly affected people with the threshold of 50 people to identify disaster months. Specifically, if I select 50 affected people as a threshold (i.e., >= 50 people), there are 206 disaster months across 50 U.S from 1999 to 2015. Panel B also presents the statistics on monthly affected people. The figures are 107 and 20 disaster months if I choose thresholds of 100 and 1000 affected people respectively. On average, the natural disasters cause 7.2 affected people during each month in each state. Other months are defined as non-disaster months.

[39] I use thresholds of $US 10M and $US 100M for robustness checks. The unreported results are available upon request.

Table 4.1: Statistics on Natural Disaster at State Level

Panel A: Monthly Adjusted Damage (Unit: $US Million)						
	N	Max	Mean	Median	Min	Std
Monthly Adjusted Damage (Crop + Property)	8,578	7313.360	5.775	0.071	0.000	104.831
Number of Disaster Months Across States (>= $US 5 million in Total Adjusted Damage) = 631						
Number of Disaster Months Across States (>= $US 10 million in Total Adjusted Damage) = 404						
Number of Disaster Months Across States (>= $US 100 million in Total Adjusted Damage) = 66						
Panel B: Monthly Affected People (Unit: 100 People)						
	N	Max	Mean	Median	Min	Std
Monthly Affected People (Injured and Dead)	8,578	23.600	0.072	0.010	0.000	0.432
Number of Disaster Months Across States (>= 50 Affected People) = 206						
Number of Disaster Months Across States (>= 100 Affected People) = 107						
Number of Disaster Months Across States (>= 1000 Affected People) = 20						

The table presents the summary statistics of monthly inflation adjusted damage and monthly affected people caused by natural disasters across U.S states in the research period from 1999 to 2015. In the essay, I base on either monthly inflation adjusted (i.e., base 2015) damage or affected people caused by natural disasters at each state to define a month-state disaster. In main analysis, I consider threshold of $US 5 million in total adjusted damage, and I use threshold of 50 affected people for the robustness checks.

The next step is to obtain credit rating information from Bloomberg ranging from 1999 to 2015. The essay focuses on three internationally recognized CRAs, S&P, Moody's and Fitch. The original credit rating scores are letters (e.g., AAA/Aaa, AA+/Aa1, AA-/Aa3). I follow the literature (e.g., Gande and Parsley, 2005; Dimitrov, Palia, and Tang, 2015; Joe and Oh, 2018) to convert alphabetic ratings to numeric ratings. The rating conversion scale is shown in Appendix C.1. The rating conversion scale is shown in Appendix C.1. I match the credit rating samples with COMPUSTAT and CRSP by using tickers or company names for accounting information. I exclude unsuccessfully matched firms. The final sample ends with 1,201, 752 and 534 firms rated by S&P, Moody's and Fitch respectively. Since the natural disaster database is monthly datasets, I also measure rating changes on monthly basis as follows:

$$\Delta CCR_{i,m} = (CCR_{i,m} - CCR_{i,m-1}) \quad (4.1)$$

where $CCR_{i,m}$ is a numeric credit rating score assigned by a rating agency to firm *i* at the end of month *m*[40]. I present the statistics on ΔCCR in Table 4.2. The positive (negative) value of ΔCCR reflects upgrade (downgrade) adjustments. The largest upgrade adjustment (i.e., maximum value of ΔCCR) made by S&P, Moody’s and Fitch is 3.5, 2 and 4 notches respectively. The largest downgrade adjustment (i.e., minimum value of ΔCCR) made by S&P, Moody’s and Fitch is -4, -3 and -4 notches respectively. The mean and median values of ΔCCR equal to zero. In other words, the number of upgrade months relatively equals to that of downgrade months.

Table 4.2: Statistics on Credit Rating Score Changes (Monthly Basis)

	Firm Rated	N	Max	Mean	Median	Min	Std
Standard & Poor's	1,201	107,952	3.500	-0.022	0.000	-4.000	0.436
Moody's	752	60,359	2.000	-0.014	0.000	-3.000	0.378
Fitch	534	63,035	4.000	-0.021	0.000	-4.000	0.436

The table presents the summary statistics of monthly credit rating score changes by “Big Three” CRAs: Standard & Poor's, Moody’s and Fitch. In the essay, I measure the credit rating change as follows:

$$\Delta CR_{i,m} = (CR_{i,m} - CR_{i,m-1}) \tag{4.1}$$

I also follow the literature (e.g., Xia, 2014; Dimitrov et al., 2015; Kedia et al., 2017) to control for a vector of firm characteristics that potentially drives the rating changes. The list of control variables includes long-term (LT) debt-to-equity, market-to-book ratio, operating margin, interest coverage, LT debt leverage, firm size and stock return standard deviation. Descriptions of control variables and their sources are presented in detail in Appendix C.2. I report the summary statistics in Table 4.3 divided into three panels: A, B and C for firms rated by S&P, Moody’s and Fitch respectively. According to the statistics, I observe several characteristics of firm covered by the CRAs. Firstly, firms rated by Fitch are relatively larger than firm rated

[40] For convenience, I also add this calculation into Appendix C.2.

S&P and Moody's. It is consistent with the previous studies that Fitch mostly rates large firms (e.g., Alsakka and ap Gwilym, 2012; Chen, Chen, Chang, and Yang, 2016). Specifically, mean (median) in size of firm rated by Fitch is 8.617 (9.037) while the figure for S&P and Moody's is 7.891 (7.981) and 7.520 (7.512) respectively. Second, firms rated by Moody's use more debts than firms rated by S&P and Fitch. Specifically, mean of LT debt-to-equity and LT Debt Leverage of firm covered by Moody's is 1.373 and 0.325, compared to 1.143 and 0.285 of firms covered by S&P, and 1.070 and 0.248 of firms covered by Fitch. Finally, there is no significant difference in other characteristics between firms rated by the CRAs.

Table 4.3: Statistics on Firm Characteristics (Control Variables)

Panel A: Firms rated by Standard and Poor's						
	N	Max	Mean	Median	Min	Std
LT Debt-to-Equity	9,588	4.036	1.143	0.736	0.000	1.156
Market-to-Book ratio	9,588	9.787	3.076	2.050	0.341	3.380
Operating Margin	9,588	0.528	0.153	0.154	-4.500	0.330
Interest Coverage	9,588	27.445	4.298	1.793	-6.779	6.560
LT Debt Leverage	9,588	0.626	0.285	0.271	0.000	0.170
Firm Size	9,588	9.198	7.891	7.981	2.868	1.127
Stock Return Standard Deviation	9,588	0.083	0.029	0.024	0.012	0.017
Panel B: Firms rated by Moody's						
	N	Max	Mean	Median	Min	Std
LT debt-to-equity	5,388	4.086	1.373	0.879	0.000	1.276
Market-to-Book ratio	5,388	11.128	3.062	1.931	0.321	3.593
Operating Margin	5,388	0.543	0.145	0.129	-4.300	0.265
Interest Coverage	5,388	16.285	2.339	1.072	-7.418	3.991
LT Debt Leverage	5,388	0.615	0.325	0.315	0.000	0.180
Firm Size	5,388	9.207	7.520	7.512	2.568	1.100
Stock Return Standard Deviation	5,388	0.088	0.033	0.028	0.018	0.017
Panel C: Firms rated by Fitch						
	N	Max	Mean	Median	Min	Std
LT debt-to-equity	5,517	4.016	1.070	0.817	0.000	0.985
Market-to-Book ratio	5,517	6.483	2.525	1.665	0.361	2.753
Operating Margin	5,517	0.517	0.188	0.149	-4.710	0.177
Interest Coverage	5,517	15.084	4.125	2.391	-1.501	2.788
LT Debt Leverage	5,517	0.636	0.248	0.210	0.000	0.158
Firm Size	5,517	9.138	8.617	9.037	4.501	0.729
Stock Return Standard Deviation	5,517	0.086	0.021	0.015	0.013	0.013

The table presents the summary statistics of control variables, which are defined in Table A2 in the Appendix.

4.3. Methodology and Empirical Results

4.3.1. *Baseline results*

To ascertain whether natural disasters trigger CRA's rating behavior, I first examine affected firms' rating changes surrounding the disaster events. As mentioned earlier, I focus on rating signals from major traditional CRAs: S&P, Moody's and Fitch. For each CRA, I estimate two separate regressions. Firstly, I run the basic regression as follows:

$$\Delta CCR_{i,m} = a + b_1\ Disaster_{i,m} + c_1 Controls_{i,m} + ei,t \quad (4.2)$$

Secondly, to examine rating behaviour before and after the disaster events, I next run the following regression:

$$\Delta CCR_{i,m} = a + b_1{*}3Mbefore_{i,m} + b_2{*}2Mbefore_{i,m} + b_3{*}1Mbefore_{i,m} + b_4 Disaster_{i,m} + b_5{*}3Mafter_{i,m} + b_6{*}2Mafter_{i,m} + b_7{*}1Mafter_{i,m} + c_1 Controls_{i,m} + ei,m \quad (4.3)$$

Where $\Delta CCR_{i,m}$ is monthly rating changes to firm i on month m calculated as in Eq. (4.1). $Disaster_{i,m}$ is a dummy variable taking one in the disaster month m at the state that the firm is headquartered and zero otherwise. As mentioned earlier, in my main analysis, I use monthly adjusted damages with the threshold of $US 5M to identify disaster months. k$Mbefore_{i,m}$ is dummy variable taking value of one in month m-k (i.e., k=1, 2 or 3) prior to the disaster month m at the state that the film is headquartered and zero otherwise. k$Mafter_{i,m}$ is dummy variable taking value one in month m+k (i.e., k=1, 2 or 3) prior to the disaster month m at the state that the film is headquartered and zero otherwise. By following the literature (e.g., Xia, 2014; Dimitrov et al., 2015; Kedia et al., 2017), I also include a set of control variables, Controlsi,m, that potentially impacts rating changes. The detail variable construction is reported in Appendix C.2.

I report results in Table 4.4. I find that affected firms tend to be downgraded following the natural disasters. Specifically, firms located at disaster affected-states are abnormally downgraded by 0.04, 0.03 and 0.05 notch by S&P, Moody's and Fitch respectively in the event-months. I also examine rating changes before and after the disaster events. I find no significant abnormal rating changes during three months before natural disasters. The findings are not surprising since natural disasters are unpredictable events that cannot create shocks to CRAs in the pre-periods. In contrast, I report that credit ratings continue to be downgraded by 0.03, 0.02 and 0.03 notch by S&P, Moody's and Fitch respectively one month after the disasters. All results are significant at 1% level. The findings are consistent with my initiate expectations that CRAs slowly take actions following the natural disasters since they need time to observe the effects of natural disasters. I also find consistent results for second measurement of natural disasters, >= 50 injured and dead people, and report in Panel A of Table C.3 in the Appendix. The findings basically provide fresh evidence that CRAs, information providers in the financial markets, do take account the consequence of natural disasters into their rating information to the public.

Table 4.4: Natural Disasters and Credit Rating Changes (Direct Effects)

	Standard & Poor's		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0793***	0.0781***	0.0419***	0.0454***	-0.0789**	-0.0808**
	(0.0119)	(0.0119)	(0.0129)	(0.0129)	(0.0353)	(0.0356)
3Mbefore Disaster		0.0035		0.0034		0.004
		(0.0036)		(0.0041)		(0.0069)
2Mbefore Disaster		0.0025		0.0074		0.0127*
		(0.0036)		(0.0051)		(0.007)
1Mbefore Disaster		0.0080		0.0059		-0.0027
		(0.0056)		(0.0041)		(0.007)
Disaster Event	-0.0431***	-0.0388***	-0.0357***	-0.0303***	-0.0559***	-0.0478***
	(0.0034)	(0.0036)	(0.0038)	(0.0041)	(0.0065)	(0.007)
1Mafter Disaster		-0.0313***		-0.0251***		-0.0346***
		(0.0036)		(0.0041)		(0.007)
2Mafter Disaster		0.0065*		0.0013		-0.0136**
		(0.0036)		(0.0041)		(0.007)
3Mafter Disaster		-0.0031		0.0037		-0.0021
		(0.0036)		(0.0041)		(0.0068)
Control variables						
Firm Size	-0.0073***	-0.0068***	-0.0028**	-0.0026**	0.0106***	0.0108***
	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0037)	(0.0037)
LT Debt Leverage	0.0563***	0.0604***	0.0014	0.0073	0.0458**	0.0452**
	(0.0123)	(0.0123)	(0.0138)	(0.0137)	(0.021)	(0.0212)
Operating Margin	0.013***	0.0084**	0.0339***	0.0285***	0.0041	0.0044
	(0.0035)	(0.0035)	(0.0042)	(0.0043)	(0.0147)	(0.0149)
Interest Coverage	0.0004***	0.0004***	0.0002*	0.0002*	0.0013***	0.0013***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Market-to-Book ratio	0.0032***	0.0032***	0.0033***	0.0034***	0.0008	0.0009
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0008)	(0.0009)
LT debt-to-equity	-0.0131***	-0.0137***	-0.0076***	-0.0086***	-0.0045	-0.0046
	(0.002)	(0.002)	(0.0021)	(0.0021)	(0.0035)	(0.0035)
Stock Return Standard Deviation	-1.8741***	-1.8243***	-1.5697***	-1.5309***	-1.5021***	-1.4686***
	(0.0951)	(0.0947)	(0.1087)	(0.1085)	(0.1872)	(0.1886)
Stock Return	0.1192***	0.1135***	0.0865***	0.0794***	0.2182***	0.2179***
	(0.009)	(0.0089)	(0.0094)	(0.0093)	(0.0205)	(0.0207)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.013	0.013	0.014	0.013	0.009	0.010
No. Observations	108,260	107,498	60,560	60,101	47,698	47,355

The table reports the results on the impact of natural disasters on credit rating changes. The models are constructed as follows:

$$\Delta\ CCR_{i,m} = \alpha + Disaster\ Event_{i,m} + Controls_{i,m} + \varepsilon \tag{4.2}$$

$$\Delta\ CCR_{i,m} = \alpha + 3Mbefore\ Disaster_{i,m} + 2Mbefore\ Disaster_{i,m} + 1Mbefore\ Disaster_{i,m} + Disaster\ Event_{i,m} + 1Mafter\ Disaster_{i,m} + 2Mafter\ Disaster_{i,m} + 3Mafter\ Disaster_{i,m} + Controls_{i,m} + \varepsilon \tag{4.3}$$

where $\Delta\ CCR_{i,m}$ is monthly credit rating changes measured as (4.1). $3Mbefore\ Disaster_{i,m}$ is dummy variable taking value one in month *m-3* prior to the disaster month *m* at the state that the film *i* is headquartered and zero otherwise. $2Mbefore\ Disaster_{i,m}$ is dummy variable taking value one in month *m-2* prior to the disaster month *m* at the state that the film *i* is headquartered and zero otherwise. $1Mbefore\ Disaster_{i,m}$ is dummy variable taking value one in month *m-1* prior to the disaster month *m* at the state that the film *i* is headquartered and zero otherwise. $Disaster\ Event_{i,m}$ is a dummy variable taking value one in the disaster month m at the state that the film is headquartered and zero otherwise. In the essay, I define a month in state A as the disaster month m if monthly adjusted damage is more than $US 5M. $1Mafter\ Disaster_{i,m}$ is dummy variable taking value one in month *m+1* after the disaster month *m* at the state that the film *i* is headquartered and zero otherwise. $2Mafter\ Disaster_{i,m}$ is dummy variable taking value one in month *m+2* after the disaster month *m* at the state that the film *i* is headquartered and zero otherwise. $3Mafter\ Disaster_{i,m}$ is dummy variable taking value one in month *m+3* after the disaster month *m* at the state that the film *i* is headquartered and zero otherwise. I also include a set of firm characteristics, $Controls_{i,m}$, as control variables across all regressions. The detailed descriptions are presented in Appendix C.2. I apply firm and month fixed effects across all regressions.

I next investigate which mechanism motivates CRAs to downgrade affected firms surrounding natural disasters. I argue that if CRAs' rating behaviors are driven by fundamental changes caused by natural disasters, I should observe the same patterns in market's reactions to the natural disasters. I apply Eq. (4.2) and Eq. (4.3) by replacing the dependent, $\Delta CCR_{i,m}$, by monthly stock return, $Return_{i,m}$. In the model, $Return_{i,m}$ is monthly return to firm *i* on month *m* calculated as the natural log (stock price of firm *i* at month *m* divided by stock price of firm *i* at month *m -1*).

The results are reported in Table 4.5. Consistent with the section of rating changes, I also use monthly adjusted damages with the threshold of $US 5M to identify disaster months. In general, I find the same patterns in market 's responses to the natural disasters. Stock returns of affected firms experience an abnormal downward trend. Specifically, abnormal stock returns of affected firms rated by S&P, Moody's and Fitch are -0.97%, -0.91% and -0.82% respectively in the event-month. I also examine abnormal stock returns before and after the disaster events. I find no significant abnormal stock returns during three months before natural disasters. The findings are reliable since natural disasters are unpredictable events that cannot lead to shocks in markets' reactions in the pre-periods. In contrast, I find negative abnormal stock returns in a month after the natural disasters. The findings support the story that financial markets, similar to CRAs, react slowly to natural disasters because they need time to assess the consequence. All results are significant at 1% level. I also find consistent results for second measurement of natural disasters, >= 50 injured and dead people, and report in Panel B of Table C.3 in the Appendix. The results show that CRAs have the same responses to natural disasters as the financial markets that react to any fundamental changes caused by the extreme exogenous shocks. This is significant evidence that CRAs' rating behaviors are driven by fundamental changes caused by natural disasters.

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Table 4.5: Natural Disasters and Stock Return (Direct Effects)

	Standard & Poor's		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0274***	0.0319***	0.0237***	0.0301***	0.0163**	0.0206**
	(0.0043)	(0.0043)	(0.006)	(0.0061)	(0.0083)	(0.0083)
3Mbefore Disaster		0.0009		0.0011		0.0001
		(0.0013)		(0.0019)		(0.0016)
2Mbefore Disaster		-0.0006		0.0028		0.0001
		(0.0013)		(0.0019)		(0.0016)
1Mbefore Disaster		-0.0018		-0.0032*		-0.0025
		(0.0013)		(0.0019)		(0.0016)
Disaster Event	-0.014***	-0.0097***	-0.0145***	-0.0091***	-0.0114***	-0.0082***
	(0.0012)	(0.0013)	(0.0018)	(0.0019)	(0.0015)	(0.0016)
1Mafter Disaster		-0.0035***		-0.0045**		-0.003*
		(0.0013)		(0.0019)		(0.0016)
2Mafter Disaster		-0.0049***		-0.009***		-0.0053***
		(0.0013)		(0.0019)		(0.0016)
3Mafter Disaster		-0.0014		-0.0001		0
		(0.0013)		(0.0019)		(0.0016)
Control variables						
Firm Size	-0.0035***	-0.0034***	-0.0031***	-0.0031***	-0.0019**	-0.0019**
	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0009)	(0.0009)
LT Debt Leverage	0.0085*	0.0092**	0.0043	0.0053	0.0029	0.0035
	(0.0045)	(0.0045)	(0.0064)	(0.0064)	(0.0049)	(0.005)
Operating Margin	0.012***	0.011***	0.0145***	0.0131***	0.0054	0.0028
	(0.0013)	(0.0013)	(0.002)	(0.002)	(0.0034)	(0.0035)
Interest Coverage	0.0001***	0.0001***	0.0001***	0.0001***	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Market-to-Book ratio	0.0021***	0.0021***	0.0024***	0.0024***	0.0012***	0.0012***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LT debt-to-equity	-0.0033***	-0.0033***	-0.0033***	-0.0034***	-0.0014*	-0.0015*
	(0.0007)	(0.0007)	(0.001)	(0.001)	(0.0008)	(0.0008)
Stock Return Standard Seviation	-1.1732***	-1.1484***	-1.1959***	-1.1734***	-0.9244***	-0.9098***
	(0.0343)	(0.0344)	(0.0504)	(0.0506)	(0.0438)	(0.044)
Stock Return	0.1192***	0.1135***	0.0865***	0.0794***	0.2182***	0.2179***
	(0.009)	(0.0089)	(0.0094)	(0.0093)	(0.0205)	(0.0207)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.046	0.045	0.046	0.044	0.041	0.040
No. Observations	108,260	107,498	60,560	60,101	47,698	47,355

The table reports the results on the impact of natural disasters on stock returns. The models are constructed as follows:

$$Return_{i,m} = \alpha + Disaster\ Event_{i,m} + Controls_{i,m} + \varepsilon \tag{4.2}$$

$$Return_{i,m} = \alpha + 3Mbefore\ Disaster_{i,m} + 2Mbefore\ Disaster_{i,m} + 1Mbefore\ Disaster_{i,m} + Disaster\ Event_{i,m} + 1Mafter\ Disaster_{i,m} + 2Mafter\ Disaster_{i,m} + 3Mafter\ Disaster_{i,m} + Controls_{i,m} + \varepsilon \tag{4.3}$$

Where $Return_{i,m}$ is monthly stock return calculated as the natural log (stock price of firm *i* at month *m* divided by stock price of firm *i* at month *m -1*). I apply firm and month fixed effects across all regressions. I have accounted for stock split when computing monthly returns. All variables are defined as in Table 4.4.

4.3.2. Spillover effects

4.3.2.1. Credit Rating Changes

I further investigate whether affected firms' rating changes by natural disasters trigger associated firms' rating changes. I apply two steps of instrumental variable (IV) analysis to test spillover transmission from affected firms' rating changes to linked firms' rating changes. The purpose is to distinguish affected firms' rating changes by natural disasters from fundamental factors . In first step, I obtain affected firms' predicted rating changes by natural disasters (i.e., instrumented) in event-month and post-event months from Eq. (4.3). In second step, I run the following regression:

$$\Delta CCR_{j,m} = a + b_1\, CRCs\_Disaster(Instrumented)_{i,m} + b_2 Disaster_{j,m} + c_1 Controls_{j,m} + e_{j,m} \tag{4.4.1}$$

$$\Delta CCR_{j,m+1} = a + b_1\, CRCs\_Disaster(Instrumented)_{i,m} + b_2 Disaster_{j,m+1} + c_1 Controls_{j,m+1} + e_{j,m+1} \tag{4.4.2}$$

$$\Delta CCR_{j,m+1} = a + b_1 CRCs\_1MafterDisaster(Instrumented)_{i,m} + b_2 Disaster_{j,m+1} + c_1 Controls_{j,m+1} + e_{j,m+1} \tag{4.4.3}$$

where $\Delta CCR_{j,m}$ is linked firm *j*'s rating change on month *m* calculated as in Eq. (4.1). $CRCs\_Disaster(Instrumented)_{i,m}$ and $CRCs\_1MafterDisaster(Instrumented)_{i,m}$ are affected firm *i's* predicted rating changes caused by natural disasters in month *m* (i.e., disaster month) and month *m+1* obtained from Eq. (4.3) respectively. One might concern about compounding effects of natural disasters since linked firm j's rating changes are not only driven by affected firm i's rating changes by natural disasters (i.e., my main interest) but also by other natural disasters at its state. Hence, I include *Disaster*$_{j,m}$ that is a dummy variable taking one in the disaster month m at the state that the firm j is headquartered and zero otherwise. The purpose of *Disaster*$_{j,m}$ is to control for the effect of local natural disasters on linked firm j's rating changes. I define a month in state A as the disaster month m if monthly adjusted damage is more than $US 5M. For the robustness checks, I also define a month in state A as the disaster month m if monthly affected people are more than 50, and I report the robust results in Table C.4 in the Appendix. In the essay, I divide the associated firms into connected firms and competitive firms, and separately test the spillover effects of natural disasters. Following the literature (e.g., Cohen and Lou, 2012; Parsons, Sabbatucci and Titman, 2016; Ali and Hirshleifer, 2020), I argue that the spillover transmission from treated firms to connected firms are different from to competitive firms.

I report the results in Table 4.6. I follow the literature to select connected firms by several ways based on fundamental similarities or economic relations to affected firms but located at different states. First, I define connected firms that are industrial peers with the affected firms (e.g., Moskowitz and M. Grinblatt, 1999; Cohen and Lou, 2012). I report the results on industrial spillover effect in Panel A of Table 4.6. I separately consider rating signals from S&P, Moody's and Fitch. I report the results of Eq. (4.4.1) in column 1, 4 and 7, of Eq. (4.4.2) in column 2, 5 and 8, of Eq. (4.4.3) in column 3, 6 and 9. In general, I find that affected firms' rating changes in month m (i.e., disaster month) by natural disasters trigger the same directional spillover effects on industrial peers' rating changes in month m and m+1. Specifically, Column 1 and 2 of Panel A shows that affected firms' one downgrade unit by S&P triggered by natural disasters in month m (i.e., disaster month) leads to industrial peers' 0.102 and 0.159 downgrade unit in month m and m+1 respectively. I also find robust results for Moody's and Fitch sample reported in Column 4-5 and 7-8 respectively. I even find that affected firms' rating changes in month m+1 (i.e., post-event month) by natural disasters trigger the same directional spillover effects on industrial peers' rating changes in month m +1. Specifically, Column 3 of Panel A shows that affected firms' one downgrade unit by S&P triggered by natural disasters in month m+1 leads to industrial peers' 0.260 downgrade unit in month m+1. The robust results for Moody's and Fitch sample are reported in Column 6 and 9 respectively. All results are significant at 5% and 1% level.

Second, I follow Parsons, Sabbatucci and Titman (2016) and Jannati (2020) to identify connected firms as geographical peers with affected firms. As mentioned earlier, geographical peers are located states that share the borders with states where affected firms are headquartered. I report the results in Panel B of Table 4.6. Third, I choose connected firms that are linked along the supply chain with affected firms (e.g., Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Ali and Hirshleifer, 2020). In the essay, I consider bi-directions in supplier-customer relationships in analysing spillover effects. I select affected suppliers and match with their customers. I select affected customers and match with their suppliers. The results are presented in Panel C and D of Table 4.6 respectively. In general, I find the consistent results with spillover effects on industrial peers in Panel A as affected firms' rating changes in month m and m+1 by natural disasters trigger the same directional spillover effects on connected peers' rating changes in month m and m+1. All results are significant at 1% and 5% levels.

I next investigate the spillover impacts from affected firms to their competitors[41]. In contrast, I find the opposite directional spillover impacts of affected firms' rating changes caused by natural disasters to their competitors' rating changes. The findings are consistent with the literature about differences in spillover transmissions from treated firms to connected firms and to competitive firms (e.g., Cohen and Lou, 2012; Parsons, Sabbatucci and Titman, 2016; Ali

[41] For a robustness check, I also exclude the overlapping sample between connected firms and competitors and replicate the analysis. I find the robust results, which are available upon on request.

and Hirshleifer, 2020). I report the results in Panel E of Table 4.6. Specifically, Column 1 and 2 of Panel E shows that affected firms' one downgrade unit by S&P triggered by natural disasters in month m (i.e., disaster month) leads to their competitors' 0.062 and 0.037 upgrade unit in month m and m+1 respectively. I also find robust results for Moody's and Fitch sample reported in Column 4-5 and 7-8 respectively. I even find that affected firms' rating changes in month m+1 (i.e., post-event month) by natural disasters also trigger the opposite directional spillover effects on their competitors' rating changes in month m +1. Specifically, Column 3 of Panel E shows that affected firms' one downgrade unit by S&P triggered by natural disasters in month m+1 leads to their competitors' 0.039 upgrade unit in month m+1. The robust results for Moody's and Fitch sample are reported in Column 6 and 9 respectively. All results are significant at 5% and 1% level.

Table 4.6: Natural Disasters and Credit Rating Changes (Spillover Effects)

Panel A: Industrial Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.054***	0.109***	0.104***	-0.024*	0.13***	0.125***	-0.339***	-0.468***	-0.474***
	(0.01)	(0.01)	(0.01)	(0.012)	(0.013)	(0.012)	(0.038)	(0.043)	(0.043)
CRCs_Dis (Instrumented)	0.102***	0.159***		0.266***	0.098**		0.115	0.153*	
	(0.03)	(0.03)		(0.038)	(0.039)		(0.085)	(0.095)	
CRCs_1MafterDisaster (Instrumented)			0.26***			0.038			-0.107
			(0.026)			(0.036)			(0.083)
Disaster Event	-0.003***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.019	0.014	0.014	0.038	0.024	0.024	0.005	0.007	0.007
No. Observations	426,954	389,900	389,900	162,561	148,303	148,303	135,790	123,830	123830

Panel B: Geographic Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.0428***	0.1008***	0.0939***	-0.0084	0.0253**	0.0223**	-0.6289***	-0.6524***	-0.6629***
	(0.0062)	(0.0069)	(0.0069)	(0.0142)	(0.0101)	(0.01)	(0.0403)	(0.0511)	(0.0509)
CRCs_Dis (Instrumented)	0.1346***	0.2099***		0.2349***	0.0817**		0.3216***	0.2486**	
	(0.0186)	(0.0204)		(0.047)	(0.0337)		(0.0853)	(0.1079)	
CRCs_1MafterDisaster (Instrumented)			0.2463***			0.0546*			0.1169
			(0.0182)			(0.0315)			(0.0948)
Disaster Event	-0.0053***	-0.0055***	-0.0055***	-0.0061***	-0.0059***	-0.0059***	-0.0058***	-0.0114***	-0.0114***
	(0.0002)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0006)	(0.0006)

Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.018	0.011	0.011	0.012	0.016	0.016	0.007	0.009	0.009
No. Observations	539,203	490,864	490,864	167,273	151,976	151,976	151,419	137,745	137,745

Panel C: Supplier-Customer Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.241***	0.224***	0.21***	0.169***	0.169***	0.159***	-0.408***	-0.41***	-0.412***
	(0.059)	(0.059)	(0.059)	(0.062)	(0.062)	(0.062)	(0.098)	(0.098)	(0.098)
CRCs_Dis (Instrumented)	0.409***	0.265***		0.554***	0.429***		0.125	0.044	
	(0.063)	(0.063)		(0.129)	(0.13)		(0.082)	(0.082)	
CRCs_1MafterDisaster (Instrumented)			0.257***			0.304***			0.04
			(0.054)			(0.115)			(0.069)
Disaster Event	-0.003***	-0.003***	-0.003***	-0.001	-0.001	-0.001	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.022	0.022	0.022	0.043	0.042	0.042	0.013	0.013	0.013
No. Observations	48,029	48,029	48,029	10,265	10,265	10,265	20,542	20,542	20,542

Panel D: Customer-Supplier Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.05***	0.05***	0.046***	0.084*	0.084*	0.069	0.087	0.087	0.081
	(0.017)	(0.017)	(0.017)	(0.047)	(0.047)	(0.047)	(0.057)	(0.057)	(0.057)
CRCs_Dis (Instrumented)	0.101	0.101		0.501**	0.501**		0.209	0.209	
	(0.073)	(0.073)		(0.231)	(0.231)		(0.143)	(0.143)	
CRCs_1MafterDisaster (Instrumented)			0.109*			0.294			0.141
			(0.062)			(0.198)			(0.118)

Disaster Event	-0.0065***	-0.0065***	-0.0065***	-0.0077***	-0.0077***	-0.0077***	-0.005***	-0.005***	-0.005***
	(0.0009)	(0.0009)	(0.0009)	(0.0012)	(0.0012)	(0.0012)	(0.0006)	(0.0006)	(0.0006)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.015	0.015	0.015	0.061	0.061	0.060	0.020	0.020	0.020
No. Observations	49,198	49,198	49,198	7,988	7,988	7,988	13,464	13,464	13,464
Panel E: Competitor Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.116***	0.117***	0.119***	0.028***	0.036***	0.035***	-0.109***	-0.107***	-0.109***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
CRCs_Dis (Instrumented)	-0.062***	-0.037***		-0.097***	0.002		-0.007	-0.034**	
	(0.01)	(0.01)		(0.012)	(0.012)		(0.017)	(0.017)	
CRCs_1MafterDisaster (Instrumented)			-0.039***			-0.007			0.016
			(0.009)			(0.012)			(0.014)
Disaster Event	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.016	0.016	0.016	0.035	0.035	0.035	0.014	0.014	0.014
No. Observations	2,693,742	2,693,742	2,693,742	1,007,735	1,007,735	1,007,735	959,837	959,837	959,837

The table reports the results on the spillover impact of affected firms' rating changes caused by natural disasters on their linked firms' rating changes. I apply two steps of instrumental variable (IV) analysis to test spillover transmission from affected firms' rating changes to linked firms' rating changes. The purpose is to distinguish affected firms' rating changes by natural disasters from fundamental factors. In first step, I obtain affected firms' predicted rating changes by natural disasters (i.e., instrumented) in event-month and post-event months from Eq. (4.3). In second step, I run the following regression:

$$\Delta CCR_{j,m} = a + b_1\ CRCs\_Disaster(Instrumented)_{i,m} + b_2 Disaster_{j,m} + c_1 Controls_{j,m} + ej,m \quad (4.4.1)$$

$$\Delta CCR_{j,m+1} = a + b_1\ CRCs\_Disaster(Instrumented)_{i,m} + b_2 Disaster_{j,m+1} + c_1 Controls_{jm+1} + ej,m+1 \quad (4.4.2)$$

$$\Delta CCR_{j,m+1} = a + b_1 CRCs\_1MafterDisaster(Instrumented)_{i,m} + b_2 Disaster_{j,m+1} + c_1 Controls_{jm+1} + ej,m+1 \quad (4.4.3)$$

Where $\Delta CCR_{j,m}$ is linked firm j's rating change on month m calculated as in Eq. (4.1). $CRCs\_Disaster(Instrumented)_{i,m}$ and $CRCs\_1MafterDisaster(Instrumented)_{i,m}$ is affected firm i's predicted rating changes caused by natural disasters in month m (i.e., disaster month) and month $m+1$ obtained from Eq. (4.3) respectively. One might concern about compounding effects of natural disasters since linked firm j's rating changes are not only driven by affected firm i's rating changes by natural disasters (i.e., my main interest) but also by other natural disasters at its state. Hence, I include $Disaster_{j,m}$ that is a dummy variable taking one in the disaster month m at the state that the firm j is headquartered and zero otherwise. The purpose of $Disaster_{j,m}$ is to control for the effect of local natural disasters on linked firm j's rating changes. I define a month in state A as the disaster month m if monthly adjusted damage is more than $US 5M. I divide linked firms into connected firms and competitive firms, and separately test the spillover effects of natural disasters. In the essay, I consider four types of connected firms including industrial peers, geographical peers, supplier-customer and customer-supplier relationships with the affected firms. I report the results in Panel A-D respectively. I report the result of competitive firms in Panel E. I also include a set of firm characteristics, $Controls_{j,m}$, as control variables across all regressions. I apply firm and month fixed effects across all regressions. The detailed descriptions are presented in Appendix C.2.

4.3.2.2. Stock Returns

I question about CRAs' sensitivity degree to natural extreme events. To answer this question, I use market's sensitivity to natural disasters as a benchmark. Specifically, I replicate the same process, two steps IV analysis, to extract affected firms' stock return caused by natural disasters and test the spillover effect of natural disasters on linked firms'stock price changes, a proxy for market reactions. In first step, I obtain affected firms' predicted stock returns driven by natural disasters (i.e., instrumented) in event-month and post-event months from Eq. (4.3) with the dependent variable of monthly stock return, *Returni,m*. In second step, I run the following regression:

$$Return_{j,m} = a + b_1\, SRs\_Disaster(Instrumented)_{i,m} + b_2 Disaster_{j,m} + c_1 Controls_{j,m} + ej,m \quad (4.5.1)$$

$$Return_{j,m+1} = a + b_1\, SRs\_Disaster(Instrumented)_{i,m} + b_2 Disaster_{j,m+1} + c_1 Controls_{jm+1} + ejm+1 \quad (4.5.2)$$

$$Return_{j,m+1} = a + b_1 SRs\_1MafterDisaster(Instrumented)_{i,m} + b_2 Disaster_{j,m+1} + c_1 Controls_{jm+1} + ejm+1 \quad (4.5.3)$$

where $Return_{j,m}$ is linked firm *j*'s stock return in month *m* calculated as the natural log (stock price of firm *i* at month *m* divided by stock price of firm *i* at month *m -1*). $SRs\_Disaster(Instrumented)_{i,m}$ and $SRs\_1MafterDisaster(Instrumented)_{i,m}$ is affected firm *i's* predicted stock return caused by natural disasters in month *m* (i.e., disaster month) and month *m+1* obtained from Eq. (4.3) with the dependent variable of $Return_{i,m}$, respectively. Other variables are defined as in Eq. (4.4.1), from Eq. (4.4.2) and from Eq. (4.4.3). A month in state A is defined as the disaster month *m* if monthly adjusted damage is more than $US 5M. For the robustness checks, I also define a month in state A as the disaster month m if monthly affected people are more than 50, and I report the robust results in Table C.5 in the Appendix

Similar to the section of credit rating changes, I separately consider the spillover transmission from treated firms (i.e., affected firms) to connected firms and competitive firms. I report the results in Table 4.7. First, I consider connected firms as industrial peers, geographical peers, supplier-customer and customer-supplier relationships with the affected firms, and the results are reported in Panel A-D respectively. In general, I find that affected firms' stock returns in month m (i.e., disaster month) by natural disasters do not trigger spillover effects on connected firms' stock return in month m. However, it is interesting that affected firms' stock returns in month m and m+1 by natural disasters significantly generate spillover effects on connected firms' stock return in month m+1. Specifically, Column 2 and 3 of Panel A shows that affected firms' one downgrade unit by S&P triggered by natural disasters in month m and m+1 leads to industrial peers' 0.043 and 0.091 downgrade unit in month m+1 respectively. I also find robust results for Moody's and Fitch sample reported in Column 5-6 and 8-9 respectively. The same patterns in spillover effects on stock returns of geographical peers, supplier-customer and customer-supplier are reported in Panel B-D. Second, I report the spillover transmission on stock return from treated firms to competitors in Panel E. Column 2 and 3 of Panel E shows that affected firms' one downgrade unit by S&P triggered by natural disasters in month m and m+1 leads to their competitors' 0.059 and 0.061 upgrade unit in month m+1 respectively. I also find robust results for Moody's and Fitch sample reported in Column 5-6 and 8-9 respectively. All results are significant at 54 and 1% level. The findings related to spillover effect on stock returns provide fresh evidence that CRAs' contagious reactions to natural disasters are timelier than market's contagious reactions. This is significant evidence to CRA's sensitivity to natural extreme events.

Table 4.7: Spillover Impact of Natural Disasters on Stock Returns (Spillover Effects)

Panel A: Industrial Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	-0.002	-0.017***	-0.017***	-0.009**	-0.011***	-0.01**	0	-0.019***	-0.02***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
SR_Disaster (Instrumented)	0.001	0.043***		-0.017	0.050**		-0.006	0.059**	
	(0.011)	(0.012)		(0.02)	(0.021)		(0.024)	(0.025)	
SRs_1MafterDisaster (Instrumented)			0.091***			0.083***			0.116***
			(0.012)			(0.021)			(0.024)
Disaster Event	-0.003***	-0.012***	-0.003***	-0.003***	-0.011***	-0.011***	-0.003***	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.063	0.077	0.077	0.067	0.086	0.086	0.073	0.054	0.054
No. Observations	426,954	389,900	389,900	162,561	148,303	148,303	135,790	123,830	123830
Panel B: Geographic Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	-0.0037**	-0.0096***	-0.0091***	-0.0034	0.0019	0.0015	0.034***	-0.0159***	-0.0158***
	(0.0019)	(0.0021)	(0.0021)	(0.0037)	(0.0041)	(0.0041)	(0.0047)	(0.0052)	(0.0052)
SR_Disaster (Instrumented)	-0.0125	0.0912***		-0.019	0.0418**		-0.0262	0.0445**	
	(0.0099)	(0.01)		(0.0188)	(0.0193)		(0.021)	(0.0218)	
SRs_1MafterDisaster (Instrumented)			0.0636***			-0.0176			0.0532**
			(0.0101)			(0.0199)			(0.0216)

Disaster Event	-0.0058***	-0.0021***	-0.0022***	-0.0078***	0.001	0.0011	-0.0163***	-0.0113***	-0.0113***
	(0.0004)	(0.0005)	(0.0005)	(0.0008)	(0.001)	(0.001)	(0.0006)	(0.0008)	(0.0008)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.078	0.069	0.069	0.089	0.080	0.080	0.092	0.058	0.058
No. Observations	539,203	490,864	490,864	167,273	151,976	151,976	151,419	137,745	137,745
Panel C: Supplier-Customer Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.065***	0.074***	0.074***	0.07***	0.063**	0.066**	-0.055*	-0.056*	-0.056*
	(0.015)	(0.015)	(0.015)	(0.027)	(0.027)	(0.027)	(0.032)	(0.032)	(0.032)
SR_Disaster (Instrumented)	0.031	0.23***		0.09	0.267***		-0.087	-0.071	
	(0.029)	(0.027)		(0.091)	(0.087)		(0.065)	(0.065)	
SRs_1MafterDisaster (Instrumented)			0.196***			0.254***			-0.059
			(0.027)			(0.087)			(0.064)
Disaster Event	0.001	0.001	0.001	-0.005*	-0.005*	-0.005*	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.040	0.042	0.041	0.049	0.050	0.050	0.038	0.038	0.038
No. Observations	48,029	48,029	48,029	10,265	10,265	10,265	20,542	20,542	20,542
Panel D: Customer-Supplier Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.002	-0.002	-0.001	-0.009	-0.015	-0.013	0.034**	0.034**	0.033**
	(0.007)	(0.007)	(0.007)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
SR_Disaster (Instrumented)	-0.046	0.141***		-0.182	0.220**		-0.052	-0.022	
	(0.05)	(0.048)		(0.121)	(0.112)		(0.1)	(0.099)	

SRs_1MafterDisaster (Instrumented)			0.130***			0.24**			-0.01
			(0.048)			(0.112)			(0.098)
Disaster Event	-0.0039***	-0.0033**	-0.0033**	0.0018	0.0017	0.0017	-0.0034*	-0.0033	-0.0033
	(0.0015)	(0.0015)	(0.0015)	(0.0038)	(0.0038)	(0.0038)	(0.0021)	(0.0021)	(0.0021)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.043	0.043	0.043	0.071	0.071	0.072	0.045	0.045	0.045
No. Observations	49,198	49,198	49,198	7,988	7,988	7,988	13,464	13,464	13,464
Panel E: Competitor Connection									
		Standard and Poor's			Moody's			Fitch	
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.014***	0.014***	0.014***	0.006***	0.007***	0.007***	-0.022***	-0.022***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SR_Disaster (Instrumented)	-0.079***	-0.059**		-0.093***	-0.002		-0.095***	-0.073***	
	(0.028)	(0.028)		(0.013)	(0.013)		(0.022)	(0.022)	
SRs_1MafterDisaster (Instrumented)			-0.061**			-0.011			-0.055***
			(0.025)			(0.013)			(0.019)
Disaster Event	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.049		0.049	0.052		0.052	0.041		0.041
No. Observations	2,693,742		2,693,742	1,007,735		1,007,735	959,837		959,837

The table reports the results on the spillover impact of affected firms' stock returns caused by natural disasters on their linked firms' stock returns. I apply two steps of instrumental variable (IV) analysis to test spillover transmission from affected firms' stock returns to linked firms' stock returns. The purpose is to distinguish affected firms' stock returns by natural disasters from fundamental factors. In first step, I obtain affected firms' predicted stock returns by natural disasters (i.e., instrumented) in event-month and post-event months from Eq. (3) with the dependent variable of $Return_{i,m}$. In second step, I run the following regression:

$$Return_{j,m} = a + b_1\ SRs\_Disaster(Instrumented)_{i,m} + b_2Disaster_{j,m} + c_1Controls_{j,m} + ej,m \quad (4.5.1)$$

$$Return_{j,m+1} = a + b_1\ SRs\_Disaster(Instrumented)_{i,m} + b_2Disaster_{j,m+1} + c_1Controls_{jm+1} + ejm+1 \quad (4.5.2)$$

$$Return_{j,m+1} = a + b_1SRs\_1MafterDisaster(Instrumented)_{i,m} + b_2Disaster_{j,m+1} + c_1Controls_{jm+1} + ejm+1 \quad (4.5.3)$$

Where $Return_{j,m}$ is linked firm *j*'s stock return on month *m* calculated as the natural log (stock price of firm *i* at month *m* divided by stock price of firm *i* at month *m -1*). $SRs\_Disaster(Instrumented)_{i,m}$ and $SRs\_1MafterDisaster(Instrumented)_{i,m}$ is affected firm *i's* predicted stock return caused by natural disasters in month *m* (i.e., disaster month) and month *m+1* obtained from Eq. (4.3) with the dependent variable of $Return_{i,m}$, respectively. I define a month in state A as the disaster month *m* if monthly adjusted damage is more than $US 5M. I apply firm and month fixed effects across all regressions. I have accounted for stock split when computing monthly returns. Other variables are defined as in Table 4.6.

4.4. Conclusion

Since natural disasters are increasingly becoming frequent and volatile with negative shocks to the community, it opens a question about how the consequences of natural disasters transmit to the financial markets. To have better understanding transmission channels of natural disasters, it is motivated to examine market participants' responses to natural disasters, key factors in the financial markets. The current literature primarily concentrates on market participants that are fundamentally impacted by natural disasters such as investors, banks and insurance firms (e.g., Chavaz, 2016 Alok, Kumar and Wermers, 2020; Huynh and Xia, 2021, Massa and Zhang, 2021). The essay is different from the previous studies by investigating how CRAs, an important information contributor in the financial markets, make rating changes to following natural disasters.

I first find CRAs' direct responses to natural disasters. Specifically, firms headquartered at the disaster affected states are abnormally downgraded in the event-months. I also extend the analysis to three months before and after the disaster events. I find no abnormal rating changes during three months before disasters. It is enlightened that natural disasters cannot lead to shocks to CRAs' rating behaviors in the pre-periods since they are unpredictable events. Interesting, I find rating downgrades during one month after the disasters since CRAs do need time to evaluate the consequences of natural disasters. I also find the market's similar reactions to natural disasters. Specifically, the stock price of firms located in the affected states abnormally decreases in event and post-event months. The results are significant evidence to hypothesis that CRA's rating changes following natural disasters are driven by fundamental changes. I next investigate the spillover effects of natural disasters to rating decisions. In other words, I question whether affected firms' rating changes instigated by natural disasters trigger associated firms' rating changes via different spillover channels. In the essay, I split the associated firms into connected firms (i.e., industrial peers, geographic peers and supplier-customer connections) and competitive firms, and separately test the spillover effects. By using IV analysis to extract affected firms' rating changes by natural disasters, I find different spillover effect to connected firms and competitive firms' rating changes. Specifically, affected firms' rating changes by natural disasters significantly trigger the same directional spillover effects on connected firms' rating changes and otherwise the opposing directional spillover effects on competitive firms' rating changes. The findings related to spillover effect on stock returns provide fresh evidence that CRAs' contagious reactions to natural disasters are timelier than market's contagious reactions. This is significant evidence to CRA's sensitivity to natural extreme events.

APPENDIX C

FOR ESSAY THREE

APPENDIX C.1

Investment grade		*Speculative grade*	
Rating	Score	Rating	Score
AAA (Aaa)	22	BB+ (Ba1)	12
AA+ (Aa1)	21	BB (Ba2)	11
AA (Aa2)	20	BB- (Ba3)	10
AA- (Aa3)	19	B+ (B1)	9
A+ (A1)	18	B (B2)	8
A (A2)	17	B- (B3)	7
A- (A3)	16	CCC+ (Caa1)	6
BBB+ (Baa1)	15	CCC (Caa2)	5
BBB (Baa2)	14	CCC- (Caa3)	4
BBB- (Baa3)	13	CC (Ca)	3
		C	2
		SD, D	1

APPENDIX C.2

Variable	*Description*	*Data source*
Section A: Dependent Variables		
Monthly rating changes	Measured as [CR(i,m) - CR (i,m-1)]/CR (i,m-1). CR(i,m) is the numeric rating score at the end of month assigned/maintained to a firm by the CRA.	Bloomberg
Stock Return	the natural log of (stock price at month m divided by stock price at month m-1)	CRSP
Section B: Independent Variables		
3Mbefore Disaster	A dummy variable taking value one in month m-3 prior to the disaster month m and zero otherwise.	SHELDUS
2Mbefore Disaster	A dummy variable taking value one in month m-2 prior to the disaster month m and zero otherwise.	SHELDUS
1Mbefore Disaster	A dummy variable taking value one in month m-1 prior to the disaster month m and zero otherwise.	SHELDUS
Disaster Event	A dummy variable taking value one in the disaster month m and zero otherwise. In my study, I define a month in state A as the disaster month if the total crop and property is more than the threshold (e.g., $US 5M, $US 10M or $US 100M).	SHELDUS
1Mafter Disaster	A dummy variable taking value one in month m +1 after the disaster month m and zero otherwise.	SHELDUS
2Mafter Disaster	A dummy variable taking value one in month m +2 after the disaster month m and zero otherwise.	SHELDUS
3Mafter Disaster	A dummy variable taking value one in month m +3 after the disaster month m and zero otherwise.	SHELDUS
Section C: Control Variables		
LT debt-to-equity	Total long-term debt divided by book value of equity.	Compustat
Market-to-Book ratio	The market value of equity divided by total stockholders' equity.	Compustat
Operating Margin	Operating income before depreciation divided by total sales.	Compustat
Interest Coverage	Income before extraordinary items divided by interest expense.	Compustat
LT Debt Leverage	Total long-term debt divided by total assets.	Compustat
Firm Size	The natural log of total assets.	Compustat
Stock Return Standard Deviation	The standard deviation of daily stock returns in the year prior.	Kenneth R. French & CRSP

Table C.3: Natural Disasters, Credit Rating Changes and Stock Returns (Alternative Definition)

Panel A: Credit Rating Changes						
	Standard & Poor's		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.08***	0.078***	0.042***	0.0448***	-0.0778**	-0.0791**
	(0.0119)	(0.0119)	(0.0129)	(0.0129)	(0.0353)	(0.0356)
3Mbefore Disaster		0.0159**		-0.0063		0.0207*
		(0.0063)		(0.0073)		(0.0124)
2Mbefore Disaster		0.0015		0.0009		-0.027**
		(0.0063)		(0.0073)		(0.0124)
1Mbefore Disaster		0.0036		0.0056		0.0039
		(0.0063)		(0.0073)		(0.0125)
Disaster Event	-0.0475***	-0.042***	-0.0767***	-0.0605***	-0.0069	0.0008
	(0.0063)	(0.0064)	(0.0072)	(0.0074)	(0.0122)	(0.0125)
1Mafter Disaster		-0.0465***		-0.0466***		-0.0487***
		(0.0063)		(0.0074)		(0.0125)
2Mafter Disaster		-0.0103*		-0.0255***		-0.0296**
		(0.0063)		(0.0073)		(0.0124)
3Mafter Disaster		-0.0053		-0.0008		-0.0197*
		(0.0062)		(0.0072)		(0.0123)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.012	0.012	0.014	0.014	0.008	0.008
No. Observations	108,260	107,498	60,560	60,101	47,698	47,355

Panel B: Stock Returns						
	Standard & Poor's		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0219***	0.026***	0.0181***	0.0237***	0.0171**	0.0213***
	(0.0041)	(0.0041)	(0.0056)	(0.0057)	(0.0079)	(0.008)
3Mbefore Disaster		0.0013		0.0046		0.0038
		(0.0022)		(0.0032)		(0.0028)
2Mbefore Disaster		-0.0022		-0.0002		-0.0023
		(0.0022)		(0.0032)		(0.0028)
1Mbefore Disaster		0.0023		0.0004		0.0033
		(0.0022)		(0.0032)		(0.0028)
Disaster Event	-0.0107***	-0.0053**	-0.0132***	-0.0066**	-0.0044*	-0.0008
	(0.0021)	(0.0022)	(0.0032)	(0.0032)	(0.0027)	(0.0028)

1Mafter Disaster		-0.012***		-0.0163***		-0.0107***
		(0.0022)		(0.0032)		(0.0028)
2Mafter Disaster		-0.0092***		-0.0077**		-0.0088***
		(0.0022)		(0.0032)		(0.0028)
3Mafter Disaster		0.001		0.0026		0.0016
		(0.0021)		(0.0032)		(0.0027)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.043	0.042	0.043	0.042	0.039	0.038
No. Observations	108260	107498	60560	60101	47698	47355

The table reports the robust results on the impact of natural disasters on credit rating changes and stock returns. I replicate the model estimations as reported in Table 4.4 and 4.5. I define a month in state A as the disaster month *m* if monthly affected people are more than 50.

Table C.4: Natural Disasters on Credit Rating Changes

Panel A: Industrial Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.098	-0.003	-0.003	-0.034***	0.029***	0.01***	-0.003	-0.061***	-0.051***
	(0.004)	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.004)	(0.007)	(0.007)
CRCs_Disaster (Instrumented)	0.298**	-0.023		0.564***	0.282***		-0.0296	-0.333	
	(0.107)	(0.175)		(0.107)	(0.079)		(0.092)	(0.171)	
CRCs_1MafterDisaster (Instrumented)			0.135			0.142**			-0.13
			(0.148)			(0.073)			(0.155)
Disaster Event	-0.01***	-0.011***	-0.011***	-0.016***	-0.004***	-0.011***	-0.003***	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.027	0.089	0.017	0.068	0.032	0.032	0.011	0.010	0.01
No. Observations	95,443	87,409	87,409	32,305	29,000	29,000	34,978	32,413	32413

Panel B: Geographic Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	-0.0072**	0.0059	0.0048	0.0031	0.0109***	0.011***	0.0144***	-0.0187***	-0.0184***
	(0.0032)	(0.0043)	(0.0042)	(0.0026)	(0.0017)	(0.0016)	(0.0022)	(0.0031)	(0.0031)
CRCs_Disaster (Instrumented)	0.228**	0.1976*		0.2357***	0.0693*		0.0314	-0.032	
	(0.0905)	(0.119)		(0.0668)	(0.0436)		(0.0615)	(0.084)	
CRCs_1MafterDisaster (Instrumented)			0.225**			0.1536***			0.0993
			(0.091)			(0.0378)			(0.0743)

Disaster Event	-0.0099***	-0.0082***	-0.0083***	-0.01***	-0.0012***	-0.0013***	-0.0022***	-0.0039***	-0.0039***
	(0.0007)	(0.0011)	(0.0011)	(0.0006)	(0.0004)	(0.0004)	(0.0003)	(0.0005)	(0.0005)
Control & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.005	0.004	0.004	0.03	0.009	0.009	0.016	0.023	0.023
No. Observations	184,401	178,150	178,150	52591	50434	50434	55339	53556	53556
Panel C: Supplier-Customer Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.033***	0.032***	0.03***	0.029**	0.029**	0.025**	0.036	0.036	0.036
	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.026)	(0.026)	(0.026)
SRs_Disaster (Instrumented)	0.286***	0.193**		0.787***	0.54**		-0.06	-0.077	
	(0.084)	(0.084)		(0.226)	(0.228)		(0.244)	(0.244)	
SRs_1MafterDisaster (Instrumented)			0.128*			0.553***			-0.025
			(0.071)			(0.187)			(0.215)
Disaster Event	-0.003***	-0.003***	-0.003***	-0.002	-0.002	-0.002	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Control & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.019	0.018	0.018	0.066	0.064	0.065	0.018	0.018	0.018
No. Observations	11,483	11,483	11,483	2,764	2,764	2,764	4,801	4,801	4,801
Panel D: Customer-Supplier Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.007	0.007	0.006	0.024*	0.023*	0.018	0.01	0.01	0.009
	(0.005)	(0.005)	(0.005)	(0.013)	(0.013)	(0.013)	(0.01)	(0.01)	(0.01)
CRCs_Disaster (Instrumented)	0.112	0.112		0.904*	0.797*		-0.121	-0.121	
	(0.231)	(0.231)		(0.5)	(0.5)		(0.303)	(0.303)	

CRCs_1MafterDisaster (Instrumented)			0.100			0.561			-0.045
			(0.189)			(0.435)			(0.267)
Disaster Event	-0.0059***	-0.0059***	-0.0059***	-0.0063**	-0.0063**	-0.0063**	-0.0029**	-0.0029**	-0.0029**
	(0.0013)	(0.0013)	(0.0013)	(0.0026)	(0.0026)	(0.0026)	(0.0011)	(0.0011)	(0.0011)
Control & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.010	0.010	0.010	0.076	0.076	0.075	0.026	0.026	0.026
No. Observations	12,888	12,888	12,888	2,439	2,439	2,439	3,416	3,416	3,416

Panel E: Competitor Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.012***	0.012***	0.013***	-0.003*	-0.003**	-0.003**	-0.018***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CRCs_Disaster (Instrumented)	-0.1**	-0.065		0.022	-0.011		-0.177***	-0.168***	
	(0.042)	(0.042)		(0.028)	(0.028)		(0.039)	(0.039)	
CRCs_1MafterDisaster (Instrumented)			-0.071**			-0.016			-0.087**
			(0.036)			(0.026)			(0.035)
Disaster Event	-0.007***	-0.007***	-0.007***	-0.01***	-0.01***	-0.01***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.010	0.010	0.010	0.051	0.051	0.051	0.015	0.015	0.015
No. Observations	600,928	600,928	600,928	201,672	201,672	201,672	259,281	259,281	259,281

The table reports the results on the spill-over impact of affected firms' rating changes caused by natural disasters on their linked firms' rating changes. I replicate the analysis in Table 4.6. I define a month in state A as the disaster month *m* if monthly affected people are more than 50. I apply firm and month fixed effects across all regressions.

Table C.5: Spillover Impact of Natural Disasters on Stock Returns

Panel A: Industrial Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	-0.027***	0.073***	0.074***	-0.049***	0.078***	0.081***	-0.015*	0.005	0.002
	(0.004)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
SR_Disaster (Instrumented)	0.034	0.141***		0.04	0.052		0.022	0.108**	
	(0.024)	(0.024)		(0.042)	(0.04)		(0.049)	(0.046)	
SRs_1MafterDisaster (Instrumented)			0.398***			0.537***			0.457***
			(0.024)			(0.038)			(0.042)
Disaster Event	-0.001	-0.001	-0.001	0.006***	-0.002	-0.002	-0.006***	-0.015***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.165	0.168	0.170	0.221	0.186	0.192	0.092	0.137	0.14
No. Observations	95,443	87,409	87,409	32,305	29,000	29,000	34,978	32,413	32413

Panel B: Geographic Connection									
	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	-0.0281***	-0.0114***	-0.0096***	-0.021***	-0.0059	-0.0002	0.0297***	-0.093***	-0.0932***
	(0.0032)	(0.0033)	(0.0033)	(0.0061)	(0.0066)	(0.0066)	(0.0068)	(0.0073)	(0.0073)
SR_Disaster (Instrumented)	-0.0054	0.0545***		0.0316	0.0672**		-0.0068	-0.025	
	(0.016)	(0.0157)		(0.0303)	(0.0307)		(0.0358)	(0.0355)	
SRs_1MafterDisaster (Instrumented)			0.1778***			0.299***			0.1154***
			(0.0156)			(0.0299)			(0.0342)

Disaster Event	-0.001	-0.001	-0.001	0.006***	-0.002	-0.002	-0.006***	-0.015***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.125	0.114	0.115	0.177	0.133	0.135	0.131	0.124	0.124
No. Observations	184,401	178,150	178,150	52,591	50,434	50,434	55,339	53,556	53,556

Panel C: Supplier-Customer Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.112***	0.114***	0.113***	0.123**	0.104**	0.112**	0.02	0.018	0.021
	(0.027)	(0.027)	(0.027)	(0.05)	(0.05)	(0.05)	(0.069)	(0.069)	(0.069)
SR_Disaster (Instrumented)	0.053	0.159***		0.101	0.454**		-0.051	0.098	
	(0.056)	(0.054)		(0.2)	(0.19)		(0.142)	(0.136)	
SRs_1MafterDisaster (Instrumented)			0.09*			0.34**			-0.109
			(0.052)			(0.165)			(0.125)
Disaster Event	-0.006**	-0.006**	-0.006**	-0.004	-0.005	-0.005	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.051	0.052	0.052	0.049	0.051	0.050	0.043	0.043	0.043
No. Observations	11,483	11,483	11,483	2,764	2,764	2,764	4,801	4,801	4,801

Panel D: Customer-Supplier Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.022*	0.016	0.022*	-0.046	-0.051	-0.05	0.088**	0.075**	0.086**
	(0.013)	(0.013)	(0.013)	(0.046)	(0.046)	(0.046)	(0.038)	(0.038)	(0.037)
SR_Disaster (Instrumented)	-0.053	0.222**		-0.151	0.474*		-0.317	0.008	
	(0.101)	(0.094)		(0.295)	(0.275)		(0.238)	(0.226)	

SRs_1MafterDisaster (Instrumented)			-0.066			0.655***			-0.298
			(0.096)			(0.253)			(0.207)
Disaster Event	-0.0058*	-0.0052	-0.0052	0.0132	0.013	0.013	-0.0096**	-0.0097**	-0.0097**
	(0.0033)	(0.0033)	(0.0033)	(0.0092)	(0.0092)	(0.0092)	(0.0041)	(0.0041)	(0.0041)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.067	0.067	0.067	0.080	0.081	0.082	0.064	0.064	0.064
No. Observations	12,888	12,888	12,888	2,439	2,439	2,439	3,416	3,416	3,416

Panel E: Competitor Connection

	Standard and Poor's			Moody's			Fitch		
	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*	month *m*	month *m+1*	month *m+1*
Intercept	0.027***	0.027***	0.027***	0.041***	0.041***	0.041***	0.004	0.005	0.005
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
SR_Disaster (Instrumented)	0.012	-0.05***		0.023	-0.031*		0.024	-0.028	
	(0.01)	(0.01)		(0.016)	(0.016)		(0.019)	(0.019)	
SRs_1MafterDisaster (Instrumented)			-0.031*			-0.028			-0.032
			(0.016)			(0.019)			(0.019)
Disaster Event	0.001	0.001	0.001	-0.002**	-0.002**	-0.002**	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Control Variable & FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.064	0.064	0.065	0.065	0.065	0.065	0.047	0.047	0.047
No. Observations	600,928	600,928	600,928	201,672	201,672	201,672	259,281	259,281	259,281

The table reports the results on the spill-over impact of affected firms' stock returns caused by natural disasters on their linked firms' stock returns. I replicate the analysis in Table 4.7. I define a month in state A as the disaster month *m* if monthly affected people are more than 50. I apply firm and month fixed effects across all regressions. I have accounted for stock split when computing monthly returns.

CHAPTER FIVE

CONCLUSION

This chapter concludes the thesis. I summarize the main findings in each chapter of the thesis.

This thesis aims to contribute to the literature on corporate credit ratings. Corporate credit ratings are one of the most important signals in financial markets. Firms with a higher credit rating score are likely to access the capital markets at a lower cost. Hence, understanding corporate credit rating properties is important. This thesis consists of three essays.

The first essay examines how institutional investors respond to changes in credit ratings issued by issuer- and investor-paid CRAs. I find that investors react asymmetrically: They abnormally sell equity stakes around rating downgrades by investor-paid CRAs, while abnormally buying around rating upgrades by issuer-paid CRAs. However, they do not react to negative or positive signals from issuer- and investor-paid CRAs respectively. The first essay suggests that, through their trades, institutional investors capitalize on value-relevant information provided by both types of credit rating agencies. More importantly, I even find that a dynamic trading strategy based on taking advantage of this information generates significant abnormal returns. The first essay contributes to the knowledge about the importance of investor-paid CRAs in financial markets, alongside traditional issuer-paid CRAs.

The second essay of this thesis examines whether credit ratings are distorted by political connections between CRAs and bond issuers. I find that that a higher degree of similarity of political affiliation leads to a decrease in timeliness and accuracy of downgrades prior to default events. The findings support the notion that CRAs tend to maintain/assign relative rating advantages to politically similar firms through favourable rating activities. I further show that these politically similar firms tend to increase the proportion of political donations to their favoured party following favourable credit ratings. Interestingly, this result is confined to Republican-leaning firms. The results indicate that CRAs successfully use biased credit ratings as an indirect channel of political party support.

The third essay investigates whether CRAs, an important information contributor in financial markets, adjust their credit ratings to affected firms following natural disasters and, more importantly, the analysis is extended to examine the spill-over effect of natural disasters on credit ratings of connected firms that are not directly affected by the extreme events. I find that that firms located in the disaster states are downgraded by S&P, Moody's and Fitch. By using instrumental variable (IV) analysis to extract affected firms' credit rating changes caused by natural disasters, a further investigation is carried out into the spill-over effects of natural disasters on credit rating changes of non-affected firms. I find that that the affected firms' rating changes have the same directional spill-over effects on the credit rating of connected firms which are not directly impacted by natural disasters. Connected firms are selected from the same industry, the adjoining states, or supplier-customer relationships with the affected firms. I second find the opposite directional spill-over effects of the affected firms' CR changes on their competitors' CR changes. I also find that credit rating changes in both direct and spill-over channels continue in next month following natural disasters. The results are highly robust with different identifications of natural disaster.

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